Abstract - Covid-19, also known as the coronavirus, is an ongoing pandemic that spreads most often when people are physically close, and it has caused a global social and economic disruption that requires both the efforts of governments and individuals to overcome it. But as governments apply their planned measures, they lack the understanding of how individuals are moving and interacting with these measures. For that purpose, the goal of this research is to develop a geographically visual and context-aware mechanism that uses social media data, such as Twitter's tweets, to improve governments' public decision making by taking into consideration social reactions and interactions. Social media provide straightforward and familiar ways to communicate with all people categories all over the country, and that can be used by governments to communicate with the people and understand their needs and satisfaction level with the provided services. By nature, social media content reflects individuals' opinion or status at the moment of posting that refers to their current feelings and sentiment as well as what topics they are discussing between them as a whole society, while also containing data on the activities they announce to the public. The challenge here is how to analyze and understand the social media content with different languages, accents, and contexts, while also extracting the locations (in words) and convert them to a digital format (geocoding) to be projected visually on a map. This research uses NLP (Natural Language Processing) methods such as Sentiment Analysis, Emotion Analysis, Keyword Extraction, and Rule-Based Extraction to help achieve this intended mechanism of this research. This mechanism depends on geographically tracking individuals' sentiments and emotions to help the government improve on their interactions with them, while also considering their discussions as a way to understand their current thoughts and opinions. It also helps extract the most-visited geographic locations at some periods where there were interactions between individuals that might have been a cause for the suddenly increased cases of Covid-19 at these periods. Working on and analyzing a sample data of 50,000+ Twitter tweets, the research could find the approximate source location of tweets, the geographic distribution of people's sentiment and emotions spanning throughout this research period, and the geographic gathering spots which contributed more to the disease spreading at some periods. It also provides a visual output of the analysis in a geographical dashboard using the ArcGIS platform that helps the decision-maker to more understand the geographic perspective of the situation of the pandemic .For future work, we can work on extracting more data from other social media sources and enhance the extraction methods that better understand text context and provide more concrete insights.

1. INTRODUCTION

COVID-19, also known as the coronavirus, was declared a Public Health Emergency of International Concern in January 2020, and a pandemic in March 2020 after first being identified in December 2019 in Wuhan, China. It is an ongoing pandemic caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), that spreads most often via physical contact of contaminated surfaces or through the air when people are at close range as an infected person breathes, coughs, sneezes, talks, or sings. As of October 9, 2020, there have been 36.5 million cases confirmed globally as well as more than 1.06 million deaths attributed to this pandemic. Both the pandemic and response measures have contributed to social and economic disruption, including the largest global recession since the Great Depression [1]. According to recent data, around 100 million people are expected to fall into extreme poverty and global famines for 130 million people. It has also led to the postponement or cancellation of events, widespread supply shortages, partial or fully closing of Educational Institutes, with various alternatives used, and many incidents of xenophobia and racism against Chinese people and against those perceived as being Chinese or as being from areas with high infection rates.

As governments try to ease these pandemic effects on society and apply their planned measures, they often forget that what they are doing might not be accepted by the people as they wanted it to be. This pandemic requires both the government and society combined effort to prevent further spread of this virus. There is always this communication gap between governments and people as most of the decisions are taken without considering what people are currently feeling and experiencing. People usually care about decisions that affect their current situation more than logical or scientific measures that they can't see the result of directly. For that purpose, governments must have more insight into people's thoughts and opinions while also having a better way to express their decisions in a way that allows people to relate to it and achieve the intended results. So, there must be a way to better understand people's thoughts and opinions and consider them when making decisions. Social media data can be one of the best sources of insights on how people currently feel and think, as they provide a way for people to express their feelings, interests, complaints, and thoughts.

People all over the world use Social Media as a platform to express themselves as it allows them to have direct access to each other to share their thoughts and feelings about what's most important to them. It is a content that expresses the different emotions, thoughts, topics, and sentiment of society and relates to their needs and priorities as a whole community. What makes this content important is that it is coming from the people who are experiencing this pandemic directly in their everyday life and have their problems and hardships that they want to overcome. Analyzing this content and visualizing it geographically on a map can help improve governments' public decisions in many fields such as maintaining public sentiment, better decision delivery, prioritizing people's needs, and getting some opinions that might be of help to the current situation.

1. PROBLEM DEFINITION

Posts are the building blocks for any Social Media Platform as they are the content that provides this platform with context and meaning. By nature, this content is unpredictable and relates to individuals who each have their unique way of expressing themselves and sharing their thoughts and opinions. These posts come in different forms and formats as they can be sent in the form of text, images, or videos while including distinct languages or language accents unique to each country or country part. That's why it's difficult to take every aspect of these forms and formats into consideration in our analysis as there is no specific standard that we can base on. Such a problem requires us to think of a way to convert and unify these different forms into one in a way that keeps the original context intact while also allowing easier text handling for analysis. Then, we face another problem of how to get the geographic location of these posts owners as we want to differentiate between different country areas in our analysis, and that will require us to think of ways to get this data taking into consideration the source we are getting the data from.

1. BACKGROUND AND RELATED WORK

intended

1. CONTRIBUTION

The purpose of the intended mechanism of this research is to find a way that visualizes and analyzes social media content to provide useful insights about public reaction and interaction with Covid-19. It allows decision-makers to have an overview of the social situation to react to and manage any public disruption that might be the result of any planned measure they applied or due to some public disturbance. Moreover, it is the link that can fill a little bit of the gap between the government and the people.

This research proposes many solutions to reach the intended mechanism where it has to gather social media posts, discover their origins, handle many different text forms and formats, and get the geographical distribution overview of public reactions and interactions.

1. Getting Data

The data source used for this research is the Twitter Social Media Platform as it provides the most direct public and social content without the need to follow or join communities like in other platforms. Keywords related to Covid-19 and its pandemic were searched to get the sample tweets for this research.

**Keywords**: Covid, Corona, Healthcare, Medical, and كورونا

1. Location Data

Getting the locations of tweets was one of the main problems that this research wanted to solve, and by default, Twitter has its own mechanism for locating tweets as they provide two public ways to do that[??].

1. Method A: User Location Access (Settings Enabled/Disabled Option)

This option, which is disabled by default, allows Twitter to know the user location and from where did he sent his tweet. That will allow other people to search for these geo-tweets if they enter `<keyword> geocode:<latitude>,<longitude>,<radius>km` and provide a geo-location near this user.

<Insert Image Here>

1. Method B: User's Profile Location

Another way is the public user-provided profile location in the Twitter user profile page that any user can customize as he wants. Twitter then tries to link this provided location to an actual real-world location and includes these tweets in the results for the geocode twitter search like in method A.

<Insert Image Here>

1. Limitations

The problem with method A is that it only shows the geo-tweets of people who enabled twitter location access from their account settings that is OFF by default. Users usually don't know about the location option and ignore it even if they knew, while many others don't provide a specific location on their profile with method B. These limitations lead to fewer geo-tweets resulting from the geo-search, as our benchmark shows that searching for tweets with the same search parameters gives us ??x times the tweets than when we searched for geo-tweets.

<Insert Benchmark Table Here>

1. Proposed Solution

We propose the use of each user's tweets as a data bank as they reflect the user's interests and concerns. We can then extract any location reference in these tweets and consider the most frequent location this user in mentioning as a place of great importance to him and so represents his address. This method requires two things: a list of known locations details and a way to extract these location references.

* 1. Locations Data

We managed to get a list of 3000+ locations in Lebanon with their name (Latin and non-Latin), latitude, longitude, mohafaza, and kadaa.

* 1. Extracting Locations

dadsa

1. Combined Solution

Ddvx

1. Handling Different Languages

As mentioned before, social media content is full of different types of text forms and formats. This research approaches this problem from its outer perspective as it proposes a solution to unify all these forms and formats while focusing on the Lebanese language that is specific to Lebanon's Social Media Platforms.

1. Lebanese Languages

Lebanese people mostly use four languages: Lebanese, Arabic, English, and French. These languages have their own standard form and format except the Lebanese language as it is a volatile language that doesn't follow any specific standard and can be written using different letters while keeping the same meaning. Although the Lebanese language uses Arabic letters and can be considered a descendant of the Arabic language, it can also be used with English letters & numbers to form what we call "The Lebanese Internet Language" that is wildly used in social media platforms. Moreover, Lebanese people usually mix some of these languages inside the same text as they consider it a part of the Lebanese language that borrowed a lot of vocabulary from other different languages.

Table 1 - Lebanese Language Example

|  |  |
| --- | --- |
| Language | Phrase |
| English | How are you? |
| Arabic | كيف حالك؟ |
| Lebanese (English) | Kifak? or Kefak? or Keefak? |
| Lebanese (Arabic) | كيفك؟ |

1. Unifying Languages

This research proposes to unify these languages into one language that is easy to handle and work on. For that, we chose the English language as our output language as it is the most wildly used language in the world and one of the easiest and straightforward languages to work on. As the English language is very popular, many tools can convert other languages to it, and one of these tools is the most popular translation tool "Google Translate" which was used in this research to unify all other languages found in our social media data. However, even though it could translate almost everything, it was still lacking on the Lebanese language side as it couldn't translate all of the Lebanese text in our data.

1. Translating Lebanese Language

As Google Translate didn't work well on all the Lebanese text we had, we decided that we needed to create a tool to help translate the rest of these texts that couldn't be translated.

* 1. Arabic Lebanese

Although Arabic Lebanese is different than standard Arabic, it still had some similarities to it as Google Translate did a good job translating it to English.

Table 2 - Google Translation of Lebanese Arabic

|  |  |
| --- | --- |
| Lebanese | Translation |
| مرحبا | Hello |
| كيفك | How are you |
| تمام | Ok |
| منيح | Good |

* 1. English Lebanese (The Lebanese Internet Language)

As English Lebanese uses English letters & numbers without having a sentence structure or fixed vocabulary, it was hard to translate its text with Google Translate. For that purpose, an external tool was needed to help handle these texts as much as we could. This tool depends on two methods:

* + 1. Lebanese-English Dictionary Of ~2500 Words

The first thing we did was to gather the most used Lebanese words and translate them manually to create a dictionary of Lebanese-To-English translation mapping. Some of these words were gathered from Google's Lebanese-To-English dictionary [1] containing around 1500 Lebanese words translated into English. The other words were gathered and filtered from a data bank of 10,000 random Twitter tweets after removing any words related to other languages and manually translating the rest of the Lebanese words. This Dictionary also includes many variations of the same word where we tried our best to keep the definition as global and general as possible to match as many use-cases as we could. We should also note that some words’ meaning can differ according to the context.

Table 3 – Lebanese to English Dictionary Example

|  |  |
| --- | --- |
| Lebanese | English |
| 2ahwe, 2hwe, 2ahwi | Coffee |
| Adiim, Adiime, Adeem, Adeeme | Old |
| Dahab, Dahabi, Dahabiiyi | Gold |
| 2sm, Esm | Name |
| Eta2es | The weather |
| Jeser | Bridge |
| 7arara | Temperature |

* + 1. English Lebanese 🡪 Arabic Lebanese 🡪 English

Another way was to convert these English Lebanese words into Arabic Lebanese by mapping English letters to their respective Arabic version so that we can approximate the Arabic word. After that, we pass this Arabic version of the word to an Arabic spell checker to help us correct the word as much as possible which is then translated into English.

Table 4 - Mapping of Single letters

|  |  |
| --- | --- |
| EN Singles | AR Mapping |
| A | ا |
| B | ب |
| D | د |
| E | ي |
| F | ف |
| G | ج |
| H |  |
| I | ي |
| J | ج |
| K | ك |
| L | ل |
| M | م |
| N | ن |
| O | و |
| Q | ق |
| R | ر |
| S | س |
| T | ت |
| W | و |
| Y | ي |
| Z | ز |
| 2 | ء |
| 3 | ع |
| 5 | خ |
| 7 | ح |
| 8 | غ |

Table 5 - Mapping of Double Letters

|  |  |
| --- | --- |
| EN Doubles | AR Mapping |
| aa | ع |
| th | ث |
| sh | ش |
| sa | ص |
| da | ض |
| ta | ط |
| fa | ف |
| 2e | ء |
| eh | اي |
| en | ين |
| ll | لا |

Table 6 - Translation Operation Example

|  |  |  |  |
| --- | --- | --- | --- |
| LB | LB-AR | AR | EN |
|  |  |  |  |
|  |  |  |  |
|  |  |  |  |
|  |  |  |  |

* + 1. Final Tool

As our dictionary didn't cover everything and still lacked a lot of words, we tried to check for similar words by using different methods (Insertion, Deletion, and Substitution) as some words differ by 1-2 letters but still have the same meaning. These methods are Fuzzy Searching [1] methods and can be observed in the following example (Table 7).

Table 7 - Fuzzy Search methods

|  |  |  |  |
| --- | --- | --- | --- |
| LB 1 | LB 2 | EN | Action |
| Hone | Hon | Here | Insert “e” into “Hon” |
| 2hwi | 2ahwi | Coffee | Delete “a” from “2ahwi” |
| Kifak | Kefak | How are you | Substitute “e” with “i” |

After this check, similar words were translated according to the dictionary while the other words were translated from Lebanese to English by mapping them to Arabic then translating to English.

1. Observations

After some observations, we found that these two methods combined give very good results for individual word translation but lack in keeping the text connected as our tool translates each word individually. Although the resulted text is not connected, we still managed to keep the mood and general intent of the text as it still contained some of its original meaning.

Table 8 - Lebanese to English Translation Samples

|  |  |  |
| --- | --- | --- |
| Lebanese | Google Translate | Tool |
| kn mnsab bas sa7 halla2 | Be the position, but correct Hala | was Position enough correct now |
| eh walla nsab bl marad | Uh, not lineage, but murad | yes indeed set up at disease |
| wasfi men edoctoor | My description is from Adster | prescription from doctor |

1. Data Study & Analysis

Our main aim was to study the social reactions and interactions between people during the Covid-19 pandemic period of this research, which needed to be preceded by location data extraction and unifying of the content to be in the English language for easier handling. We then chose to split our work into main categories and subcategories. (Figure 1)

Figure 1 - Analysis Workflow

1. Sentiment Analysis

Sentiment analysis is an already known Natural Language Processing (NLP) method that extracts text sentiment and categorizes it. It was a tool that didn't need much work to be useable. But, it was essential to note that sentiment analysis can differ based on what it has trained on as there were many variations of trained sentiment analysis models. For this research, we used the TextBlob python tool as it provided all of the three sentiment categories (positive, negative, and neutral) that we based on to study the reactions of the people during the Covid-19 pandemic. We then visualized it on our map through individual tweet sentiments, mean Kadaas sentiment, and mean Mohafazat sentient distribution.

|  |  |
| --- | --- |
| Text | Sentiment |
|  | Positive |
|  | Neutral |
|  | Negative |

1. Emotion Analysis

Another way to study public reactions was to extract the emotions of people inside our data. This study consisted of examining the tweets to probe for any reference to the eight basic emotions (anger, disgust, fear, sadness, surprise, anticipation, joy, and trust). Using a 14,000 emotion lexicon word list from the National Research Council Canada (NRC) [??], we were able to find how people felt through this research pandemic period and visualize that data as we did with the sentiment analysis.

1. Topic Extraction

We based our Topic Extraction on the popular TF-IDF model [??]. It is a numerical statistic intended to reflect how important a word is to a document in a collection or corpus. What we did here was to optimize this model's settings to best suit our use case.

* 1. Cleaning Data

Removing any non-alphabets character from our text, correcting spelling mistakes, and then lemmatizing [??] words to return them to their original form so that they are not redundant.

* 1. Creating Stopwords

Stopwords are a list of words that we tell our TF-IDF model to neglect and never consider when extracting topics. These words contained frequent words like pronouns (He, She, I, ...),

* 1. N-grams

As extracting single keywords was lacking, we set our model to return the most relative bi-grams (2 words phrases) and tri-grams (3 words phrases) so that we could have some context and not just lonely keywords.

* 1. Manual filtering

We choose to set our model to return the best 25 bi-gram and 25 tri-grams combinations that we filtered manually for better results and clarity.

1. Public Interactions

fhghfg