DISCOURSE ANALYSIS USING A CNN BASED MODEL TO PROBE THE ANTI VACCINE DEBATE

Project Synopsis submitted to

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DISCOURSE ANALYSIS USING A TF-IDF CNN BASED MODEL TO PROBE THE ANTI VACCINE DEBATE

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1. ABSTRACT:

Understanding human emotions has always been one of the primary intent of the common man , but it still remains an arduous task to date. We generally express our feelings during a discourse. Happiness, worry, wary, discontent, people's attitude can be observed by reading their words through a common language. At present the entire world is in discourse because of the pandemic and then came its solution.
But not many people look in the same direction.

Our project focuses on argument mining for identification and classification of arguments within social media where people voice their opinion and specify their stance. A sequential model wise fully connected neural network is used along with the common concept of tf-idf. Data is passed through a variety of functions in the model to determine their stance with(+ve or -ve) with an accuracy range 70-80%.

2. INTRODUCTION:

Argumentation is a linguistic, social, and rational action intended at persuading a reasonable critic of the acceptability of a viewpoint by presenting a set of assertions that validate or refute the viewpoint's claim.
We expect our model to effectively decipher the tweet’s nature towards the topic(for,against or indifferent) by learning from the annotated data we provide it beforehand.

Argument mining has been applied in many different genres including the qualitative assessment of social media content (e.g. Twitter, Facebook), where it provides a powerful tool for policy-makers and researchers in social and political sciences. Other domains include legal documents, product reviews, scientific articles, online debates, newspaper articles and dialogical domains. Transfer learning approaches have been successfully used to combine the different domains into a domain agnostic argumentation model.

Argument mining has been used to provide students individual writing support by accessing and visualizing the argumentation discourse in their texts. The application of argument mining in a user-centered learning tool helped students to improve their argumentation skills significantly compared to traditional argumentation learning applications.

PACKAGES:

A. Nltk:

Nltk or the natural language toolkit is a module for pre-processing in python it contains libraries for tokenizing,parsing and stemming and punctuations

B. Numpy:

Numpy is a module that is used for running large muti-dimensional arrays and performing operations on the same.

C. Pandas:

Pandas is a module that allows fast and flexible analysis and manipulation of data from different file formats.

D. Scikit-learn:

This is a module used for formation of regression or clustering of data.

E. Keras:

Keras is the module that provides the interface for creating neural networks by making use of another library tensorflow as the backend and its main purpose is to produce more consistent and precise API or data to work on..

CONNECTED NEURAL NETWORKS:

Fully connected neural networks (FCNNs) are a type of artificial neural network where the architecture is such that all the nodes, or neurons, in one layer are connected to the neurons in the next layer.

While this type of algorithm is commonly applied to some types of data, in practice this type of network has some issues in terms of image recognition and classification. Such networks are computationally intense and may be prone to overfitting. When such networks are also 'deep' (meaning there are many layers of nodes or neurons) they can be particularly hard for humans to understand.

We have selected a fully connected neural network because for the totality of the input there is a corresponding output for each.

SEQUENTIAL API:

The Sequential model API lets you create a model layer by layer for most problems. It’s straightforward (just a simple list of layers), but it’s limited to single-input, single-output stacks of layers.

It is a way of creating deep learning models where an instance of the Sequential class is created and model layers are created and added to it .The layers can be defined and passed to the Sequential as an array. The Sequential model API is great for developing deep learning models in most situations, but it also has some limitations.

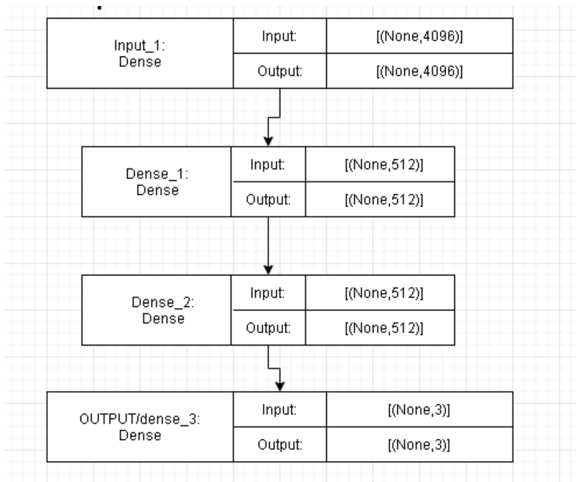


Fig.1 Sequential API - 3 I/P and 1 O/P layers

3. PROBLEM STATEMENT:

Vaccine hesitation refers to a delay in accepting or refusing immunizations despite the fact that vaccine services are available.At any given point ,it is highly necessary to note that vaccination plays a major role in saving lives. They are made with the mindset of helping people get cured rather than the contrast. They have gone through rigorous checks and experiments before being made available to the public. Despite all these facts there are quite a number of people that reject vaccinations , each with their own reasons that they voice out in available platforms and there are people who support vaccinations. There comes a need for a tool that analyses such messages in platforms and offers a clear understanding on where do people stand in this debate ,and how many people stand with them(i.e in their side). This can be important data for arriving at a conclusion for this debate. Once their stance has been identified it also makes it possible to analyze the reason that each of them specify to back their standing and determine whether it is legitimate or not.

METHODOLOGY

A. Dataset extraction:

Our dataset is a collection of for,indifference and against arguments that are prevalent to one of the well known controversial topics of vaccine debate. The dataset is a compilation of tweets scraped from twitter.com using octoparse, an intelligent bot. We targeted a few hashtags for each side(3) of the argument separately and octoparse retrieved relevant tweets accordingly. Then, we merged those collections after marking them with their respective sentiment which resulted in our raw dataset.

B. Pre-processing:

Even though we extracted the dataset with appropriate parameters, in order for the model to process the dataset, we need to streamline it. In our project's case, we will remove HTML tags, tokenize the entries, remove punctuation and special characters, convert the text to lowercase, remove stop-words, and remove all words of one character length in order to obtain our pre-processed dataset, consisting of tokens, perform one hot encoding. The next step is to vectorize these tokens with TF-IDF.

C. Feature extraction:

<u>Count vectorization</u>:

CountVectorizer is a great tool provided by the scikit-learn library in Python. It is used to transform a given text into a vector on the basis of the frequency (count) of each word that occurs in the entire text. It creates a matrix in which each unique word is represented by a column of the matrix, and each text sample from the document is a row in the matrix. The value of each cell is nothing but the count of the word in that particular text sample.

<u>Tf-idf measure:</u>

TF-IDF (term frequency-inverse document frequency) is a statistical measure that evaluates how relevant a word is to a document in a collection of documents. This is done by multiplying two metrics: how many times a word appears in a document, and the inverse document frequency of the word across a set of documents.

$$tf\,idf\,(t, d, D) = tf\,(t, d)\ .\ idf\,(t, D)$$

$$tf\,(t, d) = log\,(1 + freq\,(t, d))$$

$$idf\,(t, D) = log\,\left(\frac{N}{count\,(d \in D : t \in d)} \right)$$

We have subjected our dataset to tf-idf such that the weights assigned are more accurate and representative than that of the ones assigned through count vectorization.

D. FCNN pipeline:

In our model we use a sequential fully connected model with activation function of Relu and a L2 regularizer for the input layer where the layer checks if the ceiling of the value and makes it the closest integer and thus slowly reducing the tensorflow array and finally the the input model has a activation function of softmax with 3 units thus reducing the entire model to give value of 0,1,2 corresponding to for,neutral,against. This model is fitted with the corresponding tf-idf values and the target value from the present data set.

LITERATURE SURVEY:

[1]Argument mining on Twitter:Arguments, facts and sources.

In this paper, the authors successfully attempted to use a supervised classification model to identify arguments on the topics ‘BREXIT’ and ‘GREXIT’ on twitter. Then they have fact-checked the tweets, analysed them to identify argumentative structures and also identified the sources. They have used random forest and logistic regression classification algorithms.The reasons behind their research into the sources of the tweets is to validate them i.e, to determine facts from baseless statements. And they perform argument mining to distinguish neutral statements from biased arguments. Besides the above two reasons, they also state that their research provides a better view on identifying factual consensus from personal opinions in tweets.

[2]Cross-topic argument mining from heterogeneous sources using attention-based neural networks.

Argument mining is a foundational method for automating the search for arguments in big document sets. Despite their use for this purpose, most existing techniques to argument mining are built for certain text categories and fail when applied to diverse texts. In this research, we offer a novel sentential annotation technique that can be reliably applied to any Web documents by crowd workers. Source annotations for nearly 25,000 occurrences spanning eight contentious themes were provided by the authors. Cross-topic tests reveal that their attention-based neural network generalises the best to unknown subjects and beats vanilla BiLSTM models.

[3]Argument mining: Extracting arguments from online dialogue.

The authors aim to use the vast dialogue corpora available in online forums and message boards to automatically discover the semantic aspects of arguments that conversants are making across multiple dialogues on a topic. After performing an analysis they've used their model to rate the arguments based on argumentative strength which in turn depends on various other factors.

Online forums are now one of the primary venues for public dialogue on current social and political issues. The related corpora are often huge, covering any topic imaginable. Thus the team believed that this provides novel opportunities to address a number of open questions about the structure of dialogue.

[4]Combining argument mining techniques

We look at three distinct strategies for extracting the argumentation structure from natural language text in this research. These approaches involve language characteristics, changes in the topic being discussed and a supervised machine learning approach to detect the components of argumentation schemes, patterns of human reasoning which have been documented extensively in philosophy and psychology. We attain results equivalent to those previously reported for each of these techniques while also establishing a more thorough argument structure. Finally, we combine the findings of these distinct algorithms to improve the argument structure detection even further.

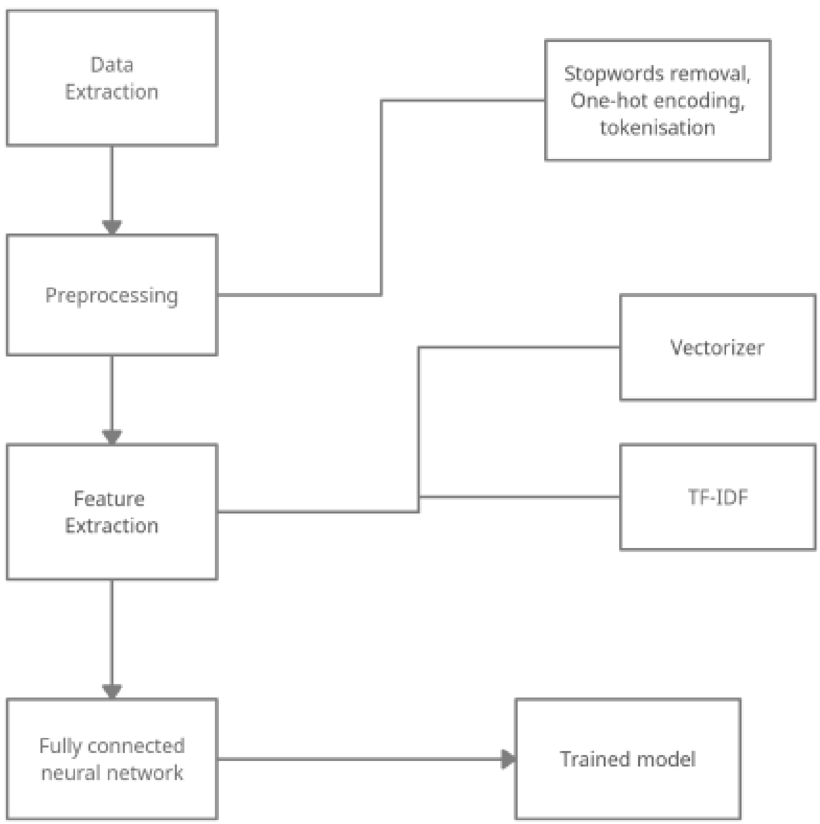
[5]"What is Your Evidence?" A Study of Controversial Topics on Social Media

This paper focuses on classifying different supporting arguments users on twitter provide to justify their stances on a particular argument. They planned to use an SVM model to achieve high accuracy in their classification. They chose to concentrate on content related to the FBI-Apple encryption debate and extracted tweets related as their dataset.On social media sites, especially on Twitter, user text contains arguments with inappropriate or missing justifications.

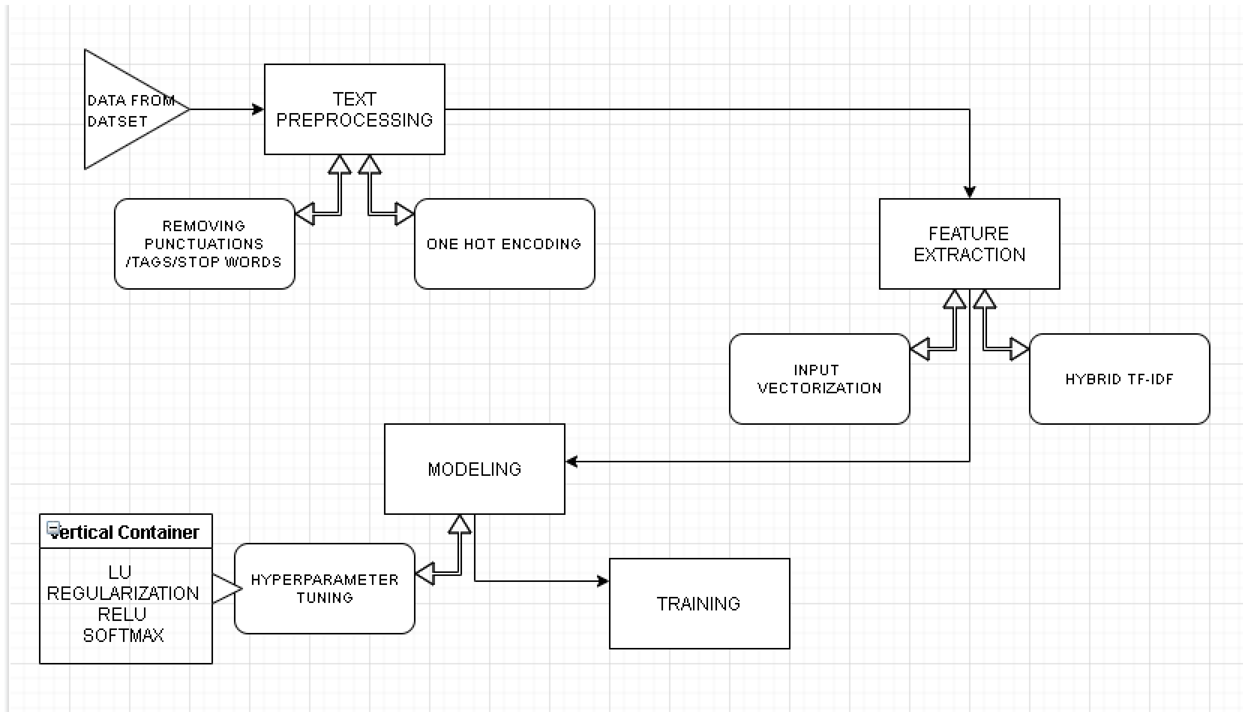
[6]Benchmarking twitter sentiment analysis tools.

Twitter has become one of the quintessential social media platforms for user-generated content. Researchers and industry practitioners are increasingly interested in Twitter emotions.The results of a rigorous benchmark examination of Twitter sentiment analysis tools, which included 20 tools and 5 distinct test beds, are presented in this article. A thorough mistake analysis is utilised to illustrate the most common issues faced by Twitter sentiment analysis tools, in addition to offering extensive performance evaluation data. The results have substantial implications for many stakeholder groups, including social media analytics researchers, NLP developers, and industry managers and practitioners using social media attitudes as input for decision-making..

3.1 ARCHITECTURE DIAGRAM:



3.2 FLOW DIAGRAM:



3.3 PSEUDOCODE:

<u>Stop word removal:</u>

Initialize the variable train_data= dataset excel sheet
Function remove_stopwords(argument)

Initialize stpwords = english stopwords from nltk
No_punctuation = words in function argument without punctuations imported from String

Add a new column to test_data and call remove_stopwords from the sentences

<u>One-hot encoding:</u>

Initialize train_one_hot to get the unique values of the sentiment column

One hot encoding is done to the matrix of sentences,train_one_hot to give us a separate column for each sentiment.
Initialize y_train to only the hot encoded values from the train_data

Word vectorization:

Initialize sentence_train=string array of stopwords removed sentences
Initialize vectorizer to CountVectorizer() which is imported from sklearn
Intialize x_train = fit of the vectorizer of the sentences

Tf-idf tagging:

Initialize tfidf= TfidfTransformer() which is another feature of sklearn
Reinitialize x_train=fit of the tfidf of itself and convert it to an array

Fully connected Sequential model pipeline:

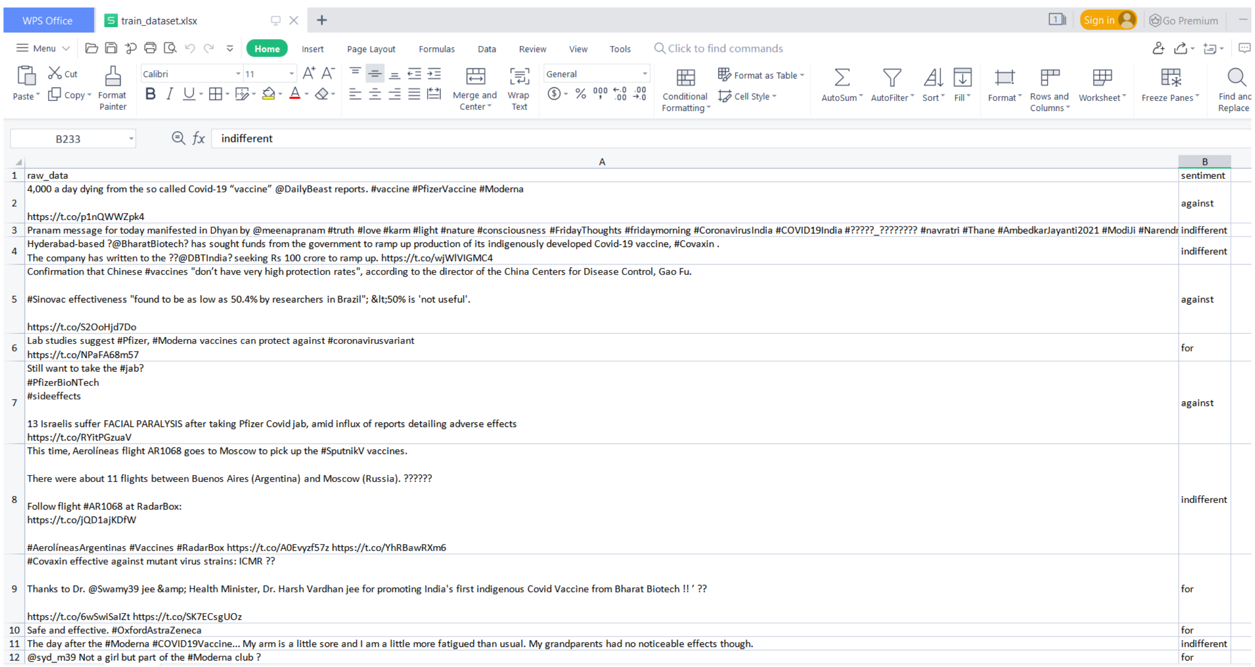
Function create_deep_model(factor,rate)
    Initialize model to be sequential
    Add to the model 3 layers with units 4096,512,512 with regularizer of l2 and activation of Relu
    Add a output layer of unit 3 and activation of softmax
We create the model with a l2 regularizer factor of 0.0001 and dropout rate of 0.2

EarlyStopping will monitor our loss and when it reduces too much it will stop training and adams optimizer to monitor learning rate. From this model we predict a value and classify it with indifferent,for and against .

4. EXPERIMENTAL AND RESULTS:

4.1 DATA SET:

Our dataset is a collection of tweets from twitter that belong to for,indifference and against categories of arguments that are prevalent to one of the well known controversial topics of vaccine debate. The dataset is a compilation of tweets scraped from twitter.com using octparse, an intelligent bot. We targeted a few hashtags for each side(3) of the argument separately and octoparse retrieved relevant tweets accordingly. Then, we merged those collections after marking them with their respective sentiment which resulted in our raw dataset.



	A	B
1	raw_data	sentiment
2	4,000 a day dying from the so called Covid-19 “vaccine” @DailyBeast reports. #vaccine #PfizerVaccine #Moderna https://t.co/p1nQWWZpk4	against
3	Pranam message for today manifested in Dhyan by @meenapranam #truth #love #karm #light #nature #consciousness #FridayThoughts #fridaymorning #CoronavirusIndia #COVID19India #?????_???????? #navratri #Thane #AmbedkarJayanti2021 #ModiJi #Narendr	indifferent
4	Hyderabad-based ?@BharatBiotech? has sought funds from the government to ramp up production of its indigenously developed Covid-19 vaccine, #Covaxin . The company has written to the ??@DBTIndia? seeking Rs 100 crore to ramp up. https://t.co/wjWlVIGMC4	indifferent
5	Confirmation that Chinese #vaccines "don’t have very high protection rates", according to the director of the China Centers for Disease Control, Gao Fu. #Sinovac effectiveness "found to be as low as 50.4% by researchers in Brazil"; <50% is 'not useful'. https://t.co/S2OoHjd7Do	against
6	Lab studies suggest #Pfizer, #Moderna vaccines can protect against #coronavirusvariant https://t.co/NPaFA68m57	for
7	Still want to take the #jab? #PfizerBioNTech #sideeffects 13 Israelis suffer FACIAL PARALYSIS after taking Pfizer Covid jab, amid influx of reports detailing adverse effects https://t.co/RYitPGzuaV	against
8	This time, Aerolíneas flight AR1068 goes to Moscow to pick up the #SputnikV vaccines. There were about 11 flights between Buenos Aires (Argentina) and Moscow (Russia). ?????? Follow flight #AR1068 at RadarBox: https://t.co/jQD1ajKDfW #AerolíneasArgentinas #Vaccines #RadarBox https://t.co/A0Evyzf57z https://t.co/YhRBawRXm6	indifferent
9	#Covaxin effective against mutant virus strains: ICMR ?? Thanks to Dr. @Swamy39 jee & Health Minister, Dr. Harsh Vardhan jee for promoting India's first indigenous Covid Vaccine from Bharat Biotech !! ’ ?? https://t.co/6wSwiSaIZt https://t.co/SK7ECsgUOz	for
10	Safe and effective. #OxfordAstraZeneca	for
11	The day after the #Moderna #COVID19Vaccine... My arm is a little sore and I am a little more fatigued than usual. My grandparents had no noticeable effects though.	indifferent
12	@syd_m39 Not a girl but part of the #Moderna club ?	for

Fig. 4 Dataset scraped from twitter using octoparse

4.2 SAMPLE OUTPUT SCREEN

train_data - DataFrame

Index	raw_data	sentiment	stop_rem
0	4,000 a day dying from the so called Covid-19 “vaccine” @DailyBeast reports. #vaccine #PfizerVaccine #Moderna https://t.co/p1nQWWZpk4	against	4000 day dying called Covid19 “vaccine” DailyBeast reports vaccine PfizerVaccine Moderna httpstcop1nQWWZpk4
1	Pranam message for today manifested in Dhyan b…	indifferent	Pranam message today manifested Dhyan meenapra…
2	Hyderabad-based ?@BharatBiotech? has sought fu… The company has written to the ??@DBTIndia? se…	indifferent	Hyderabadbased BharatBiotech sought funds gove…
3	#Sinovac effectiveness "found to be as low as …	against	Confirmation Chinese vaccines don’t high prote…
4	Lab studies suggest #Pfizer, #Moderna vaccines… https://t.co/NPaFA68m57	for	Lab studies suggest Pfizer Moderna vaccines protect coronavirusvariant httpstcoNPaFA68m57
5	#sideeffects	against	Still want take jab PfizerBioNTech sideeffects…
6	Follow flight #AR1068 at RadarBox:	indifferent	time Aerolíneas flight AR1068 goes Moscow pick…
7	Thanks to Dr. @Swamy39 jee & Health Minist…	for	Covaxin effective mutant virus strains ICMR Th…
8	Safe and effective. #OxfordAstraZeneca	for	Safe effective OxfordAstraZeneca
9	The day after the #Moderna #COVID19Vaccine... …	indifferent	day Moderna COVID19Vaccine arm little sore lit…
10	@syd_m39 Not a girl but part of the #Moderna club ?	for	sydm39 girl part Moderna club

Fig5 : Raw data

train_data - DataFrame

Index	stop_rem	against	for	ndifferent
0	4000 day dying called Covid19 “vaccine” DailyBeast reports vaccine PfizerVaccine Moderna httpstcop1nQWWZpk4	1	0	0
1	Pranam message today manifested Dhyan meenapranam truth love karm light nature consciousness FridayThoughts fridaymorning CoronavirusIndia COVID19India navratri Thane AmbedkarJayanti2021 ModiJi NarendraModi SecondCOVIDWave Covaxin httpstcobQNoMVowJg	0	0	1
2	Hyderabadbased BharatBiotech sought funds government ramp production indigenously developed Covid19 vaccine Covaxin company written DBTIndia seeking Rs 100 crore ramp httpstcowjWlVIGMC4	0	0	1
3	Confirmation Chinese vaccines don’t high protection rates according director China Centers Disease Control Gao Fu Sinovac effectiveness found low 504 researchers Brazil 1t50 useful httpstcoS2OoHjd7Do	1	0	0
4	Lab studies suggest Pfizer Moderna vaccines protect coronavirusvariant httpstcoNPaFA68m57	0	1	0
5	Still want take jab PfizerBioNTech sideeffects 13 Israelis suffer FACIAL PARALYSIS taking Pfizer Covid jab amid influx reports detailing adverse effects httpstcoRYitPGzuaV	1	0	0
6	time Aerolíneas flight AR1068 goes Moscow pick SputnikV vaccines 11 flights Buenos Aires Argentina Moscow Russia Follow flight AR1068 RadarBox httpstcojQD1ajKDfW AerolíneasArgentinas Vaccines RadarBox httpstcoA0Evyzf57z httpstcoYhRBawRXm6	0	0	1
7	Covaxin effective mutant virus strains ICMR Thanks Dr Swamy39 jee amp Health Minister Dr Harsh Vardhan jee promoting Indias first indigenous Covid Vaccine Bharat Biotech ’ httpstco6wSwiSaIZt httpstcoSK7ECsgUOz	0	1	0
8	Safe effective OxfordAstraZeneca	0	1	0
9	day Moderna COVID19Vaccine arm little sore little fatigued usual grandparents noticeable effects though	0	0	1
10	sydm39 girl part Moderna club	0	1	0

Fig6: After count_vectorization

```
val_loss: 1.5317 - val_accuracy: 0.7040
Epoch 6/50
36/36 [==============================] - 14s 403ms/step - loss: 0.0838 - accuracy: 0.9978 -
val_loss: 1.4016 - val_accuracy: 0.7333
Epoch 00006: early stopping
Model: "sequential_12"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_40 (Dense)             (None, 4096)              54816768
_________________________________________________________________
dense_41 (Dense)             (None, 512)               2097664
_________________________________________________________________
dense_42 (Dense)             (None, 512)               262656
_________________________________________________________________
dense_43 (Dense)             (None, 3)                 1539
=================================================================
Total params: 57,178,627
Trainable params: 57,178,627
Non-trainable params: 0
_________________________________________________________________
```

Fig.7 Model summary

```
Trainable params: 57,178,627
Non-trainable params: 0
_________________________________________________________________
              precision    recall  f1-score   support

 indifferent       0.40      0.06      0.11        65
         for       0.74      0.65      0.69       251
     against       0.74      0.88      0.80       434

    accuracy                           0.73       750
   macro avg       0.63      0.53      0.53       750
weighted avg       0.71      0.73      0.71       750


In [19]:
```

Fig8. Accuracy report

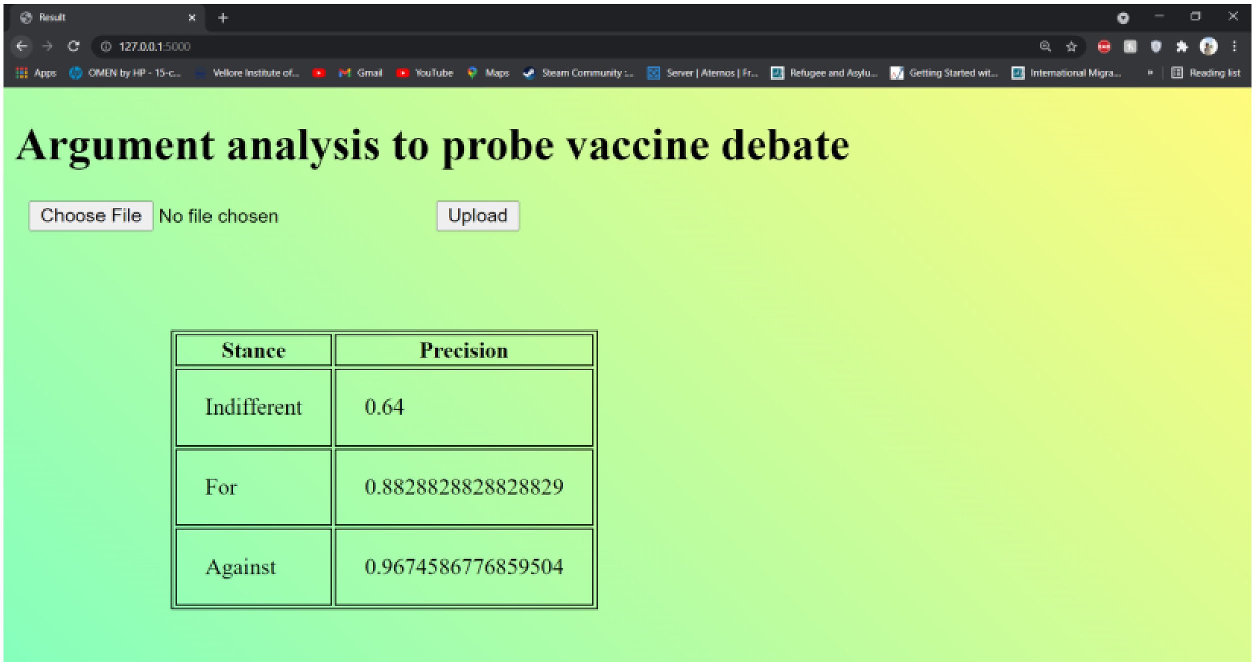


Fig.9 API created for better User Experience

Fig.10 The predicted values against the annotated dataset target.

TABULATION:

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Title:	Proposed Framework / Methodology	Advantages over prior papers-Results	Comparison with our model	Disadvantages:
[1]Argument mining on Twitter: Arguments, facts and sources.	The authors successfully attempted to use a supervised classification model to identify arguments on the topics 'BREXIT' and 'GREXIT' on twitter. Then they have fact-checked the tweets, analysed them to identify argumentative structures and also identified the sources. They have used random forest and logistic regression classification algorithms with the main purpose of the project being validation.	This paper, while covering the source identification and argument-opinion differentiation concepts, does not put in much effort in identifying extremely one sided tweets with respect to a single topic.	Similarity:Data pipeline have major similarities. Difference:While their models struggled to identify polarised tweets, it helped us finalize our decision of using a fully connected sequential neural network model.	Not a fully connected neural network. Because, a fully connected neural network eliminates the need for hypotheticals at input layers as all neurons of one layer are connected to their counterparts in the next one.
[2]Argument mining: Extracting arguments from online dialogue.	They consider the following two tasks as the center of their research: argument extraction and argument facet similarity. Their approach to the argument extraction task is driven by a novel hypothesis, the IMPLICIT MARKUP hypothesis model.	Works based on the similarity of structure and consequently clustering.. Their model is trained in topic and tested across topics revealing that the accuracy was not affected.	Similarity:Long-term aim is to first extract arguments from online dialogues, and then use them to produce a summary of the different facets of an issue Difference: Topic independent - but less emphasis	The implicit hypothesis follows biases that are not necessarily endorsed and that may even be contradictory to what one consciously believes.
[3]Discourse-driven argument mining in scientific abstracts.	They undertake a pilot research by adding a new argumentation annotation level to a corpus of computational linguistics abstracts that contain discourse annotations. The experimental findings showed that the proposed approach has potential	The authors used 3 different models BiLSTM-ST,BiLSTM-MT and CRF tagger and compared the results obtained from the baseline annotations and the augmented annotation. and the	Similarity: All models in this paper are supervised models, so is ours. Difference: It focuses on analysing scientific domains and corpas to add	In terms of drawbacks the added annotation might result in misclassifying the proposal which accounts for over 20% of the miscalculations in the argument which

	utility to figure whether discourse level analysis	model of BiLSTM-MT produced the highest results of 71.88 over the base of 57.04.	augments to the annotations to improve results in this particular domain .	should have been right.
[4]Cross-topic argument mining from heterogeneous sources using attention-based neural networks	They've used BiLSTM and inner-attention BiLSTM models and the results prove that their attention-based BiLSTM models are more accurate than the vanilla models. And also noted from a survey that even amateur annotators could adapt their model.	Current approaches to argument mining are designed for use only with specific text types and fall short when applied to heterogeneous texts, thus they performed a study on whether it is possible to achieve reasonable data quality using crowdsourced annotations.	Similarities: Both our models use attention-based neural networks. Differences: In this paper, the sentiment(stance) behind the entries are irrelevant to the model.	Since the dataset is crowd-sourced, it could never match the accuracy of an expert-annotated dataset.
[5]A Dependency Parser for Tweets	The authors have created a new dependency parser for English tweets .The parser uses modern adaptations to a statistical parsing algorithm, and a new approach to exploiting out-of-domain Penn Treebank data for pos-speech tagging.	Achieves >80% unlabeled attachment score on a new test set.This is on par with state-of-the-art reported results for news text in Turkish (77.6%; Koo et al., 2010) and Arabic (81.1%; Martins et al., 2011)	Similarity: Parsing algorithm is similar for tweets(uses turbo parser) Difference: Preprocessing flow is different.	Dependency parser is used for pos tagging mainly - even words and slangs but slangs change with a period of time .
[6]Benchmarking Twitter Sentiment Analysis Tools	Large-scale benchmark study of Twitter sentiment analysis tools was performed.They examined the sentiment polarity classification performance of 20 tools, including both commercial & freely available offerings - 5 carefully crafted Twitter test beds.	Amazon Mechanical Turk used for better annotation which is constantly updated. Gives people an easy understanding of tools , their characteristics , and accuracy in different settings.	Similarity: Can be used cross-topic like our pertained model. Difference:It is a comparison model for different tools and not a model for a tool itself.	The tools selected are pretty old . New and better tools have emerged, making the paper obsolete for general comparison use by people but is used as a basis for comparison model.
[7]Improving agreement and	Conditional Random Fields (isotonic CRF)-based	For agreement and disagreement	Similarity: Focuses mainly on	The paper is an analysis of

disagreement identification in online discussions with a socially-tuned sentiment lexicon.	sequential model to generate predictions at the segment level for improving agreement and disagreement identification.	detection, the isotonic CRF model achieves F1 scores of 0.74 and 0.67, respectively, while the linear chain CRF achieves 0.58 and 0.56 for debates on Wikipedia Talk pages.	2 propositions -supporting & opposing like our project. Difference: Analysis of Wikipedia page where emotional speed and internet abbreviations are not involved.	wikipedia talk pages and uses an isotronic CRF model to achieve better results than linear models, but this model still falls behind a neural network model that we use.
[8]"What is Your Evidence?" A Study of Controversial Topics on Social Media	This paper focuses on classifying different supporting arguments users on Twitter provide to justify their stances on a particular argument. They planned to use an SVM model to achieve high accuracy in their classification. They chose to concentrate on content related to the FBI-Apple encryption debate and extracted tweets related to their dataset.	This paper helped us understand the significance of argumentative tweets that lack proper justification and what they contribute to the model. Additionally, this paper cleared a misconception we had about Twitter: that it is frequented mainly by debaters; by showing that the majority of tweets are attempts to spread information.	Similarities: Just like their model, we tuned the model to suit a single topic's analysis in order to maintain high accuracy. Differences: While their pipeline ignores neutral tweets that do not have the structure of an argument, our model learns from them through clustering.	Due to the model's inclusive nature, many unrelated and unargumentative tweets were tagged incorrectly.
[9]A Deep Sequential Model for Discourse Parsing on Multi-Party Dialogues	This work proposes a deep sequential approach for parsing multi-party discussion discourse dependence structures. The suggested model tries to build a discourse dependency tree by predicting dependency links and building the discourse structure.	It aims to for a sequential scan of the units in the tree called the Elementary Discourse unit and it checks the link between each unit to finally build the discourse structure to prediction and also give the relation classifier of the discourse.	Similarity: Sequential model used for implementation. Differences: Deep sequential model by splitting word into smaller units and these units are used to train the model, in comparison our project's sequential model but instead of using unit words	It works on a tree like structure and backwards parsing of the tree increases the execution time which will be significant when using large data.

			we feed the model tf-idf weights for test analysis.	
[10]Combining Lexicon-based and Learning-based Methods for Twitter Sentiment Analysis	In this paper, the authors propose a new entity-level sentiment analysis method that adopts a lexicon-based approach to perform entity-level sentiment analysis. This method can give high precision, but low recall. A classifier is then trained to assign polarities to the entities in the newly identified tweets.	To improve recall, additional tweets that are likely to be opinionated are identified automatically by exploiting the information in the result of the lexicon-based method.Experimental results show that the proposed method dramatically improves the recall and the F-score, and outperforms the state-of-the-art baselines.	Similarities: Both our models take a hybrid approach to the task. Differences: Without their lexicon-based model, their classifier works on datasets containing only contradictory topics, unlike our moel.	This research focuses on the commercialized topic analysis of twitter data, and thus, the model is designed to perform better as a topic classifier than a sentiment analysis tool.

5. CONCLUSION:

Thus we were able to analyze tweets involved in the topic of vaccine debate and classify them based on their views on the topic(positive, negative or neutral) . We achieved a model which recalled about 0.06 'indifferent' topics but for 'against' and 'for' with the recall of 0.88 and 0.65 the application was significantly better, and with an accuracy of 70-80% on average the model was very successful in deciphering the different opinions on our chosen topic. We plan to further improve upon it, check the accuracy when testing is done on varying topics, and visualize the findings with respect to different factors. We believe our project could be adapted by social media sites and message boards to let users know the general consensus of the community on desired topics.

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