

# The impact of the Covid-19 pandemic on education: Natural Language Processing

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**Abstract**—Because of the circumstances of our day, social media plays a significant part in our lives. Twitter is currently the most popular social media tool for posting relevant material. Users may post their thoughts and ideas on Twitter, which generates massive amounts of data. Examine your own thoughts, feelings, and experiences, as well as the viewpoints of others. The Coronavirus-2019 (Covid-19) is a disease carried by minute droplets transferred by close contact. Coughing, sneezing, and speaking have caused social and economic scars all over the world. More than 185 million individuals have been diagnosed with the New Coronavirus (Covid-19) as of July 7, 2021, and nearly 4 million people have perished as a result of this deadly sickness. Using the tweets that individuals communicate about the Covid-19 pandemic on the Twitter platform, this work focuses on the analysis of the feelings that Covid-19 leaves on people.

Deep learning techniques are used in the analyses. Sentiment analysis may be quite beneficial. A network model based on Long-Short Term Memory (LSTM) was employed in this investigation. Our suggested technique may successfully execute sentiment analysis on the Twitter dataset (by using Twint), according to experimental results.

**Index Terms**—Deep Learning, Social Media, Sentiment Analysis, Covid-19, Education

## I. INTRODUCTION

The tweets on the relationship between Covid-19 and education will be included in our dataset. We used these tweets to generate our own dataset, which we used to investigate the impact of Covid-19 on schooling.

According to our definition, conditions in education, like all other fields, alter during a pandemic. Many governments have opted to continue schooling online in order to adapt to this new climate. For the past two years, and even now, certain schooling and even tests have been completed online. But what impact does this have on students? Was it better or worse for their learning? These impacts can vary from person to person, and various learning skills may react differently. The goal of this project is to use tweets to investigate this issue from many angles and dimensions.

Twitter is one of the most popular social media platforms, with a fast growing number of daily users. With 340 million active members as of 2020 and 98 thousand tweets per minute, Twitter is a social networking website where users post and exchange messages called "tweets" and engage with one another, dubbed "the SMS of the internet." [3]

A field study or surveys cannot provide such important data in such a short period of time. Big data like Twitter, where millions of individuals contribute their thoughts, is extremely tough to handle. Many academics were drawn to the analysis of these data, which allowed them to develop methodologies. Sentiment Analysis Methods are one of the most extensively utilized ways for analyzing Twitter data. Sentiment analysis is the process of automatically extracting subjective information from a text. We can determine whether a text has a favorable or negative subjective orientation using sentiment analysis. The notion of sentiment analysis has made the processing of this data easier, revealing what society says, intends, or desires.

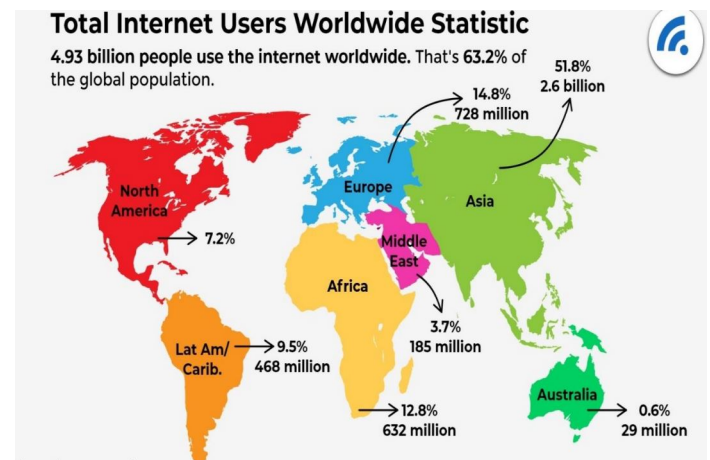


Fig. 1. Statistics on Internet Use in 2022 [1]

## II. CONNECTED WORKS

The fast growth of information sharing and access in social media networks has given rise to the notion of translating information into informatics in this industry. In this context, the notion of sentiment analysis, or opinion mining, is on its way to becoming the bright star of the information industry, which is growing in lockstep with technological advancements. If we look at the cause behind this, we can see that the internet is an excellent source of emotional information [4]. While emotion is an attitude, cognition is an emotional judgment.



effectively the data has been preprocessed. Text preprocessing is the initial stage in the NLP model-building process. Pre-processing processes were applied according to the table order below:

Drop Retweet
Remove Punctuations, URLs
Remove private contacts and emojis
Remove Stopwords
Tokenization

Fig. 3. Pre-processing Steps of the subject

### A. Drop the Unnecessary Columns

To begin, we remove any extraneous columns from the data collection. When we acquire data from somewhere, in this example tweets from Twitter, it is often enormous. There might be a trove of data that adds no value to our model. Such information should be eliminated since it wastes memory and processing time.

```
#df.drop(columns=['id', 'conversation_id', 'created_at', 'date', 'time', 'timezone',
# 'user_id', 'username', 'name', 'place', 'language', 'mentions', 'urls',
# 'photos', 'replies_count', 'retweets_count', 'likes_count', 'hashtags',
# 'casshtags', 'link', 'retweet', 'quote_url', 'video', 'thumbnail',
# 'near', 'geo', 'source', 'user_rt_id', 'user_rt', 'retweet_id',
# 'reply_to', 'retweet_date', 'translate', 'trans_src', 'trans_dest'], axis=1, inplace=True)
```

Fig. 4. Drop the Unnecessary Columns

### B. Punctuation Marks Removal

The removal of punctuation marks, which are used to break text into sentences, paragraphs, and phrases, impacts the findings of any text processing strategy, especially those that rely on word and phrase occurrence frequencies, because punctuation marks are used often in text. Stop-words are often used in language and are deleted before any NLP procedure. Stop-words are a collection of words that are commonly used without any further information, such as articles, determiners, and prepositions. We may focus on the key terms instead by deleting these frequently used words from the text.

```
for line in lines:
    tokens=word_tokenize(line)
    tokens=[w.lower() for w in tokens]
    table=str.maketrans('','',string.punctuation)
    stripped = [w.translate(table) for w in tokens]
    words=[word for word in stripped if word.isalpha()]
    stop_words=set(stopwords.words('english'))
    words=[w for w in words if not w in stop_words]
    train_all_data.append(words)
```

Fig. 5. Punctuation Marks Removal

### C. Replace Upper-case Characters to Lower-case

Words like book and book have the same meaning, yet in the vector space model, they are represented as two separate words when not transformed to lower case (It results in more dimensions). As a result, it has an impact on our processing speed and deep learning model correctness.

### D. Tokenization

Identifying the words that make up a string of characters before processing a natural language. Tokenization is therefore a fundamental step in Natural Language Processing. This step is crucial because the meaning of the text may be deduced from an examination of the words in the text. Tokenization is the process of separating source text into distinct tokens for examination. Tokens are fragments of the original text that have not been reduced to their simplest form.

```
from keras.preprocessing.text import Tokenizer

train_data=train_data.astype(str)
test_data=test_data.astype(str)
tokenizer = Tokenizer()
tokenizer.fit_on_texts(train_data)

X_train = tokenizer.texts_to_sequences(train_data)
X_test = tokenizer.texts_to_sequences(test_data)

word_index = tokenizer.word_index
print('Unique tokens:%d' %len(word_index))
```

Fig. 6. Tokenization

### E. Stop Words Removal

Stop words are often used terms (a, an, the, etc.) in texts that should be removed. These terms have no actual meaning because they don't assist distinguish between two publications.

```
import string
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords

train_all_data=list()
lines = counts

for line in lines:
    tokens=word_tokenize(line)
    tokens=[w.lower() for w in tokens]
    table=str.maketrans('','',string.punctuation)
    stripped = [w.translate(table) for w in tokens]
    words=[word for word in stripped if word.isalpha()]
    stop_words=set(stopwords.words('english'))
    words=[w for w in words if not w in stop_words]
    train_all_data.append(words)
```

Fig. 7. Stop Words Removal

The total results shown in these figures:

```
"@AaronKaviiri Well, it's not like we've a choice when they still contribute a huge chunk to our countries ' budgets, fund our
essential services including education, military and health (donated Covid-19 vaccines), huge loans and grants! Worst of it, ou
r leaders making home hell for us to stay"
```

Fig. 8. Stop Words Removal

```
['aaronkaviiri',
'well',
'like',
'choice',
'still',
'contribute',
'huge',
'chunk',
'countries',
'budgets',
'fund',
'essential',
'services',
'including',
'education',
'military',
'health',
'donated',
'vaccines']
```

Fig. 9. Stop Words Removal

We then created and trained our algorithm to categorize the emotions of tweets. We built the model using a Sequential network for this purpose. The Sequential network model is explored in depth.

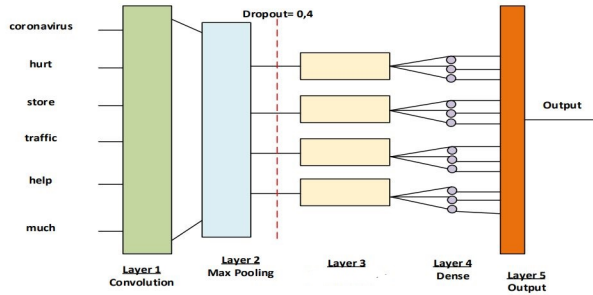


Fig. 10. Sequence Network Model's Architecture

## V. INVESTIGATIONAL OUTCOMES

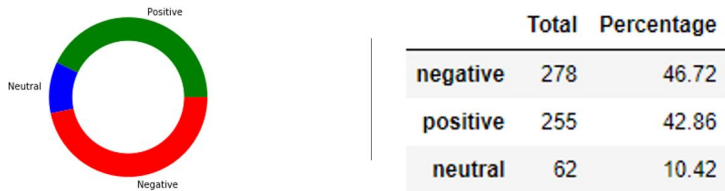


Fig. 11. Sequence Network Model's Architecture

As we can see from the Sentiment analysis results, we can conclude that the rates of positive and negative tweets are very close to each other. The number of people who are neutral at this point is comparatively less.

## VI. CONCLUSION

Because of the circumstances of our day, social media plays a significant part in our lives. Twitter is the most popular social networking site, with millions of users. It provides researchers with a vast data set for data mining. Users on Twitter share 140-character tweets expressing their emotions.

We want to look at how people feel about Covid 19 pandemics in this study. A deep neural network was used to create the suggested model.

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