Journal of Advanced Research in Library and Information Science
Volume 11, Issue 2 - 2024, Pg. No. 20-28
Peer Reviewed Journal

Research Article

Echoes of Crisis: A Sentiment Analysis of Sri Lanka's Economic Tragedy

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I N F O

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How to cite this article:
Shuubha T A, Ali P M N. Echoes of Crisis: A Sentiment Analysis of Sri Lanka's Economic Tragedy. *J Adv Res Lib Inform Sci* 2024; 11(2): 20-28.

Date of Submission: 2024-09-02
Date of Acceptance: 2024-10-16

A B S T R A C T

Background: Sentiment analysis has become famous for extracting human emotions from text. The current study uses Twitter to show how people perceive Sri Lanka's economic woes. In the year 2022, Sri Lanka experienced a significant economic breakthrough.

Objective: The current study presents a novel viewpoint on how individuals responded to Sri Lanka's economic crisis in terms of sentiments. There can be particular information requirements because of the crisis. This study is essential for authorities to make decisions.

Method: The qualitative method was used to conduct the study with the help of the qualitative data analysis software NVivo. The researchers downloaded two sets of data regarding Sri Lanka's economic crisis corresponding to two different periods using Twitter's hashtag #SriLankaEconomicCrisis. Then, NVivo processed and analysed both data sets to identify positive, negative, and neutral sentiments.

Findings: In the first dataset, which included 2687 tweets, 82.81% expressed negative sentiment, 11.31% expressed positive sentiment, and the remaining tweets expressed neutral sentiment. Meanwhile, with the second data set, out of 1,555 tweets, 98.59% of the tweets exhibit negative sentiment, 14.21% exhibit positive sentiment, and only 1.41% exhibit neutral sentiment.

Conclusion: The research indicates that the majority of the tweets in both datasets have negative opinions on Sri Lanka's economic problems, underscoring the depth of the public's dissatisfaction. The study also fills a significant vacuum in the literature and provides crucial information for decision-makers.

Keywords: Sentiment Analysis, Sri Lanka's Economic Crisis, Twitter, Microblogging, Social Media

Introduction

In the modern world, social media has become an integral aspect of people's lives. As a result, it is now important to be aware of what is taking place on social media and what people have to say and perceive about different issues. We can gauge the state of mind of individuals by analysing the contents of social media.[1] Social media has turned out to be a very effective and efficient medium during times of crisis, such as during the COVID-19 outbreak. During the pandemic, people expressed their concerns, feelings, and the impact of the pandemic on different social media platforms as a reliable source of communication.

Thus, understanding the importance of those opinions and sentiments has become more crucial before taking any steps by authorities.[2] Understanding public-related concerns raised on the social internet through digital media channels has made it substantially easier to track how the public anticipates issues or crises. Effective communication during a crisis may alleviate social concerns and support the adoption of essential measures to mitigate risk. In a decade, social media has quickly emerged as a significant source of information and other first-hand information.[3]

As social media has grown, an abundance of information is shared there all the time. Additionally, more people have begun using various social media platforms.[4] A single tap can provide users with a lot of information. Information produces opinions, and opinions produce both positive as well as negative perspectives of a matter. Undoubtedly, social media facilitates the rapid dissemination of information that educates users about the issue and provides a viewpoint on people's thoughts.[5] Social media is an important avenue for information dissemination during times of emergency and facilitates the administration's decision-making process. The whole picture of people's demands and concerns can be ascertained with its help as well.[6] Microblogging is one of the social networking sites that reflect the public's perception. One of the most popular and advanced micro-blogging platforms that give us a place to share our thoughts and opinions in just 140 characters or less is Twitter. When there was a national or international catastrophe, whether it was the death of a famous individual or a natural or human-induced calamity, it turned out to be a social support system or suggestion forum.[7]

Sentiment analysis involves extracting human emotions as well as thoughts out of text" through computational linguistics, analysis of text, and natural language processing techniques to get insight into how individuals feel about a specific incident or issue. As a method to understand people's interest in something in terms of positive, negative, and neutral attitudes, sentiment analysis on social media platforms has grown over time. It facilitates business growth, gives insight into consumer perceptions of a brand, and tracks consumer demand for a certain product.[8] Sentiment analysis is one of the most popular and rapidly developing qualitative data analysis techniques that has greatly aided in the support of business decisions.[9] In addition to being used by businesses, sentiment analysis is increasingly being used by governments to comprehend public interest and opinions on issues to develop policies and interact with the public.[10] It has now become an important area of study. It can be used to gain an understanding of how the public feels about several different concerns in terms of favourable, unfavourable, and unbiased sentiments. It can also assist with arriving at suitable conclusions in a variety of instances, including business, politics, and social issues.[11] Twitter sentiment analysis likewise serves to evaluate the social environment and foresee potentially dangerous crises. The Twitter dataset relating to Sri Lanka's economic crisis is being analysed in this research using "qualitative data analysis" software, NVivo.

The worst financial crisis to affect Sri Lanka since it gained independence in 1948 has recently taken place. The Sri Lankan government attributes the global slump in the economy caused by COVID-19, which simply halted all economic activity for more than a year, to this country's current financial woes.[12] Due to prolonged periods of economic stability, Sri Lanka is suffering. Due to an array of events, including Sri Lanka's government's ineffective policies and their considerable decline in foreign reserves, they were unable to recover, and then in April 2022, the bubble finally burst in front of the entire the whole world. Protests then broke out all around the nation, starting in Colombo, the capital. The nation is experiencing a severe economic crisis.[13] People on social media, particularly on Twitter, express a broad spectrum of emotions and views during this challenging time.

Review of Literature

By reviewing the contributions of past research, the literature review reassures that the work has been thoughtfully conceived. A study was performed related to Syria's Chemical Attack. After physically analysing 13,156 tweets, it was found that the majority of the tweets show negative sentiments, 12.67% show "positive sentiments", and "33.63%" show a "neutral" opinion towards the incident. About 35.71% of the tweets are related to "sharing news and information," with only 2.12% "supporting the government." 77.05% of tweets were done by individuals, followed by 8.91% and 7.22% by news channels and organisations, respectively.[14] Another study analysed COVID-19-related tweets from November 2019 to May 2020 in India. Monthly, state-by-state and consolidated datasets are prepared for every state. It was found that initially, the sentiment of people in India was negative but with time despite the lockdowns people's sentiments moved towards positive and neutral comments.[15] A study examined 100,000 tweets about COVID-19 that were retrieved using various COVID-related hashtags. After an analysis with Python, Google NLP, and NVivo, it was discovered that 18.069% of tweets reflect negative attitudes, whereas 29.61% reflect positive opinions, 29.49% represent mixed sentiments, and 23.23% correspond to neutral sentiments. The popular keywords were also listed in the study.[16] In a study, a negative correlation was found between US President Trump's tweets and the COVID-19 rise in the US, and there was also an unfavourable attitude found in tweets against China and the virus.[17] R was used to carry out sentiment analysis on tweets to determine how people felt about the recent general elections in India. According to the investigation, contestant 1, Narendra Modi has greater popularity and is more publicly recognised than contestant 2, Rahul Gandhi. The results of the study mirrored the actual election results from May 2019.[18] A study was done to evaluate the relationship between Facebook comments and the results of the 2017 election in the State of Mexico. The results showed that the victorious party had unfavourable feelings on Facebook, while the losing party had positive sentiments.[19]

Sentiment analysis was used to show how changes in stock prices and public disposition are related. In this study, the DJIA (Dow Jones Industrial Average) and public sentiment were predicted by employing tweeter data. They predicted the DJIA using Twitter opinions and past DJIA prices. Self-organising fuzzy neural networks (SOFNN) and Dow Jones Industrial Average (DJIA) values were utilised to verify the proposed conclusion using a unique cross-test approach, which they applied to Twitter data from June 2009 to December 2009 to achieve a precision of 75.56%. In line with the study, confirms that public opinion can affect people's stock market investments.[20] Emotions derived from social media have been found to have an impact on market sentiment while forecasting swings in commodity markets.[21] A study performed sentiment analysis from Facebook comments. Using the Ncapture browser extension, they downloaded 626 comments and posts from Facebook onto NVivo 11's settings for analysis. Following further investigation, researchers discovered that, of the 626 comments, 215 were extremely negative, 173 were somewhat negative, 110 were fairly positive, 75 were very positive, and the remaining were neutral.[22] On mining of texts and sentiment analysis of 1500 reviews found online for e-wallet from various blogs, social media sites, and other sources, it was discovered that out of 1500 reviews, 603 had been classified as extremely unfavourable, 783 as moderately unfavourable, 848 as moderately favourable, and 457 as very favourable. The investigation included a word cloud of all sentiment terms as well as the most common words used to describe positive and negative comments.[23] In a study, tweets related to the "2010 earthquake in Chile" were examined to analyse Twitter sentiments before, during, and following the tragedy. As rumours can be deemed to be more suspicious than news among Twitter users, the results showed that the distribution of tweets relating to disinformation may be distinguished from those that are under the news.[24] The Bidirectional Encoder Representations from Transformers (BERT) model was adopted to perform a sentiment analysis study on the effects of COVID-19 on social life. Two datasets—one containing tweets from Twitter users in India and the other containing tweets from users worldwide—were used in the study. The study's findings suggest that Indian Twitter users tend to respond more positively and spread negativity less frequently.[25]

Furthermore, sentiment analysis was carried out about India's demonetisation of currency and tweets were collected through the Twitter API and processed into text in advance. A fresh strategy for SA was used to address demonetisation, the repercussions it had, and the surge of popular sentiment it had caused.[26] To better understand the "Peshawar School Attack" in Pakistan, a quantitative and qualitative study was conducted by collecting 500 tweets on the Peshawar School Attack. The study found that emotional tweets are the most common, followed by those raising questions. These tweets were primarily sent by ordinary individuals who expressed grief and prayers for the losses and questioned the Pakistani government and world leadership's submissive attitude. Many also expressed shock and outrage at the horrific incident.[27] Using a big data approach to examine the real-time tweets during the FIFA World Cup 2014, American football supporters' opinions were extracted. The study reveals that US fans exhibit no negative emotions toward games involving other teams, despite fear and fury when an opponent scores a goal.[28]

Upon reviewing the literature, it is evident that no study with the same scope and objectives has been done on the economic crisis in Sri Lanka. Thus, the researchers decided to conduct a study on the current topic.

Objectives of the Study

The study's primary objective is to examine how Twitter users interacted with the Sri Lankan economic crisis phase. Additionally, it attempts to comprehend the resemblances and distinctions between diverse Twitter responses to the crisis.

The study's objectives are presented below:

1. To examine Twitter data to determine how the general population perceives Sri Lanka's economic crisis.
2. To comprehend how the public views Sri Lanka's economic circumstances in terms of the three sentiments—positive, negative, and neutral.
3. To compare the emotions drawn from two datasets referring to different periods.

Methodology

This study employed a qualitative methodology and the qualitative research tool QSR NVivo 11 Plus to analyse the unstructured data and draw out sentiments from it. Using the hashtag #SriLankaEconomicCrisis, tweets about the economic crisis in Sri Lanka were gathered as a dataset using the browser extension N-Capture for NVivo. The tweets about Sri Lanka's economic crisis were obtained through the Twitter API in two different sets of data, spanning a period from August 28, 2022, to September 13, 2022. The first dataset includes 2,687 tweets and 1555 tweets are included in the second.

To begin the process of analysis, the datasets were subsequently loaded into the "NVivo" environment. NVivo is a research software designed for qualitative and mixed-methods studies. Its purpose is to analyse unstructured written material, audio recordings, video recordings, and visual information gathered from various sources, such as focus group discussions, interviews, surveys, social networking sites, and journal papers. QSR International is the business in charge of NVivo. Both Mac OS and Windows are compatible with it. To elicit sentiments that could be positive, negative, or neutral, data filtering was done by removing unwanted data such as "user ID, name, time and date of the tweet," etc. As this study only considers the main text of the tweets, unwanted data was removed. Then, the classification of the tweets in their respective sentiments was done using the autocode feature of NVivo.

Analysis and Result

The study's methodology is qualitative, and NVivo (QSR International), the well-known software for unstructured data analysis, is being utilised to perform the data analysis. Using the hashtag #SriLankaEconomicCrisis, tweets with two different data sets were gathered for two distinct time frames. Two thousand six hundred eighty-seven tweets about the aforementioned Sri Lanka crisis have been captured in the first dataset, corresponding to August 28 to September 6, 2022. The second dataset contains 1555 tweets from September 7 to September 13, 2022. Both datasets have been analysed using NVivo, and the following diagrams and tables illustrate the findings.

Analysis of 1st Dataset Referring to the Time Period between August 28 and September 6, 2022

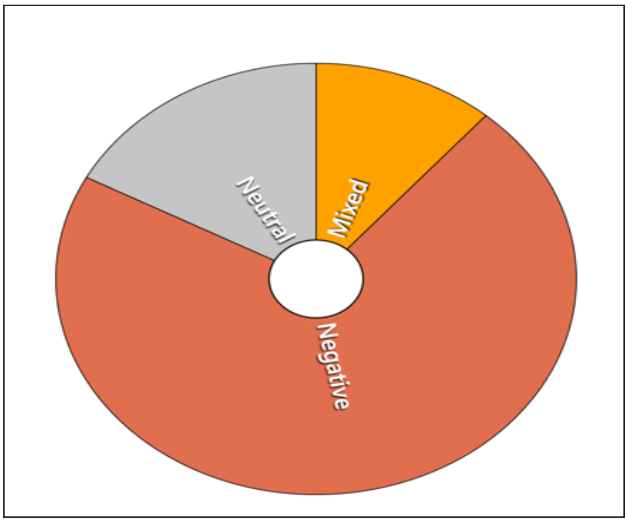

Figure 1.Sentiment Coding of 1st Dataset

In Figure 1, a sunburst chart illustrates how the first information set sentiments were expressed. The data shows that a more significant percentage of the total references express negative attitudes, whereas neutral and positive sentiments are less prevalent. The dataset was analysed using NVivo 11 Plus's auto-coding function. The attitudes derived from the dataset following analysis using NVivo 11 Plus's auto-coding function are as follows: Out of 2687 tweets on analysis, 1921 references reveal negative sentiment, 462 references reflect neutral sentiments, and 304 references exhibit mixed sentiments. In terms of percentage, 82.81% of tweets are negative, 11.31% are positive, and the remaining tweets are mixed.

Table 1 shows the words that most often appeared in the 1st dataset to represent perspectives. The most frequently occurring words are subsequently presented through calculated ranks, and a word cloud representing the same has been shown in Figure 2.

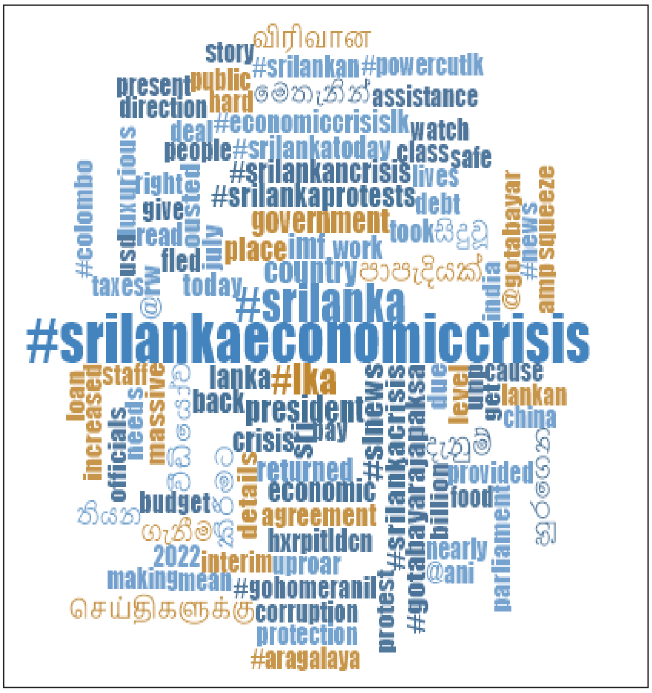

Figure 2.Word Cloud for the Most Frequent Words in the 1st Data Set

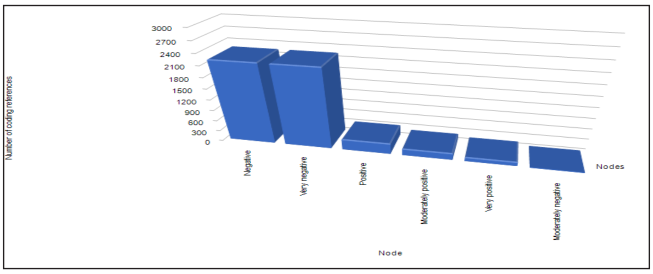

Figure 3.Summarised Result of the 1st Dataset

Table 1.Most Frequently Appearing Terms in 1st Dataset

Word	Length	Count	Weighted Percentage (%)	Similar Words
Srilankaeconomiccrisis	23	2697	4.72	#srilankaeconomiccrisis
Country	7	700	1.10	Country, 'country, land, nation, countries, nations, state, national, stated, states
President	9	641	1.12	Presidency, president, chair, chairman, president
Place	5	618	0.73	Aim, aimed, commitment, committed, direction, home, invest, investments, investing, local, locals, office, officer, officers, order, places, place, point, positions, positive, 'positive, post, posts, properties, put, ranked, rate, rates, rating, ratings, set, seating, seats, sending, situation, spot, station, stations, target, targets
Returned	8	570	0.66	Counter, comeback, deliver, delivering, generate, generation, generations, give, gives, giving, issue, issued, issues, issuing, pass, passed, passes, proceed, repay, repaying, restoring, return, returned, returning, returns, reverse, take, takes, taking, yields, yield
Government	10	536	0.81	#government, #governance, #governments, #political, #politics, authorities, authority, control, established, governing, government, order, organic, organisation, politic, political, politics, ruling, regime
Give	4	508	0.32	Applies, #breaking, afford, afforded, big, breaking, collapse, collapsed, committed, commitment, contribute, contributing, contribution, dedicated, established, feed, gift, give, gives, giving, hand, hands, hold, holding, leaves, leaving, make, makes, making, open, opens, pass, passed, passes, present, presented, presents, reach, reached, reaches, reaching, reaches, yields, yield
IMF	3	494	0.86	IMF, IMF', #IMF
Back	4	459	0.61	Back, cover, fund, funding, funds, #funds, second, stake, stakes, support, supporters, supported
Economic	8	388	0.63	#economics, #economic, economic, economically, economics, save, savings

Figure 3 shows that of the 2687 tweets analysed, 2223 were rated as very negative and two as moderately negative. Thus, 82.81% of the data set comprises tweets expressing negative emotions. While 11.31% of tweets have positive emotion, 115 have been rated as "very positive" and 189 as "moderately positive." Neutral tweets are identified as not fitting into any of these classifications. NVivo analyses words separately instead of sentences in the framework of its auto-code capability. It reflects the contrasting nature of some tweets, which fall into multiple categories.

Analysis of 2nd Dataset Referring to the Time Period between September 7 and September 13, 2022

A sunburst chart has been used in Figure 4 to illustrate how sentiments for the 2nd data set are represented. It is clear from the data that negative sentiments are expressed

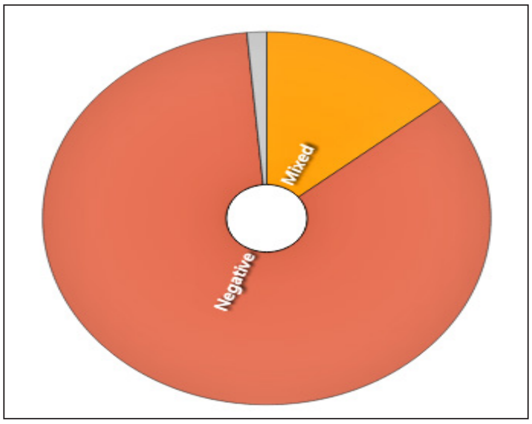

Figure 4.Sentiment Coding of 2nd Dataset

in a more significant proportion of the total references, whereas neutral and positive sentiments are less prevalent. On analysis of the dataset via NVivo 11 Plus' auto-coding function, the sentiments retrieved from it are as follows: Among the 1555 tweets analysed, 1533 references reflect negative sentiment, 22 reflect neutral sentiments, and 221 have mixed opinions. Regarding percentages, 98.59% of tweets express negative sentiment, and 14.21% represent mixed sentiment. Percentage-wise, 98.59% of tweets express negative opinions, while 14.21% reflect opinions that fall under both positive and negative sentiments. Only 1.41% of tweets were neutral.

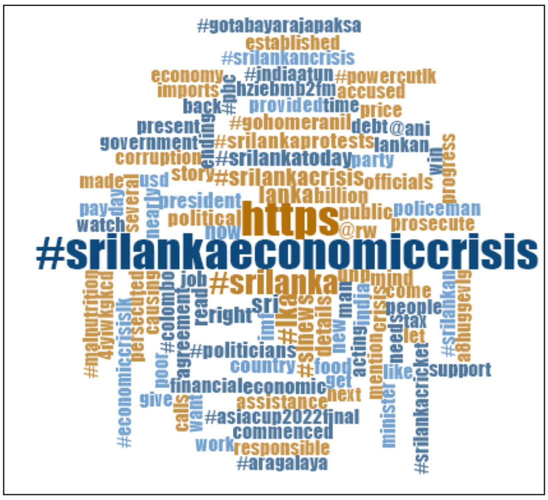

Figure 5.Word Cloud for the Most Frequent Words in the 2nd Dataset

Table 2.Most Frequently Appearing Terms in 2nd Dataset

Word	Length	Count	Weighted Percentage (%)	Similar Words
Srilankaeconomiccrisis	23	1557	4.91	#srilankaeconomiccrisis
Get	3	256	0.21	Arrest, arrested, become, becomes, bring, bringing, captured, catch, #development, development, drawing, drives, experience, fathers, find, finding, fix, fixed, generational, generations, get, gets, getting, going, growing, make, making, produce, producers, receive, receiving, suffer, suffering, sustainability, takes, take
Right	5	241	0.56	Corrected, correct, good, just, law, laws, power, powerful, proper, rights, right
Political	9	210	0.53	#political, #politics, civil, cultivation, culture, governance, #governments, governing, government, political, politics
Now	3	207	0.59	Immediately, immediate, now, nowadays, present, today
Details	7	206	0.60	Details, detail, elaborates, items, point, points, particularly
Give	4	194	0.15	Affordable, apply, big, break, breaking, #breaking, collapse, commit, commitment, contribute, contribution, feed, generations, generational, gift, give, giving, granted, hand, hands, hold, holding, leaving, liberal, make, making, open, opens, pass, passed, passes, reached, return, returns, returned, returning,

Read	4	189	0.37	Read, record, recorded, records, learn, learning, saying, show, study, studying, take, takes, understandable, understand
Public	6	179	0.42	Public, air, issue, issues, issued, issuing, package, promote, world
Causing	7	175	0.28	Case, cause, caused, causing, campaign, drives, effort, efforts, get, getting, gets, ground, make, making, reason

Table 2 represents the most frequently used words to express sentiments in the 2nd dataset, and subsequently calculated ranks show the most frequently occurring words and the same has been visualised in Figure 5 through word cloud.

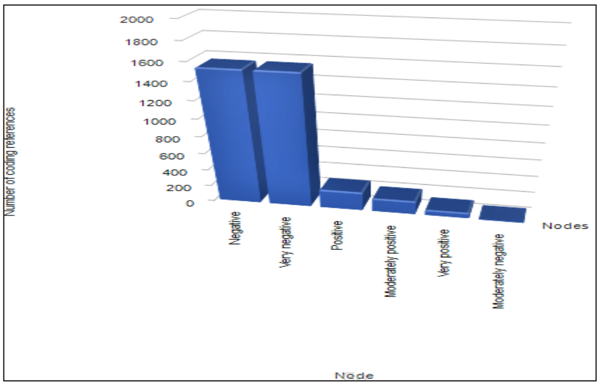

Figure 6.Summarised Result of the 2nd Dataset

Figure 6 shows that of the 1555 tweets in the 2nd dataset, 1532 were rated as very negative and one as moderately negative. Thus, 98.59% of the data set is made up of tweets that express negative emotions. 14.21% of tweets have positive sentiments, of which 159 have moderately positive sentiments and 62 have very positive attitudes. Tweets not categorised under these classifications are considered neutral.

The findings presented above in Table 3 for both datasets reflect that, even though they cover different time frames, there is no significant variation in the sentiments of the people involved in the event. However, the 2nd dataset's tweets show a relative increase in negative sentiment, indicating that the public's views of the incident are progressively more negative. When comparing the two data sets regarding the percentage of tweets, the second data set only has 98% negative sentiment, whereas the first data set has 82% negative sentiment. The following graphical representation in Figure 7 shows the comparative sentiment deviations in both datasets.

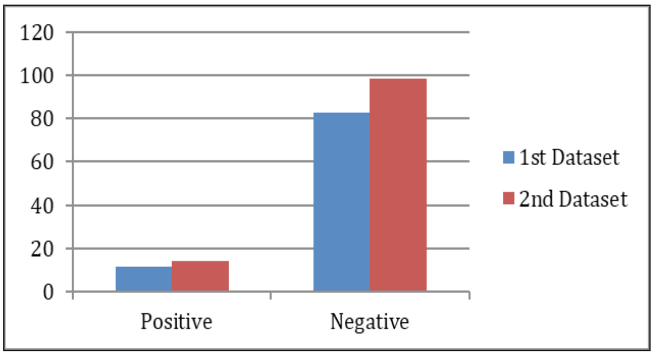

Figure 7.Summarised Comparative Sentiments of Both Datasets

Table 3.Summarised Result of Sentiments

S No.	Sentiment Values		1st Dataset	Total Inclination		2nd Dataset	Total Inclination	
				Tweets	%		Tweets	%
1	Positive	Very positive	115	304	11.31	62	221	14.21
		Moderately positive	189			159		
2	Negative	Very negative	2223	2225	82.81	1532	1533	98.59
		Moderately negative	2			1		

Conclusion

Social media has gained a significant amount of importance and influence over traditional media at present. Twitter has evolved into one of the most popular mediums of information exchange during times of crisis. Thus, it has become crucial to analyse the content over there during times of crisis. There might be specific informational requirements for such crises. During the Sri Lankan economic crisis, there were some informational needs that authorities needed to be aware of. Along with the specific informational need, general information requirements must be at the end of the authorities' decision-making process. To gather sentimental insights and explore potential similarities and contrasts in themes, the study has thoroughly analysed tweets' content regarding Sri Lanka's economic crisis.

Source of Funding: None

Conflict of Interest: None

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