Public Perception of Myocarditis and Pericarditis Risk after Covid-19 Vaccination

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Abstract. Due to widespread development of COVID, there are health concerns across the world. The vaccinations are created as a result. Myocarditis and pericarditis are a couple of the adverse effects connected to COVID-19 immunizations, particularly the Pfizer-BioNTech and Moderna vaccines. As a result, it is necessary to examine people's sentiment. Social media is now a rich source of information where users may publish, comment, or tweet about their thoughts and experiences. In this study, we used a Fine-tuned BERT deep learning model and assess 2980 tweets from Twitter using tweepy to find people's perspectives on myocarditis and pericarditis following immunization. We discovered that negative tweets made up around 74.47% of the entire data while positive tweets made up 25.53% with Overall accuracy, F1-score, precision, and recall for the model were 0.911, 0.912, 0.926, 0.928 respectively.

Keywords: Sentiment classification, Fine-tuned BERT Model, pretraining, Covid-19, vaccines, vaccination, myocarditis, pericarditis.

1 Introduction

The viral condition known as Coronavirus disease 2019 (Covid) is invited on by a serious extreme respiratory problem Coronavirus 2 (SARS-CoV-2). The primary case was announced found in Wuhan, China, in December 2019 [1]. The COVID-19 pandemic was sparked by the rapid spread of the infection.

Despite the fact that Coronavirus side effects can change, they most often incorporate fever, hacking, migraines, weariness [2], respiratory issues, loss of smell, and taste [3-6]. Side effects might begin in one to fourteen days following infection openness. More established are more inclined to encounter extreme side effects. Coronavirus might spread when sullied spores were inhaled or come into contact with the eyes, nose, or mouth. When people were close to one another, the risk was greatest.

In a number of countries that have launched significant vaccination initiatives, variety of COVID-19 vaccines have been licensed and made accessible. Although vaccines provide positive benefits, they can have adverse effects.Information chronicles have

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shown a relationship between's getting Coronavirus immunization and a raised gamble of myocarditis and pericarditis.

Heart muscle inflammation is known as myocarditis. The term "pericarditis" refers to inflammation of the heart's outer lining [7]. In this paper, it is found that the heart-related problem of myocarditis and pericarditis can be occurred in both normal patients and covid-19 vaccinated patients. According to one estimate, there were 39 instances of myocarditis worldwide in 2017 for every 100,000 people [8]. Data from post-marketing surveillance show that receiving the COVID-19 vaccine, especially the mRNA-based COVID-19 vaccine, increases the risk of myocarditis and pericarditis [9, 10]. Myocarditis/pericarditis signals was examined by the Pharmacovigilance Risk Assessment Committee of the European Medicines Agency, which shows that incidences were "rare," occurring up to once every 10,000 vaccine recipients [11]. After receiving the COVID-19 immunisation, the risk of myocarditis and pericarditis varying by age, sex, vaccine type, and dose [12, 13]. A study from the UK shows that those who receive the immunisations against ChAdOx1 and BNT162b2 are at increased risk of developing myocarditis [15]. Comparing recipients of the BNT162b2 and CoronaVac vaccinations for myocarditis/pericarditis risk was research from Hong Kong [14]. Deeper knowledge of characteristics of population that experienced myocarditis/pericarditis following vaccination would make developing prevention methods easier.

As of November 4, 2021, the United States VAERS had received 1,783 cases of myocarditis or pericarditis among individuals aged 12-29 who has received COVID-19 vaccinations, notably after getting the BNT162b2 and mRNA-1273 vaccines [16]. As of July 9, 2021, BNT162b2 vaccination has resulted in 145 myocarditis cases and 138 pericarditis cases, whereas the mRNA-1273 vaccination has resulted in 9 myocarditis cases and 19 pericarditis cases [17]. 275 cases of myocarditis were reported in Israel between December 2020 and May 2021 among more than 5 million people who got BNT162b2 vaccination [18-21]. These occurrences primarily occurred after second dosage, according to same research, and young people and teenagers were more prone to experience them. After the good result, determine if the risks associated with the immunisation outweigh the risks. By assessing the chances of negative side effects following vaccination in various age groups, the SARS-CoV-2 test.

To know people's sentiments about the problem of myocarditis and pericarditis following Covid-19 vaccine, sentimental analysis using Fine-tuned BERT is done. Sentiment Analysis is the method for determining what the general population thinks about certain topic. One of the numerous functions performed by NLP, a subfield of artificial intelligence that enables computers to comprehend, interpret, and use human languages, is sentiment analysis. Like other machine learning models, emotion categorization model requires an input of fixed-sized vector of numbers. To encode text's crucial information, we must transform text—a string of words represented as ASCII or Unicode—into fixed-sized vector. For it, number of statistical and deep learning NLP models had been presented [22].

BERT (Bidirectional Encoders Representations from Transformers), the first-ever bidirectional language model, will be used to construct a Sentiment Classifier in this project. The Google AI Language team created BERT, an open-source NLP pre-training model, in 2018. It is sometimes likened to the ImageNet breakthrough in computer vision and is regarded as the most significant advancement in the field of NLP.

Numerous websites and online social media platforms generate a significant quantity of data each day. Twitter is among the most widely used. Hence twitter is used here to extract user's tweets with the help of Tweepy. An accessible Python module for using Twitter API is called Tweepy.

For the suggested model, we got the Twitter data set from 17 April to 11 May 2023 and then pre-processed it to make it usable. Then, to assess, pre-train, and create the model, we utilized the Fine-tuned BERT model and the Hugging Face library. Using the BERT model, we next carried out the emotional categorization and continued with the data visualization. The goal of the study was to:

- Use the emotive categorization Fine-tuned BERT Model to examine public anxiety around the possibility of these cardiac issues following Covid vaccination.
- To group the discoveries into positive and negative classifications.
- To evaluate the performance using metrics such as F1-score, accuracy, precision and recall.

Six sections make up the remainder of the essay. We discuss the reasons we are doing this work in Section 2. The connected works are discussed in Section 3. In Section 4, we went into great depth about our model data, design and methods. Then, in Section 5, we report and discuss the findings. In Section 6, we offer final thoughts

2 Motivation

A portion of the secondary effects related with Coronavirus inoculations, remarkably the Pfizer-BioNTech and Moderna immunizations, incorporate myocarditis and pericarditis. As a result, it is necessary to examine people's sentiments. After receiving the Covid 19 vaccine, myocarditis and pericarditis were the subjects of studies. Be that as it may, we haven't yet seen any exploration on how individuals see heart issues like myocarditis and pericarditis in the wake of getting the Coronavirus immunization. We adopted this Model because Fine-tuned BERT had gained prominence, and academics sought to apply it to other NLP tasks after its popularity. This became the primary driving force behind continuing this endeavour.

3 Related Work

One of the most well-liked NLP tasks is sentiment categorization, thus there has been a lot of study and advancement in precisely doing this work. The majority of methods have emphasized binary sentiment categorization. Finding people's opinions on vaccination reluctance requires a lot of research. Researchers are able to pinpoint a root reasons of vaccination resistance and create persuasive public health campaigns and interventions by analysing people's opinions on social media to gauge their emotional state [23, 24]. In recent years, various research utilizing machine learning and deep learning techniques have shown great deal of interest in sentiment analysis (SA) of vaccination hesitancy for many illnesses, including COVID-19 pandemic as well as many other diseases (e.g., HPV, Measles). Majority of these research categorize social media communications as having neutral, favorable, or adverse views on vaccination. Delcea, Cotfas, 2021 evaluates dynamics of the opinions regarding COVID-19 vaccination by taking into account month that passed after initial vaccine announcement and before first vaccination occurred in the UK. A total of 2 349 659 tweets have been gathered, analyzed, and connected to the news events. Traditional machine learning and deep learning algorithms have been compared to see which classifier works better with BERT with an accuracy of 78.94%. According to the data, it can be shown that the majority of tweets take a neutral position, with more tweets in favour than against [25]. Umair and Masciari [26] have utilised the COVID vaccination data from Twitter and examined it using artificial intelligence and geospatial techniques. They classified the tweets based on their polarity using the TextBlob() method. Then, using the BERT model, They had earned, for the positive class and negative class, 55% and 54% accuracy, 69% and 85% recall, and 58% and 64% F scores, respectively [26]. Chen and Crooks [27] analyse vaccination attitudes in space and time. They employ the United States Twitter dataset from January 2015 to July 2021. Using "1st December 2019" as the starting point—the day the first patient in Wuhan, China, had their initial symptoms—they split the whole research period into two stages. Overall data indicate that of all users, the proportion of "pro-vaccine" users fell from 61.56% to 56.20% after the pandemic. Additionally, the percentage of individuals who identified as "anti-vaccine" increased somewhat after the epidemic, increasing from 20.17% to 23.28%, indicating that the outbreak did, in fact, slightly alter people's opinions on vaccination [27]. D'Andrea, Ducange [28] describe a method for tracking Italian public opinion using a study of tweets related to the issue of vaccination. The Simple Logistic classifier they used allowed them to attain an average accuracy of 75.5% [29]. Bellos and Karageorgiou [30] explain the Covid-19 vaccine-associated myocarditis patients, their clinical features, and identify the risk factors that made them susceptible to life-threatening disease. The study comprised 129 participants from 39 studies in all. After the second vaccination dosage, young males accounted for the majority of cases. The results of a logistic regression study showed that the likelihood of developing a critical illness was predicted by the presence of heart failure. According to a percentage meta-analysis, 7.0% of participants required admission to an intensive care unit, whereas 80.5% of patients reported full symptom remission [30]. 20-year-old guy who went to emergency room complaining of chest pain but who had no medical history was the subject of study by Watkins and Gryphon in 2021. Two days before he was seen in the ED, he had gotten the BNT162b2 immunisation. The patient's elevated troponin level was 89 ng/L at the time of the second assessment. His EKG revealed extensive concave ST segment elevations, and myocarditis was subsequently confirmed by an MRI. The patient was identified as having myocarditis as a result of these results. It seems doubtful that the patient's past SARS-CoV-2 infection—which occurred around two months before the beginning of his symptoms—caused the myocarditis because he had fully recovered by the time he presented to the ED [31]. Mouch and Roguin [32] describes six myocarditis instances that occurred soon after receiving BNT162b2 immunisation. All patients had myocarditis, and there was no sign of COVID-19 infection. The patients' average age, who were all male, was 23 years. One patient and five patients, respectively, appeared following the second and first doses of the vaccination. Concomitant infection was ruled out by laboratory tests, and autoimmune illness was deemed improbable. The BNT162b2 vaccination had an effect on every subject. All six patients' clinical courses were rather modest [32]. Goddard and Lewis [33] objective to determine whether risk varies between the two vaccination kinds. Both vaccinations were associated with a higher incidence of myocarditis and pericarditis in people between the ages of 18 and 39. Estimates of risk following mRNA-1273 were a little higher than those following BNT162b2 [33].

4 Methodology

Sentiment categorization divides sentiment into positive and negative categories based on the input dataset. Here, a sentiment classifier is created using a Fine-tuned BERT model and the DistilBERT by hugging Face library. As a result, we divide this section into two parts; we briefly discuss BERT in this section before outlining the architecture of our model.

4.1 BERT Model

Google created a language representation paradigm called Bidirectional Encoder Representations from Transformers, or BERT. BERT comes in two variations:

- The BERT Base has 110M parameters, 12 attention heads, and 12 Transformer Encoders. For this project, we're going to use BERT Base.
- The BERT Large system has 340M parameters, 16 attention heads, and 24 Transformer Encoders [34].
- To create a BERT model, follow these 2 steps:
- Pre-training BERT: Various pre-training activities are used to train the model using unlabeled data.
- BERT fine-tuning: utilising labelled data from the downstream tasks, each parameter is adjusted once the model has been initialised with pre-trained values [34].

Without requiring critical undertaking explicit compositional changes, the pre-prepared BERT model might be adjusted to become familiar with different errands, including feeling investigation, brain machine interpretation, and text outline, with only one extra result layer [35].A BERT model's parts consolidate bidirectional, encoder depiction, transformer, and pre-arranged word introducing.

- Bidirectional: Unlike past language depiction models, it was made as setting focused model to commonly condition on both left and right setting in all layers to pre-train significant bi-directional depictions from unlabeled text [35].
- Encoder Representation, or ER Self-attention and a feed-forward neural network make up a two-layer encoder. In self-attention, when analysing the word, scans every

other word in the text and pays close attention to the keywords. Non-linear hierarchical characteristics are computed via feed-forward neural networks. Each layer practises self-attention before broadcasting its findings to the following encoder through a feed-forward network [34].

- Transformer: BERT uses Transformer, an attention mechanism that analyses the precise positioning of each word in the sentence to assess its relative importance in the phrase. Transformer establishes the contextual links between words and sub-words in text. The Transformer evaluates whole sequences of tokens at once and disregards directionality, whereas the attention mechanism focuses on one word in a phrase at a time. Hugging Face, free Transformer library, will be used for this project. Hugging Face is among top startups in NLP industry. Its software was utilised for context- and emotion-based question answering and emotion identification.
- Pre-prepared Word Installing: BERT also utilized the feature-based training strategy known as Embedding from Language Model. This method makes use of pre-trained neural networks to generate word embeddings that are then utilized as features in deep bidirectional language models (biLM) [34].

BERT Design: The symbolic representation vectors Ei, which are all three representation vectors for each token - the typical word facility vector, the location facility vector, and the sentence vector - are the organization's contributions to the base BERT plan. Since transformer models miss the mark on understanding, the position inserting gives the model data about the symbolic's area inside the expression. Essential BERT plan with a two-layer encoder is found in Fig. 1. At the first level of the encoder, Ti(1) is the attention-based representation and at the second level of the encoder, Ti(2) is the same representation. The input representation vectors, one vector for each input chip Wi, are denoted by Ei for i=1,2,....,N Also, the output map vectors for each chip are Ti=Ti(2).

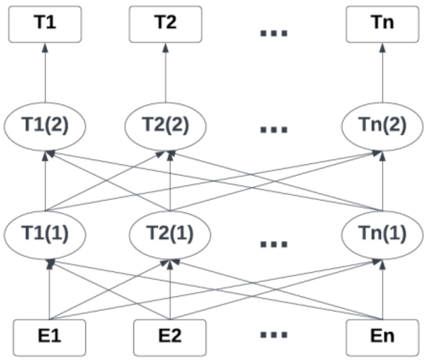

Fig. 1. BERT Architecture (Adapted from [35])

4.2 Proposed Architecture

The recommended engineering of our model is displayed in Fig. 2.

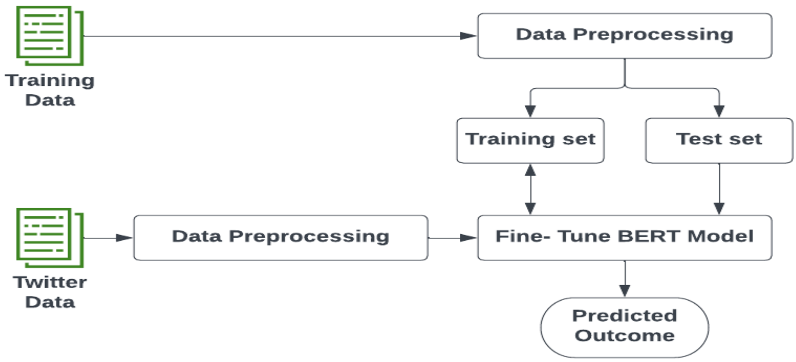

Fig. 2. The proposed Model

Training Data: For training the model or text analytics or natural language processing, 'Covid Tweets- Sentimental Analysis and Trends' from the Kaggle dataset (dataset 1) is used as a pre-training. Compared to past benchmark datasets for binary sentiment categorization, this dataset has a lot more data.

For this study, a dataset of opinions on COVID-19 immunisation (dataset 2) was also employed. There are 6000 samples in the dataset. ID, Sentiment, and Tweet are the three categories of data collection. So, use classification or deep learning techniques to determine the ratio of positive to negative reviews.

Data Preprocessing: For the purposes of this work, data set was transformed into a data frame using the Panda's library, which made data handling and analysis simpler. The computational linguistics software programme called Natural Language Toolkit offers simple user interfaces to more than 50 lexical resources. Text pre-processing and sentiment analysis (using NLTK Sentiment Intensity Analyzer) were done using this package.

The various process involves in pre-processing of data are –

- Tokenization: To prepare papers for future processing, documents (crawled reviews) can be divided into list of tokens, such as words, numbers, special characters, etc.
- Normalisation: This procedure changes all of document's word tokens to either lowercase letters or capital letters.
- Stop Word Elimination: Stop words are any words that, when combined with other words, give phrase its overall structure and meaning. These terms have to be deleted since they do not improve the model's performance.
- Stemming: This technique involves converting each token into its stem or root form.

- Noise Removal: The fundamental noise-cleaning steps of removing whitespace, punctuation, URLs, and hashtags are included in this stage. Correction of acronyms and misspellings has been done.

Dataset Splitting: Our dataset must be parted into a preparation set and a test set.The holdout set, which makes up the remaining 15% of the dataset, will be used to evaluate performance after training on 85% of the dataset.

Model Training: For model training BERT Base model is used with 110M parameters, 12 attention heads, and 12 Transformer Encoders. Our refined BERT model is set up in four steps with the help of the training set during model training:

- Load Pre-prepared BERT: Because BERT aims to pre-train deep bidirectional representations from unlabeled text by co-conditioning left and right contexts at all levels, the pre-trained BERT model can be extended with just one additional output level. [35].
- Create DataLoader: TensorDataset generates DataLoader that offers mechanism to create dataset using data that has previously been loaded into memory. It takes data in tensor and numpy array formats. For the fine-tuned BERT, batch_size = 32 is employed.
- Optimizer configuration: AdamWHuggingface gave examples of how to use transformers library.
- Create a scheduler: Every time a batch is supplied to model, scheduler is invoked.

Model Testing: In this phase, Remaining 15% of data i.e. test data is used to test the data. After that our model is evaluated based on performance metrics such as: Accuracy, Precision, F1- Score & Recall.

- Precision: Accuracy is defined as the ratio of true positives to the total number of false positives and true negatives. Eq. (1) shows the formula for measuring precision.

$$\frac{True\ Positive}{True\ Positive+False\ Positive} \tag{1}$$

- Recall**:** Recall is percentage of events that were correctly predicted compared to all forecasts. The recall measurement formula is shown in Eq. (2).

$$\frac{True\ Positive}{True\ Positive+False\ Negative} \tag{2}$$

- Accuracy: Accuracy is defined as ratio of accurate forecasts to all other predictions made by algorithm. The formula for calculating accuracy is shown in Eq. (3).

$$\frac{True\ Positive + True\ Negative}{True\ Positive + False\ Positive + True\ Negative + False\ Negative} \quad (3)$$

- F1-score: above three measurements were merged to create the F1-score, a new metric with scale from 0 to 1 that took into account both Precision and Recall. The algorithm for calculating F1-score is shown in Eq. (4).

$$2 * \frac{Precision * Recall}{Precision + Recall} \quad (4)$$

Twitter Data: After model making, Twitter dataset using Tweepy is used to retrieve Actual 2980 Tweets from Tweeter between April 1 and May 18, 2023 by using hashtags such as #myocarditis and #pericarditis, etc and is applied to our Model after preprocessing.

Prediction: Above model is used here to predict the actual tweets dataset. Pre-processed tweets data is applied to the Model to predict the sentiments. It will convert the tweets into the sentiment either Positive or Negative as expressed by them. Result of our proposed model is shown in section 5.

5 Results

To examine the feelings, a total of 2980 tweets from Twitter have been collected. After data preparation, 1100 rows are removed. Of the 1880 tweets in the data, only 480 are favourable, and 1400 are negative. Data visualization is done using word clouds, bar charts, and pie charts. A bar graph showing the number of positive and negative sentiments is shown in Fig. 3. This demonstrates that even though Myocarditis and Pericarditis are extremely rare after receiving the COVID vaccination, the majority of people still have anxiety and resentment against the shot. People may be reluctant to receive the COVID vaccination as a result of these unfavourable opinions. It is significant to highlight that, depending on individual views, the prevalence of negative feelings might change. Having negative feelings about the COVID-19 vaccination can Concerns, skepticism, or reluctance are some of the negative feelings people may have about the COVID-19 vaccination. Typical causes of bad feelings include: Concerns concerning the safety of the COVID-19 vaccination, particularly about potential adverse effects, have been raised by some people. Some people could be apprehensive to take any vaccinations, including the COVID-19 vaccines, for a variety of reasons, such as a lack of faith in medical institutions, inaccurate information, or personal convictions. Misinformation regarding the COVID-19 vaccinations might increase vaccine reluctance and skepticism because people may have concerns about the vaccines' effectiveness, safety, or ulterior motives. Inverse responses or worries based on stories from friends or family members might also result from personal experiences or tales. Although these stories are credible, it's crucial to take into account the total safety and effectiveness data from large-scale clinical trials.

Approximately 74.47% of all tweets are negative, compared to 25.53% of all tweets that are positive. Fig.4. shows a pie chart depicting the percentage of positive and negative tweets.

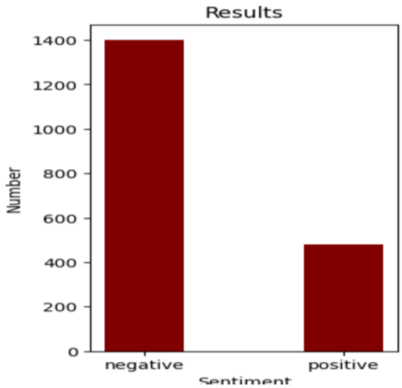

Fig. 3. It represents total number of positive and negative sentiments.

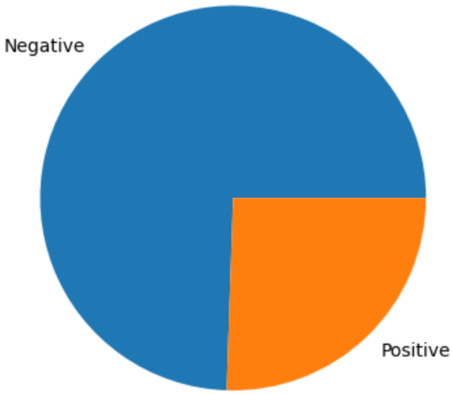

Fig. 4. It represents percentage of positive and negative sentiments.

The word cloud in Fig. 5 displays the keywords that are present in the dataset. Fig. 6 and Fig. 7 shows negative and positive keywords found in the dataset respectively. Keywords like ‘spike’, ‘risk’, ‘damage’, ‘dead’, ‘collapsed’ shows negative sentiments. Keywords like ‘cure’, ‘less’, ‘normal’, ‘immunity’ shows positive sentiments.

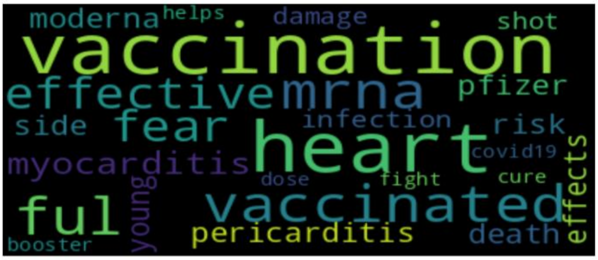

Fig. 5. WordCloud of keywords found in the Dataset.

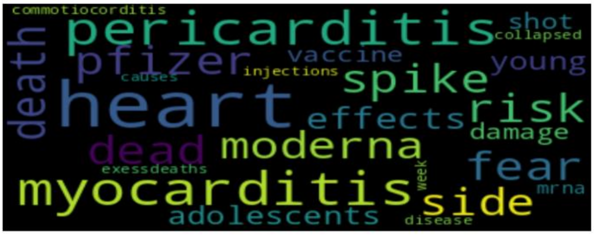

Fig. 6. WordCloud of Negative keywords found in the dataset.

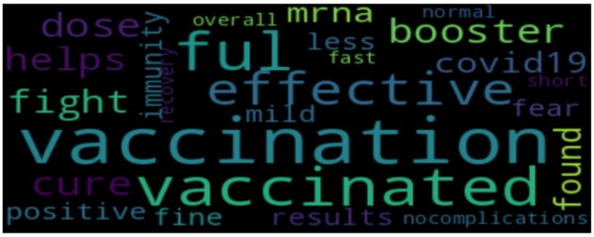

Fig. 7. WordCloud of Positive keywords found in the dataset.

The General exactness of 0.911, F1-score of 0.912, accuracy of 0.926, and review of 0.928 for the model is achieved.

6 Conclusion and Future Work

This study shows that although the problem of myocarditis and pericarditis after covid19 vaccination are rare, most of the people have negative sentiment towards it. In this study, we utilised the Fine-tuned BERT model to classify sentiments in tweets about people's perceptions of myocarditis and pericarditis issues after receiving the COVID vaccination. There are more negative sentiments (74.47%) than positive sentiments (25.53%). Our model was able to achieve high accuracy of 91.1% even with such a straightforward downstream design.

This study's analysis was restricted to English-language tweets. The analysis can be expanded into more languages in future research. The results of this study are also restricted to users of the Twitter platform; future studies may examine text material from other social media platforms to compare the findings. These conclusions are based solely on the 91.1% accurate Fine-tuned BERT model; further study may examine more effective models.

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References

1. Page, J., Hinshaw, D., McKay, B.: In hunt for Covid-19 origin, patient zero points to second Wuhan market, https://www.wsj.com/articles/in-hunt-for-covid-19-origin-patient-zero-points-to-second-wuhan-market-11614335404, (2021)
2. Islam, M.A., Alam, S.S., Kundu, S., Hossan, T., Kamal, M.A., Cavestro, C.: Prevalence of Headache in Patients With Coronavirus Disease 2019 (COVID-19): A Systematic Review and Meta-Analysis of 14,275 Patients. Front Neurol. 11, (2020). doi: 10.3389/fneur.2020.562634
3. Saniasiaya, J., Islam, M.A., Abdullah, B.: Prevalence of Olfactory Dysfunction in Coronavirus Disease 2019 (<scp>COVID</scp> -19): A Meta-analysis of 27,492 Patients. Laryngoscope. 131, 865–878 (2021). doi: 10.1002/lary.29286
4. Saniasiaya, J., Islam, M.A., Abdullah, B.: Prevalence and Characteristics of Taste Disorders in Cases of COVID-19: A Meta-analysis of 29,349 Patients. Otolaryngology–Head and Neck Surgery. 165, 33–42 (2021). doi: 10.1177/0194599820981018
5. Agyeman, A.A., Chin, K.L., Landersdorfer, C.B., Liew, D., Ofori-Asenso, R.: Smell and Taste Dysfunction in Patients With COVID-19: A Systematic Review and Meta-analysis. Mayo Clin Proc. 95, 1621–1631 (2020). doi: 10.1016/j.mayocp.2020.05.030
6. "Post-COVID Conditions". U.S. Centers for Disease Control and Prevention (CDC), (2021)
7. Myocarditis and Pericarditis After mRNA COVID-19 Vaccination | CDC
8. Wang, X., Bu, X., Wei, L., Liu, J., Yang, D., Mann, D.L., Ma, A., Hayashi, T.: Global, Regional, and National Burden of Myocarditis From 1990 to 2017: A Systematic Analysis Based on the Global Burden of Disease Study 2017. Front Cardiovasc Med. 8, (2021). doi: 10.3389/fcvm.2021.692990
9. Bozkurt, B., Kamat, I., Hotez, P.J.: Myocarditis With COVID-19 mRNA Vaccines. Circulation. 144, 471–484 (2021). doi: 10.1161/CIRCULATIONAHA.121.056135
10. Karlstad, Ø., Hovi, P., Husby, A., Härkänen, T., Selmer, R.M., Pihlström, N., Hansen, J.V., Nohynek, H., Gunnes, N., Sundström, A., Wohlfahrt, J., Nieminen, T.A., Grünewald, M., Gulseth, H.L., Hviid, A., Ljung, R.: SARS-CoV-2 Vaccination and Myocarditis in a Nordic

Cohort Study of 23 Million Residents. JAMA Cardiol. 7, 600 (2022). doi: 10.1001/jamacardio.2022.0583

11. https://www.ema.europa.eu/en/documents/prac-recommendation/signal-assessment-report-myocarditis-pericarditis-tozinameran-covid-19-mrna-vaccine_en.pdf.
12. Pillay, J., Gaudet, L., Wingert, A., Bialy, L., Mackie, A.S., Paterson, D.I., Hartling, L.: Incidence, risk factors, natural history, and hypothesised mechanisms of myocarditis and pericarditis following covid-19 vaccination: living evidence syntheses and review. BMJ. e069445 (2022). doi: 10.1136/bmj-2021-069445
13. Wong, H.-L., Hu, M., Zhou, C.K., Lloyd, P.C., Amend, K.L., Beachler, D.C., Secora, A., McMahill-Walraven, C.N., Lu, Y., Wu, Y., Ogilvie, R.P., Reich, C., Djibo, D.A., Wan, Z., Seeger, J.D., Akhtar, S., Jiao, Y., Chillarige, Y., Do, R., Hornberger, J., Obidi, J., Forshee, R., Shoaibi, A., Anderson, S.A.: Risk of myocarditis and pericarditis after the COVID-19 mRNA vaccination in the USA: a cohort study in claims databases. The Lancet. 399, 2191–2199 (2022). doi: 10.1016/S0140-6736(22)00791-7
14. Lai, F.T.T., Li, X., Peng, K., Huang, L., Ip, P., Tong, X., Chui, C.S.L., Wan, E.Y.F., Wong, C.K.H., Chan, E.W.Y., Siu, D.C.W., Wong, I.C.K.: Carditis After COVID-19 Vaccination With a Messenger RNA Vaccine and an Inactivated Virus Vaccine. Ann Intern Med. 175, 362–370 (2022). doi: 10.7326/M21-3700
15. Patone, M., Mei, X.W., Handunnetthi, L., Dixon, S., Zaccardi, F., Shankar-Hari, M., Watkinson, P., Khunti, K., Harnden, A., Coupland, C.A.C., Channon, K.M., Mills, N.L., Sheikh, A., Hippisley-Cox, J.: Risks of myocarditis, pericarditis, and cardiac arrhythmias associated with COVID-19 vaccination or SARS-CoV-2 infection. Nat Med. 28, 410–422 (2022). doi: 10.1038/s41591-021-01630-0
16. Selected adverse events reported afer COVID-19 vaccination. Centers for Disease Control and Prevention; https://www.cdc.gov/coronavirus/2019-ncov/ vaccines/safety/adverse-events.html (2021).
17. Comirnaty and Spikevax: possible link to very rare cases of myocarditis and pericarditis. European Medicines Agency; https://www.ema.europa.eu/en/news/ comirnaty-spikevax-possible-link-very-rare-cases-myocarditis-pericarditis (2021).
18. Surveillance of myocarditis (infammation of the heart muscle) cases between December 2020 and May 2021 (including). Ministry of Health of the Israeli Government; https://www.gov.il/en/departments/news/01062021-03 (2021).
19. Ab Rahman, N., Lim, M.T., Lee, F.Y., Anak Jam, E.B., Peariasamy, K.M., Sivasampu, S.: Myocarditis/pericarditis following vaccination with BNT162b2, CoronaVac, and ChAdOx1 among adolescent and adult in Malaysia. Vaccine X. 14, 100303 (2023). doi: 10.1016/j.jvacx.2023.100303
20. Sinnenberg, L., Buttenheim, A.M., Padrez, K., Mancheno, C., Ungar, L., Merchant, R.M.: Twitter as a Tool for Health Research: A Systematic Review. Am J Public Health. 107, e1–e8 (2017). doi: 10.2105/AJPH.2016.303512
21. Jordan, S., Hovet, S., Fung, I., Liang, H., Fu, K.-W., Tse, Z.: Using Twitter for Public Health Surveillance from Monitoring and Prediction to Public Response. Data (Basel). 4, 6 (2018). doi: 10.3390/data4010006
22. Twitter Sentiment Analysis with Deep Learning using BERT and Hugging Face | by Bao Tram Duong | MLearning.ai | Medium

23. Alamoodi, A.H., Zaidan, B.B., Al-Masawa, M., Taresh, S.M., Noman, S., Ahmaro, I.Y.Y., Garfan, S., Chen, J., Ahmed, M.A., Zaidan, A.A., Albahri, O.S., Aickelin, U., Thamir, N.N., Fadhil, J.A., Salahaldin, A.: Multi-perspectives systematic review on the applications of sentiment analysis for vaccine hesitancy. Comput Biol Med. 139, 104957 (2021). doi: 10.1016/j.compbiomed.2021.104957
24. Karafillakis, E., Martin, S., Simas, C., Olsson, K., Takacs, J., Dada, S., Larson, H.J.: Methods for Social Media Monitoring Related to Vaccination: Systematic Scoping Review. JMIR Public Health Surveill. 7, e17149 (2021). doi: 10.2196/17149
25. Cotfas, L.-A., Delcea, C., Roxin, I., Ioanas, C., Gherai, D.S., Tajariol, F.: The Longest Month: Analyzing COVID-19 Vaccination Opinions Dynamics From Tweets in the Month Following the First Vaccine Announcement. IEEE Access. 9, 33203–33223 (2021). doi: 10.1109/ACCESS.2021.3059821
26. Umair, A., Masciari, E.: Sentimental and spatial analysis of COVID-19 vaccines tweets. J Intell Inf Syst. 60, 1–21 (2023). doi: 10.1007/s10844-022-00699-4
27. Chen, Q., Crooks, A.: Analyzing the vaccination debate in social media data Pre- and Post-COVID-19 pandemic. International Journal of Applied Earth Observation and Geoinformation. 110, 102783 (2022). doi: 10.1016/j.jag.2022.102783
28. Mahdikhani, M.: Predicting the popularity of tweets by analyzing public opinion and emotions in different stages of Covid-19 pandemic. International Journal of Information Management Data Insights. 2, 100053 (2022). doi: 10.1016/j.jjimei.2021.100053
29. D'Andrea, E., Ducange, P., Marcelloni, F.: Monitoring negative opinion about vaccines from tweets analysis. In: 2017 Third International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN). pp. 186–191. IEEE (2017)
30. Bellos, I., Karageorgiou, V., Viskin, D.: Myocarditis following mRNA Covid-19 vaccination: A pooled analysis. Vaccine. 40, 1768–1774 (2022). doi: 10.1016/j.vaccine.2022.02.017
31. Watkins, K., Griffin, G., Septaric, K., Simon, E.L.: Myocarditis after BNT162b2 vaccination in a healthy male. Am J Emerg Med. 50, 815.e1-815.e2 (2021). doi: 10.1016/j.ajem.2021.06.051
32. Abu Mouch, S., Roguin, A., Hellou, E., Ishai, A., Shoshan, U., Mahamid, L., Zoabi, M., Aisman, M., Goldschmid, N., Berar Yanay, N.: Myocarditis following COVID-19 mRNA vaccination. Vaccine. 39, 3790–3793 (2021). doi: 10.1016/j.vaccine.2021.05.087
33. Goddard, K., Lewis, N., Fireman, B., Weintraub, E., Shimabukuro, T., Zerbo, O., Boyce, T.G., Oster, M.E., Hanson, K.E., Donahue, J.G., Ross, P., Naleway, A., Nelson, J.C., Lewin, B., Glanz, J.M., Williams, J.T.B., Kharbanda, E.O., Katherine Yih, W., Klein, N.P.: Risk of myocarditis and pericarditis following BNT162b2 and mRNA-1273 COVID-19 vaccination. Vaccine. 40, 5153–5159 (2022). https://doi.org/10.1016/j.vaccine.2022.07.007
34. Alammar, J.: The Illustrated BERT, ELMo, and co. (How NLP Cracked Transfer Learning), https://jalammar.github.io/illustrated-bert/
35. Devlin, J., Chang, M.-W., Lee, K., Toutanova, K.: BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. (2018)