**Evaluating the Effect of Covid-19 on Emotional and Mental Health**

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**Abstract**

Covid-19 has caused unprecedented times full of shutdowns, unemployment, death, and isolation. The impact of Covid-19 is investigated in this study through the use of sentiment analysis and emotion recognition. The dataset is formed by collecting tweets from the seven months before Covid-19 became prevalent in March 2020 and the following seven months after. VADER sentiment analysis was used to determine if a tweet was positive, negative, or neutral. For emotion recognition, several machine learning algorithms were evaluated and Convolutional Neural Network (CNN) Long-Short Term Memory (LSTM) performed better than the other models. Hence, for emotion recognition CNN LSTM was used to classify the emotion of each tweet as either anger, fear, joy, or sadness. Each tweet has a longitude and latitude stored with it that was geocoded to give the exact location, which was used to compare the counties within the state of Ohio, compare the states with the USA, and finally compare the USA as a whole with Canada, and Mexico. Sentiment analysis shows that all countries have experienced an increase in negative tweets. Emotion recognition shows that compared to Canada and Mexico, Ohio and the rest of the USA have experienced a steep drop in emotional health.

1. **Introduction**

The year 2020 will certainly go down as one of the most impactful years in history in large part due to the Covid-19 virus. As of December 5th 2020, there have been over 1.5 million deaths worldwide and over 270 thousand deaths in the US alone [1]. In the 15 weeks from mid-March to the end of June, nearly 49 million Americans filed new claims for unemployment, compared to the year before when only 3.3 million filed during the same time frame [2]. In addition, close to 100 thousand businesses in the US have permanently closed due to the pandemic [3]. These factors including others such as being in quarantine for months, unable to see friends and love ones, has led to a decrease in the mental health of society. A poll released by the American Psychiatric Association in October, revealed that 62% of Americans feel more anxious now than they did at the same time a year ago [4]. While polls have typically been the standard of acquiring data about people, social media is a large untapped resource that could give a more in-depth insight to the state of the public’s mental health.

Social Media has grown exponentially since 2004 and its reach will only continue to grow as technology becomes more easily accessible and each new generation grows up using it. Specifically, Twitter is an application that already has a base of 330 million people with over 500 million tweets sent per day [5]. Tweets are defined as messages of up to 280 characters that users post to their timeline for their friends to see. The application is designed so users will post rapid reactions about how they are feeling and what is going on in their world. This constant mood update can be used to better detail the mental and behavioral wellbeing of the country.

This study evaluates the condition of the mental and behavioral health of twitter users with the use of both sentiment analysis and emotion detection after the data has been collected and preprocessed. Sentiment analysis is a form of natural language processing in which text is run through an algorithm to assign the text a sentiment of positive, negative, or neutral. Sentiment analysis will be used to find the general overall feeling of the dataset. Emotion recognition is a machine learning technique that predicts the emotion of a given string based upon data it was trained on. Emotion recognition will be used to determine the prevalent emotion for each tweet in the dataset.

There has been similar work done on the subject of sentiment analysis and emotion recognition. A study was done in the UK by Kleinberg et al. [6] where a linear regression model was used to predict emotion about Covid-19 from data collected in a 2,500-participant survey. Our study improves upon this by using a more accurate model, applying sentiment analysis, and working on a much bigger dataset that comes from twitter instead of a survey. Ohashi [7] performs sentiment analysis and emotion recognition on a twitter dataset giving a total score for each emotion for the entire dataset. Our study goes beyond this by predicting emotions for each individual tweet and applying comparing the entire United States over time as well as the individual counties in Ohio. Another study was done by Martinez [8] to detect depression from tweets using machine learning but this was limited to simply determining if a tweet was positive or negative and nothing more. Mohammad et al. conducted a study in which they run emotion detection on tweets and focus on the relationship between different emotions and determine which emotions appear together in tweets [9].

To address the existing limitations in the literature pertaining to the study of the effect of covid-19 on the mental and behavioral health of society, the contributions of this study are to: (1) visualize how the general sentiment of the United States and Ohio has changed seven months prior and after COVID-19 , (2) visualize how the emotion of the US and Ohio residents has changed seven months before and after COVID-19 in order to identify specific areas that could be in need of more immediate help and (3) visualize how the general sentiment and the emotion of the residents of US compare with the residents of Mexico and Canada seven months before and after the COVID-19 pandemic.

The rest of the paper is organized as follows. Section 2 describes the data and methodology used for the experimentation and analysis. Section 3 presents the emotion detection and sentiment analysis experimentation results. Section 4 discusses current limitations and future work recommendations. Finally, section 5 provides the summary and conclusion.

1. **Data and Methodology**

The main workflow of this study can be seen below in Figure 1. The Twitter data is first collected using Twitter’s API. Then the data is prepared for the next steps by being preprocessed which converts the tweets to a usable format. The dataset is then reverse geocoded using the longitude and latitude stored in each tweet. The dataset is then run through the sentiment analysis model to give it a score of either -1,0, or 1. Finally the dataset is run through the emotion recognition model to assign an emotion for each tweet The sentiment analysis and emotion recognition results are then visualized for Ohio counties and the US states comparing the months before and after covid-19.

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Figure 1. Overall research workflow

* 1. **Dataset and Preprocessing**

The dataset used was created using the Twitter Stream API and consists of 5,678,432 tweets posted from the months of July 2019 to early September 2020. This data set was separated into two periods: before Covid-19 was prevalent which consists of tweets from July 2019 to February 2020 and after Covid-19 which is the tweets from the remaining months of March 2020 to September 2020. This cutoff time was chosen as Ohio went into an official state of emergency in March as well as a stay-at-home order being issued. In order to speed up the model run times, the dataset was split into smaller datasets such as countries, months, and a separate dataset for Ohio. The data was then reverse geocoded using the reverse\_geocoder Python library [10] which takes in the longitude and latitude as parameters and returns a list of four location columns that for the US includes the country, state, city, and county. These values were added to the existing columns of TweetID, Date, TweetMessage. A sample dataset can be seen below in Table 1.

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**Table 1.** Sample Dataset

Before the data can be run through the models, it must be cleaned up with text preprocessing. This includes removing links usernames, char repetitions, common stop words and transforming emojis to text. The characters are then all converted to lowercase.

* 1. **Sentiment Analysis**

Sentiment analysis is used to assign a positive, negative or neutral score to a given string. It is useful to gauge how the general emotion of the dataset changes over time. Each tweet is given a floating-point type score which is then compared to a threshold range to determine the sentiment. If the score is above the threshold, it is assigned a ‘1’ to represent a happy emotional state. A score below the threshold will result in a ‘-1’ that corresponds to a negative emotional state. Any score inside the threshold range will return a ‘0’ representing a neutral emotional state. In order to implement sentiment analysis, the python model VADER (Valence Aware Dictionary and sEntiment Reasoner) was used. VADER uses a dictionary of words that maps lexical features to emotion intensities otherwise known as the sentiment score [11]. Each word in the dictionary has an intensity assigned by individual human raters so for example, “excellent” has a higher score than “good.” The sentiment score is obtained by summing the intensity of each word in the tweet. Other rules can affect the score such as punctuation, capitalization, degree modifiers, and negation. A sample output after running the model is shown below in table 2.

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**Table 2**. Sentiment Analysis Output

Typically, only a score of ‘0’ would be classified as neutral. However, since there is the possibility that the model may be slightly biased towards either the positive or negative side, the threshold is made of the range from -0.05 to +0.05. This insures there is no imbalance and improves the overall accuracy.

The overall flow of the sentiment analysis can be seen in the following steps. 1) The dataset is run through VADER which returns a raw score for each tweet. 2) The raw score is converted into a ‘1’ if the raw score is above 0.05, a ‘-1’ if the raw score is below -0.05 and a ‘0’ otherwise. 3) The data is then aggregated by count for the months before and then after covid-19 in Ohio and the whole US as well as Canada and Mexico to see if there are noticeable dips in the overall sentiment over time.

* 1. **Emotion Recognition**

While sentiment analysis is useful to determine the general feeling of the dataset, a different model is required to determine specific emotions contained in a given tweet. According to a recent study [12] there are as many as 27 distinct categories of emotion therefore making it difficult to predict a specific emotion with only 240 or less character. Therefore, to simplify it for the model to work properly, only 4 main emotions were chosen: joy, fear, sadness, and anger. Many different models were tested but the most accurate was found to be the CNN LSTM model architecture.

* + 1. **Evaluation of Emotion Recognition Algorithms**

In order to select the best model to use, a variety of ML algorithms were evaluated using the training dataset. The training dataset was split into two, 80% of which was used to train, evaluate and select the best model, while the remaining 20% was used for validating the predictions. Among the models evaluated were Logistic Regression, Linear Discriminant Analysis, KNeighbors Classifier, Decision Tree Classifier, GaussianNB, Support Vector machine, and Convolutional Neural Network (CNN) Long-Short Term Memory (LSTM). Logistic Regression works by estimating discrete values such as 0/1 or yes/no based on independent variables. It predicts the probability of an occurrence of an event by fitting data to a logit function [13]. Linear Discriminant Analysis consists of statistical properties of the data, calculated for each class such as the mean and variance. These properties are calculated from the data and then plugged into the LDA equation to make predictions. KNeighbors works by storing all available cases and classifying new cases by a majority vote of its k neighbors. The case assigned to the class is the most common amongst its K nearest neighbors by a distance function. The Decision Tree Classifier is a supervised learning algorithm that splits the population into two or more homogeneous sets. These slits are based upon the most significant attributes and independent variables to make as distinct groups as possible. The GaussianNB algorithm is a special type of NB (Naïve Bayes) that works when the features have continuous values. NB works on conditional probability to calculate the probability of an event using its prior knowledge. The Support Vector Machine algorithm plots each data item as a point in n-dimensional space with the value of each feature being the value of a particular coordinate. Then a line is made to split the data into two differently classified groups of data based on which side of the line the data point lands. Finally, CNN LSTM is an architecture that uses the CNN layers to extract features from the input data and combines with the LSTM layer to support sequence prediction These models were all trained with the same data and given an accuracy score, macro f1 score, recall, and precision based on how well their predictions matched the validation data. A comparison of the accuracy scores as well as macro f1-score, recall, and precision for each model can be seen below in figure 2. From the chart it can be seen that the CNN LSTM has the best overall accuracy with a score of 93%. This trend is also reflected in the macro f1, recall, and precision scores as CNN LSTM is determined to be the best all-around model.

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**Figure 2:** Algorithm Comparisons

* + 1. **Data Preparation**

In order to train the model, a new dataset was created using the Twitter API. This dataset needed to be already labeled with an emotion so that the model would be able to learn from it. This was done by searching for tweets with hashtags such as #joy, #sad, and etc. as well as emojis such as crying\_face, pouting\_face, and face\_with\_tears\_of\_joy. These queries were all then mapped with a json file to 1 of the 4 main emotions: joy, anger, fear, and sadness. Once each emotion had a size of around 3500 entries, they were combined into a single dataset that can be seen below in figure 3.

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**Figure 3**. Training Dataset

* + 1. **CNN LSTM**

Convolutional Neural Network (CNN) Long-Short Term Memory (LSTM) is a machine learning model architecture that involves using CNN layers for feature extraction on input data combined with LSTMs to support prediction. The basic overview of the model can be see below in figure 4.

Diagram

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**Figure 4**. CNN LTSM Overview

The model works by first instantiating a Keras tensor object with the input layer. The dataset is then embedded in the output layer. The embedding step encodes the data so that each word is represented by a unique integer. The embedding function sets the input\_dim to 100 so the values are between 0-99, while the output\_dim which defines the size of the output vectors from this layer for each word is set to 500. The embedding input length is the length of the sequences so it is set to 100. For the SpatialDropout1D layer, if adjacent sequences within feature maps are strongly correlated then it will regularize the activations and will help promote independence between feature maps.[14].

The next layer is where the Bidirectional LSTM begins. This layer runs the input in two ways, one from the past and other from the future. Doing this will create two copies of the hidden layer, one fit in the input sequences as-is and one on a reversed copy of the input sequence. By default, the output values from these LSTMs will be concatenated. LSTM is made up of repeating modules of neural network as can be seen in Figure 5. The cell state is the horizontal line across the top where information can flow unchanged unless changed by gates which are composed of a sigmoid neural net layer and pointwise multiplication operation. In a typical run through the LSTM, the first step is deciding which data to get rid of from the cell state. This is decided by the sigmoid which will output a number between 0 and 1 where 0 means no data is let through and 1 meaning all data is allowed through. The next step is to decide what new information to store in the cell. The sigmoid will again decide which values to update while the tanh layer creates a vector of new values that could potentially be added. These two layers combined by multiplying the old state by which forgets the things that were decided to forget earlier, and then adding ∗ , the new candidate values scaled by how much was decided to update each state value. The final step, deciding what to output, is based on a filtered version of the cell state. A sigmoid layer is run to decide which part of cell state to output, followed by a tanh, and multiplied by the output of the sigmoid gate so only the desired parts are output [15].

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**Figure 5.** LSTM Network

The next layer of the model is the convolutional neural network. Convolutions are linear operations that multiply the input with the set of saved weights called a filter. The filter is smaller than the dataset and the multiplication used is a dot product. After all the filters are applied, the output is saved in a feature map [16]. In the next layer, average pooling calculates the average value for each patch on the feature map while max pooling calculates the max value for each patch of the feature map and the results of these two functions are concatenated together. The final step in the model is the Dense layer which implements the operation of activation(dot(input, kernel) + bias). The activation function performs element-wise activation, while the kernel is the weights matrix, and the bias is a vector created by the layer. The output is a vector set to the size of many classes there, which in this case is the four emotions of anger, fear, joy and sadness. For each tweet, the model returns a score for each emotion and the emotion with the highest score is set as that tweet’s main emotion.

1. **Experimental Results and Discussion** 
   1. **Sentiment Analysis** 
      1. **Ohio Sentiment Analysis**

Figure 6 displays a choropleth map of the state of Ohio where each county is colored by how many negative tweets were sent from there. The aggregate of negative tweets in the months before covid-19 (July 2019-Feb 2020) is shown on the left while the months after covid-19 (March 2020-September 2020) is displayed on the right. These were created by finding all the tweets in each time frame that had a sentiment score of -1 and then the data was grouped by county and the totals were summed to give the final numbers.

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**Figure 6.** Ohio Counties Sentiment Map

|  |  |  |  |
| --- | --- | --- | --- |
| **Sentiment** | **Before Covid-19** | **After Covid-19** | **% Change** |
| **Negative** | 34369 | 44021 | 28.0834 |
| **Positive** | 33462 | 34324 | 2.57606 |
| **Total Dataset** | 86545 | 90609 | 4.69582 |

**Table 3.** Ohio Counties Sentiment Table

Table 3 displays the negative sentiment numbers represented in figure 6 as well as the positive aggregate and the size of the entire Ohio dataset. It can be seen from both the map and the table that the number of negative tweets in Ohio has grown exponentially since covid-19 became prevalent. While the full dataset only grew by 4.7%, the number of negative tweets grew by 28%. On the other hand, the number of positive tweets only increased by 2.6%, close to half the amount the full dataset grew meaning the percent of positive tweets in the dataset went down.

* + 1. **US Sentiment Analysis**

Figure 7 displays a choropleth map of the entire USA where darker colors represent a larger quantity of negative tweets. Once again, the aggregate of negative tweets in the months before covid-19 (July 2019-Feb 2020) is shown on the left while the months after covid-19 (March 2020-September 2020) is displayed on the right.

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**Figure 7.** USA Sentiment Map

|  |  |  |  |
| --- | --- | --- | --- |
| **Sentiment** | **Before Covid-19** | **After Covid-19** | **% Change** |
| **Negative** | 211943 | 263074 | 24.1249 |
| **Positive** | 169924 | 201991 | 18.8714 |
| **Total Dataset** | 446756 | 544023 | 21.7718 |

**Table 4.** USA Sentiment Table

Table 4 illustrates the trend shown in figure 7, that the number of negative tweets in the whole US has increased in the months since the covid-19 pandemic began. The number of negative tweets increased by 24% while the dataset increased by only 21%. Furthermore, the positive tweets only increased by 18.9%, well below the increase of the dataset, meaning the percent of positive tweets in the dataset decreased.

* + 1. **North America Sentiment Analysis**

Figure 8 displays a line graph comparing the sentiment scores of the North America countries of USA, Canada, and Mexico. The data was constructed using the raw value that came out of the sentiment analysis function and averaged with the other tweets from the month. The graph shows the average score over the 14 months of interest with the US in blue, Canada in orange, and Mexico in Green.

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**Figure 8. North America Sentiment Graph**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Sentiment** | **Before Negative** | **Before Positive** | **Total** | **After Negative** | **After Positive** | **Total** | **Total % Change** | **Pos % Change** | **Neg % Change** |
| **USA** | 211943 | 169924 | 446756 | 263074 | 201991 | 544023 | 21.77 | 18.8714 | 24.124 |
| **CANADA** | 37552 | 43834 | 98895 | 37110 | 41226 | 97764 | -1.14 | -5.95 | -1.18 |
| **MEXICO** | 3933 | 2958 | 12661 | 3863 | 2567 | 12252 | -3.230 | -13.218 | -1.78 |

**Table 5.** North America Sentiment Table

In figure 8 it is notable that each country takes a large dip in the month of April, which corresponds to when the Covid-19 virus became prominent and the lockdowns began. It can also be seen that Canada has a much higher overall sentiment score over the months than both the US and Mexico. Table 5 compares the aggregate sentiment scores for the countries. It is notable that for each country, the number of negative tweets grows by much more than the positive tweets increased. The USA and Canada both had higher negative tweet percent increases than the overall dataset growth percentage.

* 1. **Emotion Analysis** 
     1. **Ohio Emotion Analysis**

Figure 9 displays a choropleth map of the aggregate of fear tweets from July 2019 to September 2020 of Ohio counties. Darker shades refer to a higher concentration of tweets in that area. The map on the left is pre-covid-19 (July 2019 to February 2020) while the map on the right displays data post covid-19 (March 2020 to September 2020).

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**Figure 9.** Ohio County Fear Map

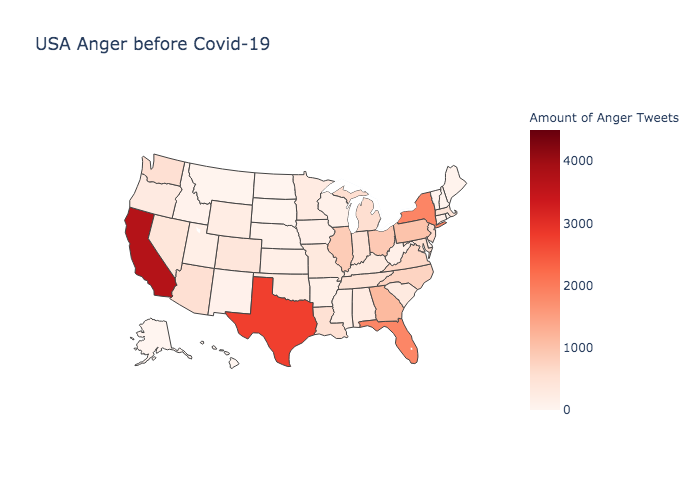
|  |  |  |  |
| --- | --- | --- | --- |
| **Emotion** | **Before Covid-19** | **After Covid-19** | **% Change** |
| **Anger** | 6064 | 6604 | 8.9 |
| **Fear** | 35638 | 46325 | 29.99 |
| **Joy** | 22802 | 23123 | 1.41 |
| **Sadness** | 14469 | 14802 | 2.24 |
| **Total Dataset** | 86545 | 90609 | 4.69 |

**Table 6.** Ohio County Emotions

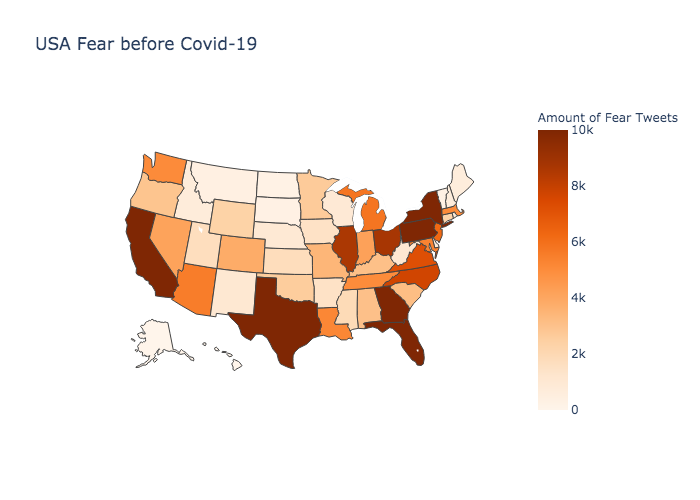
In figure 9 it can be seen that a good portion of the counties become darker on the map post covid-19 compared to the pre-covid19 map. This is reflected in the table 6 where the data for all four emotions is displayed. It can be seen that both fear and anger increase at a rate higher than that of the dataset. Joy on the other hand, decreases compared to the overall dataset.

* + 1. US Emotion Analysis

Figure 10 displays choropleth maps of the aggregate of each emotion from July 2019 to September 2020 for the entire USA. Each row of maps compares a different emotion: anger, fear, joy, and sadness. The maps on the left display the data before Covid-19 (July 2019 to February 2020) while the maps on the right display the data after Covid-19 (March 2020 to September 2020).

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**Figure 10.** Emotion Maps for Entire USA

|  |  |  |  |
| --- | --- | --- | --- |
| **Emotion** | **Before Covid-19** | **After Covid-19** | **% Change** |
| **Anger** | 25340 | 58597 | 131.2 |
| **Fear** | 255450 | 544023 | 112.97 |
| **Joy** | 139142 | 142739 | 2.585 |
| **Sadness** | 26824 | 29095 | 8.46 |
| **Total Dataset** | 446756 | 774454 | 73.35 |

**Table 7.** USA Emotion data

The maps in figure 10 show how the emotions in the US have changed over time with noticeable increases coming in the anger and fear maps. Those increases are reflected in table 7 where fear increased by 113% and anger by 131%. Compared to the dataset’s growth of 74% those two emotions have grown considerably while joy with a 2.6% growth has once again decreased.

* + 1. **North America Emotion Analysis**

Figure 11 displays choropleth maps of each of the four different emotions for the three main North American countries: USA, Canada, and Mexico. Each row of maps compares a different emotion: anger, fear, joy, and sadness. The maps on the left display the data before Covid-19 (July 2019 to February 2020) while the maps on the right display the data after Covid-19 (March 2020 to September 2020).

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**Figure 11.** North America Emotion Maps

|  |  |  |  |
| --- | --- | --- | --- |
| USA Emotion | Before Covid-19 | After Covid-19 | % Change |
| Anger | 25340 | 58597 | 131.2 |
| Fear | 255450 | 544023 | 112.97 |
| Joy | 139142 | 142739 | 2.585 |
| Sadness | 26824 | 29095 | 8.46 |
| Total Dataset | 446756 | 774454 | 73.35 |

|  |  |  |  |
| --- | --- | --- | --- |
| **Canada Emotion** | **Before Covid-19** | **After Covid-19** | **% Change** |
| **Anger** | 4180 | 4353 | 4.14 |
| **Fear** | 53408 | 53743 | 0.63 |
| **Joy** | 38528 | 37409 | -2.9 |
| **Sadness** | 2779 | 2286 | -17.74 |
| **Total Dataset** | 98895 | 97791 | -1.12 |

|  |  |  |  |
| --- | --- | --- | --- |
| Mexico Emotion | Before Covid-19 | After Covid-19 | % Change |
| Anger | 127 | 83 | -34.65 |
| Fear | 5016 | 4809 | -4.13 |
| Joy | 7377 | 7212 | -2.24 |
| Sadness | 141 | 155 | 9.93 |
| Total Dataset | 12661 | 12259 | -3.18 |

**Table 8.** North America Emotion Data

The maps in figure 11 are a good way to visualize the size of each emotion dataset but the changes over time are best seen in table 8. In contrast to the steep increase in fear in the US, Canada and Mexico only see slight gains. Where the US saw a large increase in anger tweets, Canada barely increased while Mexico went down. Canada remains even-keeled with the exception of sadness which has a sizeable decrease. In Mexico, anger decreases significantly while joy and sadness both increase relative to the dataset. Overall this suggests that the US was affected more significantly by Covid-19 than its fellow North American countries.

1. **Limitations and Future Works**

One major limitation in this study was the use of only four emotions. A human on average has as many as 27 emotions [12], but for this study it was not feasible to train the model for each of these specific emotions based solely off of small tweets. It would be possible If there was a larger dataset already labeled for each of these emotions, but it is difficult since many emotions are very similar to each other for example, excitement, triumph, and joy or fear and horror. When emotions are so closely linked, it is difficult for even a human to determine the emotion, much less a computer.

Another limitation was the size of the dataset. While close to 6 million tweets collected over 14 months may seem large, it’s a drop in the bucket compared to the 500 million tweets per day [5]. With so many tweets out there, it would be near impossible to run them all through the model with current technology. The tweets collected are a good representation of the full dataset, but it will never be 100% accurate of the public’s emotions.

For future work on this study, more countries could be added to do a global comparison of how mental and emotional health has changed. Increasing the dataset to include every country would also give a much better understanding of how the USA differs compared to the rest of the world. In addition, specific problem areas such as US state counties or entire US states with low sentiment and emotion scores could be targeted as needing more immediate help. Future work could include reaching out to leadership in these areas to better inform them of the state of their residents.

1. **Conclusion**

This study analyzed the effect of Covid-19 on the emotional and mental health of the general public in North America, USA, and Ohio using sentiment analysis and emotion recognition on a twitter dataset. Sentiment analysis was used to give each tweet a score which was used to classify tweets as positive, negative, or neutral. Emotion recognition was used to classify each tweet with an emotion of either anger, fear, joy, or sadness. These techniques were useful to visualize the data from July 2019 to September 2020) and evaluate how they changed as Covid-19 began affecting the world.

Many different machine learning algorithms were evaluated in this study in order to determine the best possible option for emotion recognition. The algorithms evaluated were Logistic Regression, Linear Discriminant Analysis, KNeighbors Classifier, Decision Tree Classifier, GaussianNB, Support Vector machine, and Convolutional Neural Network (CNN) Long-Short Term Memory (LSTM). These models were trained with a test dataset and compared using the accuracy, f1-score, precision, and recall. The CNN LSTM model was found to be the best in each of these categories, so it was chosen as the model for emotion recognition.

The effect of Covid-19 is negative overall as in both Ohio and the USA, the number of negative tweets increased while the number of positive tweets decreased as Covid-19 became prominent. In addition, the amount of fear and anger tweets in Ohio and the USA grew exponentially while the amount of joy tweets decreased. Comparatively, Canada and Mexico experienced a relatively stable 14 months as the only notable changes were decreases to Canada’s sadness and Mexico’s anger. The USA should put an emphasis on emotional and mental health as this pandemic could have long term effects such as depression and increased rates of suicide.

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