CUSTOMER FEEDBACK ANALYSIS FOR FOODBORNE ILLNESS DETECTION USING BERT

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***Abstract*—Foodborne illness outbreaks have serious consequences, including loss of life and productivity. Detecting outbreaks early is crucial to reduce the threat. While social media is a promising source for uncovering unreported cases, there's a lack of labeled datasets for effective outbreak models. Understanding consumer responses and leveraging social media posts can help mitigate outbreaks. We propose a BERTweet model that connects unreported foodborne illnesses and related information. Our model addresses the gap between sporadic cases and early outbreak detection, outperforming previous approaches. Further, we shall make a delicate analysis of our proposed algorithm and draw a relative study with other algorithms and machine literacy models.**

***Index Terms*—Foodborne Illness Detecion, NLP, BERT**

I. Introduction

Detecting foodborne outbreaks beforehand is pivotal for reducing the threat of infections. still, the current outbreak discovery system in the United States, carried out by the Centers for Disease Control and Prevention(CDC), suffers from a significant delay between the first infections and public mindfulness of the outbreak. In addition, threat assessment tools similar as Qualitative Microbial Risk Assessment(QMRA) are grounded on hypotheticals and may not be suitable to grease a fast outbreak discovery for reducing the losses. On the other hand, these approaches are frequently counting on structured data that are collected via planned field- trial studies. These data are precious to gain and frequently not available in the most up- to- date form. In recent times, the readily available and fleetly circulated digital data have been utilised for detecting foodborne ails. Crowdsourcing, a approach that leverages hefty online data from user responses, coupled with machine learning strategies, give a new means for conducting food safety threat analysis and threat dispatches. With crowdsourcing, labelled data can be attained with low cost, which facilitates the medication of training sets for fabricating machine literacy models. Crowdsourcing and machine literacy have been applied to the food safety field. The models have been espoused by a number of original health departments. gradually, the eventuality of employing social media data for public health surveillance has gained the attention of governments. In the past, forestallment of foodborne outbreaks has substantially counted on reducing pollutants that can be throughout the food supply chain, including the production, processing, packaging, transport, and storehouse. In comparison, the objectification of social media data explores the part that consumers can play in forestallment of foodborne outbreaks. Twitter has been recognized as one of the most popular social media platforms employed in public health- related studies. Using text mining and machine literacy ways, experimenters have explored the use of intelligent systems that can identify trending motifs, mine consumer opinions, and capture food safety hazards from Twitter. still, the characteristics of Twitter — short tweets, informal grammar, abbreviations, typographical errors, and hashtags make the text analysis of the data grueling . With the rapid-fire development of natural language processing(NLP) technology, the state- of- the- art approaches have upgraded the performances in colorful NLP tasks. The language model BERTweet, a variant of BERT(Bidirectional Encoder Representations from Mills) was designed specifically for NLP tasks on Twitter. The BERTweet model outperforms strong baselines in name- entity extraction and text classification tasks. The usefulness of Twitter for foodborne illness outbreak discovery continues to be estimated. In addition, we plan to apply advancements to the check and produce a restaurant grounded feedback system to promote survey responses and make a strict check on the prevailing foodborne ails to promote public health surveillance conditioning.

II. Related Work

In recent years, there has been growing interest in using social media data for disease surveillance, including the detection of foodborne illnesses. Several studies have explored the use of Twitter data for surveillance of foodborne illnesses.[8] In one study, researchers collected tweets containing food-related terms and used natural language processing (NLP) techniques to identify tweets that mentioned symptoms of foodborne illness.[10] The study found that Twitter-based surveillance could provide an early warning system for foodborne illness outbreaks. In another study, researchers used Twitter data to track food poisoning outbreaks in real-time.[2] The researchers collected tweets that contained the terms ”food poisoning” or ”foodborne illness” and used machine learning algorithms to classify the tweets as either related or unrelated to food poisoning. The study found that Twitter-based surveillance could identify food poisoning outbreaks earlier than traditional surveillance methods.[2]

NLP techniques have been widely used in the field of tweet data analysis for foodborne illness detection. Researchers have used NLP techniques to extract and classify tweets related to foodborne illness outbreaks. The accuracy of the classification improved with the use of more advanced NLP techniques. Additionally, a combination of NLP techniques and machine learning algorithms has been employed to detect foodborne illness outbreaks from Twitter data, resulting in improved detection accuracy.

Machine learning algorithms have also been used in conjunction with NLP techniques for tweet data analysis in foodborne illness detection. These algorithms accurately classify tweets related to foodborne illness, providing an early warning system for outbreaks and information about the spread of foodborne illnesses across different regions.

Integration of NLP-based tweet data analysis with existing public health surveillance systems has been explored in several studies. By integrating NLP-based tweet data analysis with data from relevant health organizations, such as the Centers for Disease Control and Prevention (CDC) and the European Centre for Disease Prevention and Control (ECDC), the accuracy, timeliness, and effectiveness of foodborne illness detection have been improved.

Deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have also been utilized for tweet data analysis in foodborne illness detection.

Research on foodborne illness detection has utilized various machine learning, deep learning, and natural language processing models. These studies have employed different methodologies and datasets to achieve accurate results. For example, Bidirectional Long Short-Term Memory Networks (BLSTM) have been applied to achieve high accuracy on specific datasets. Other studies have utilized models like RoBERTa, BiLSTM, MGADE, and BERT, combined with review-based methodologies, logistic regression models, and aspect-based sentiment analysis (ABSA). These advanced models and methodologies have shown promise in accurately detecting foodborne illnesses, extracting nuanced sentiments, and capturing relevant information from social media data.

By leveraging the power of machine learning and natural language processing, researchers are paving the way for more effective and efficient detection and monitoring of foodborne illnesses in real-time.

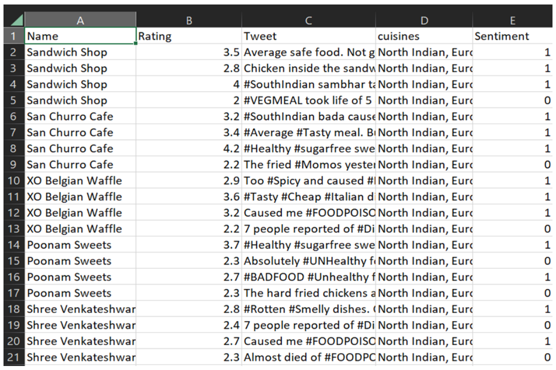
III. Problem Formulation

Foodborne illnesses continue to be a public health concern. It causes lost productivity, medical costs, and even death. Because the world of social media and other platforms is open to the public, we can conduct an analysis of the data obtained from Tweets about foodborne illness. Foodborne illnesses are a major public health concern globally, causing significant morbidity and mortality every year. Early detection and response to foodborne illness outbreaks are critical to prevent further spread of the disease and reduce its impact. Traditional surveillance systems for foodborne illness detection are often slow and resource-intensive, which limits their effectiveness in responding to outbreaks in a timely manner. In recent years, there has been increasing interest in using social media platforms, such as Twitter, for foodborne illness surveillance. However, the large volume of unstructured data generated by social media platforms poses significant challenges for traditional surveillance methods. This research paper aims to address this problem by exploring the use of natural language processing (NLP) techniques and deep learning models, specifically BERT, for tweet data analysis to improve foodborne illness detection and response. The research paper will investigate the effectiveness of BERT in accurately classifying tweets related to foodborne illnesses and its potential for improving the timeliness and accuracy of foodborne illness surveillance systems. The study will also explore the limitations and ethical considerations associated with using social media data for public health surveillance.[6] The findings from this research paper will have implications for improving public health surveillance systems and enhancing the ability to detect and respond to foodborne illness outbreaks in a timely manner. The problem addressed in this research paper is the detection of foodborne illness outbreaks using tweet data analysis. Foodborne illnesses are a significant public health concern, and traditional surveillance systems for detecting outbreaks have limitations in terms of timeliness and accuracy. Tweet data analysis offers a potential solution to these limitations, but the effectiveness of this approach depends on the development of accurate and efficient natural language processing (NLP) techniques. This paper focuses on the use of the BERT (Bidirectional Encoder Representations from Transformers) model for tweet data analysis and aims to evaluate its performance in detecting foodborne illness outbreaks. The research aims to contribute to the development of effective NLP-based approaches for foodborne illness detection and improve public health surveillance systems. The goal is to create an analysis model using BERT based on foodborne illness Tweet topics to extract the type of information from the given data that is associated with foodborne illness. The proposed method analyses collected Tweet data for classification using various feature sets and categorises it.

IV. Proposed Methodology

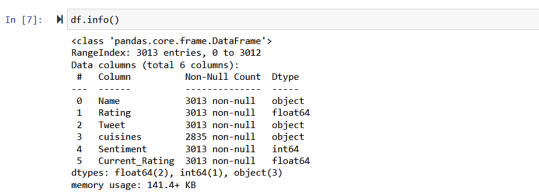
A. Data Collection

The first step is to collect data related to foodborne illness from different sources such as Twitter, websites, and blogs. The data should be collected using relevant keywords and hashtags related to foodborne illness. The collected data should be stored in a .csv file format for further processing. It is important to collect a large and diverse dataset for training the model effectively. Since there were no pre-existing datasets available to meet the demands of our use-case and machine learning needs, we have self-generated a dataset using data from various sources like Google Reviews, various restaurant reviews on the web and from a Zomato Dataset from Kaggle. Further, we have labelled it based on the tweet sentiments and performed data cleaning [4][8].



	A	B	C	D	E
1	Name	Rating	Tweet	cuisines	Sentiment
2	Sandwich Shop	3.5	Average safe food. Not g	North Indian, Eur	1
3	Sandwich Shop	2.8	Chicken inside the sandw	North Indian, Eur	1
4	Sandwich Shop	4	#SouthIndian sambhar ta	North Indian, Eur	1
5	Sandwich Shop	2	#VEGMEAL took life of 5	North Indian, Eur	0
6	San Churro Cafe	3.2	#SouthIndian bada cause	North Indian, Eur	1
7	San Churro Cafe	3.4	#Average #Tasty meal. B	North Indian, Eur	1
8	San Churro Cafe	4.2	#Healthy #sugarfree swe	North Indian, Eur	1
9	San Churro Cafe	2.2	The fried #Momos yester	North Indian, Eur	0
10	XO Belgian Waffle	2.9	Too #Spicy and caused #	North Indian, Eur	1
11	XO Belgian Waffle	3.6	#Tasty #Cheap #Italian d	North Indian, Eur	1
12	XO Belgian Waffle	3.2	Caused me #FOODPOISO	North Indian, Eur	1
13	XO Belgian Waffle	2.2	7 people reported of #Di	North Indian, Eur	0
14	Poonam Sweets	3.7	#Healthy #sugarfree swe	North Indian, Eur	1
15	Poonam Sweets	2.3	Absolutely #UNHealthy f	North Indian, Eur	0
16	Poonam Sweets	2.7	#BADFOOD #Unhealthy f	North Indian, Eur	1
17	Poonam Sweets	2.3	The hard fried chickens a	North Indian, Eur	0
18	Shree Venkateshwar	2.8	#Rotten #Smelly dishes. (	North Indian, Eur	1
19	Shree Venkateshwar	2.4	7 people reported of #Di	North Indian, Eur	0
20	Shree Venkateshwar	2.7	Caused me #FOODPOISO	North Indian, Eur	1
21	Shree Venkateshwar	2.3	Almost died of #FOODPC	North Indian, Eur	0

Fig. 1. Dataset generated



```
In [7]:  df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3013 entries, 0 to 3012
Data columns (total 6 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Name            3013 non-null   object
 1   Rating          3013 non-null   float64
 2   Tweet           3013 non-null   object
 3   cuisines        2835 non-null   object
 4   Sentiment       3013 non-null   int64
 5   Current_Rating  3013 non-null   float64
dtypes: float64(2), int64(1), object(3)
memory usage: 141.4+ KB
```

Fig. 2. Dataset details

B. Data Cleaning

The collected data may contain irrelevant characters, white spaces, HTML snippets, links, punctuations, and junk terms. Therefore, it is important to clean the data before training the model. The data cleaning process involves removing irrelevant features, normalization of text, and handling missing data. Techniques such as regular expressions, stop words removal, and stemming can be used for cleaning the data.

C. Data Preprocessing

After cleaning the data, the next step is to preprocess it for training the model. The data preprocessing step involves tokenization, word embedding, and feature extraction. Tokenization is the process of breaking down the text into smaller chunks or tokens. Word embedding is the process of representing the text in a high-dimensional vector space, which can be used as input to the model. Feature extraction involves selecting relevant features from the text for training the model.

D. Model Selection

After preprocessing the data, the next step is to select the appropriate machine learning model for sentiment analysis. There are various models that can be used for sentiment analysis, such as RNN, SVM, LSTM, Random Forest Model, Hist Gradient Boosting, XGB Classifier, Static Gradient Descent, and Support Vector Machine. The models should be evaluated based on their accuracy, precision, recall, and F1 score.

E. Tokenization

We use the BERT tokenizer to tokenize our text samples. Tokenization converts the input text into a sequence of tokens that can be processed by the model. The tokenizer will also add special tokens like '[CLS]' (classification) and '[SEP]' (separator).

F. Data encoding

We encode the tokenized sequences into input features that the BERT model expects. This involves converting the tokens into their corresponding token IDs, creating attention masks, and segment IDs if required.

G. BERT Model Implementation

We load the pre-trained BERT model using the Hugging Face's Transformers library. We may need to modify the model architecture if the pre-trained BERT model is not specifically trained for sentiment analysis. For sentiment analysis, we might add a classification layer on top of BERT.

H. Fine-tuning

Fine-tuning the BERT model on our dataset involves training the model using our labelled dataset. We define a loss function (e.g., cross-entropy loss) and choose an optimizer (e.g., Adam). We iterate through our training dataset in batches and compute the gradients, backpropagate the loss, and update the model parameters.[11]

I. Performance Evaluation

We evaluate our model on the validation set to monitor its performance. We calculate metrics such as accuracy, precision, recall, or F1 score to assess the model's sentiment classification performance and also compare the same with other existing algorithms.

J. Save the trained model

Once our model has been trained and evaluated, we save it to a file (e.g., pickle or PyTorch's '.pt' format) for later use in the flask app.

In summary, the proposed methodology involves data collection, data cleaning, data preprocessing, model selection, BERT model implementation, model training, model testing, and model deployment. Each step is crucial for building an accurate and effective sentiment analysis model for detecting foodborne illness from a tweet and reflecting the result on a UI interface.

V. Experimental Results

As a result, we use certain metrics to draw a comparative study between the different algorithms we used in the process. The metrics we will be using are as follows:

- **Precision:** Precision is defined as the ratio of correctly classified positive samples (True Positive) to the total number of classified positive samples (either correctly or incorrectly). Hence, precision helps us to visualize the reliability of the machine learning model in classifying the model as positive.
- **Recall:** The recall is calculated as the ratio between the numbers of positive samples correctly classified as positive to the total number of positive samples. The recall measures the model's ability to detect positive samples. The higher the recall, the more positive samples detected.
- **F-Score:** The F-measure is calculated as the harmonic mean of precision and recall, giving each the same weighting. It allows a model to be evaluated taking both the precision and recall into account using a single score, which is helpful when describing the performance of the model and comparing models.
- **Accuracy:** Accuracy is a metric that generally describes how the model performs across all classes. It is useful when all classes are of equal importance. It is calculated as the ratio between the number of correct predictions to the total number of predictions.
- **Confusion Matrix:** A confusion matrix helps us to display the performance of a model or how a model has made its predictions in Machine Learning. It helps us visualize the point where our model gets confused in discriminating two classes. It can be understood well through a 2×2 matrix where the rows represent the actual truth labels, and the columns represent the predicted labels.

Here are the results obtained after a thorough sentiment analysis of the tweet dataset using four major algorithms based on the above metrics:

A. LSTM:

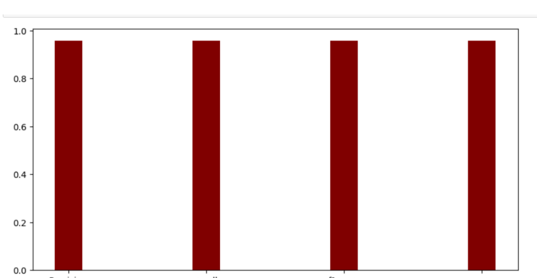


Fig. 3. Metrics obtained for LSTM Algorithm

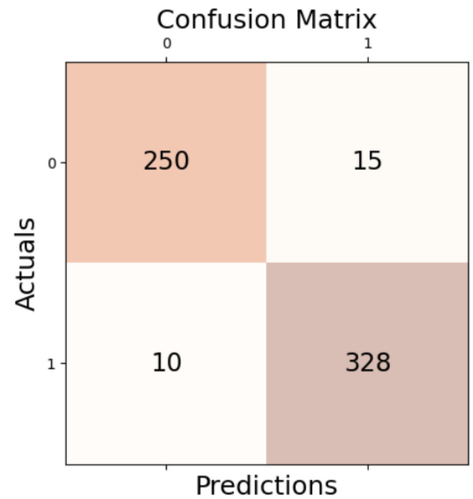


Fig. 4. Confusion Matrix obtained for LSTM Algorithm

B. XGBoost:

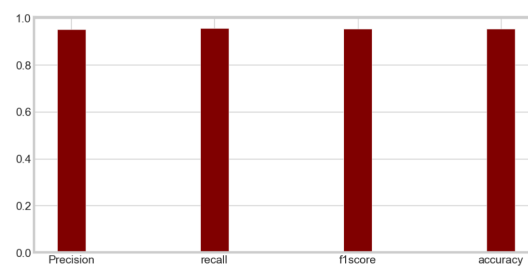


Fig. 5. Metrics obtained for XGBoost Algorithm

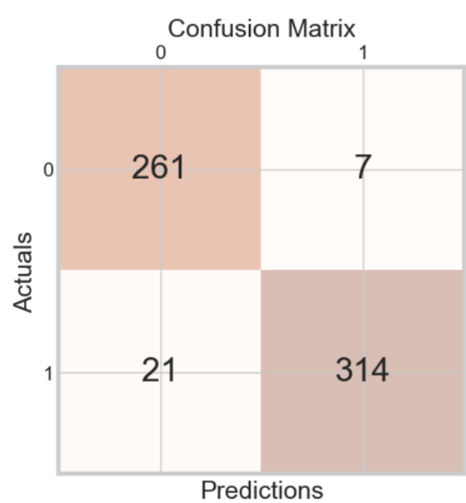


Fig. 6. Confusion Matrix obtained for XGBoost Algorithm

C. Stochastic Gradient Descent (SGD):

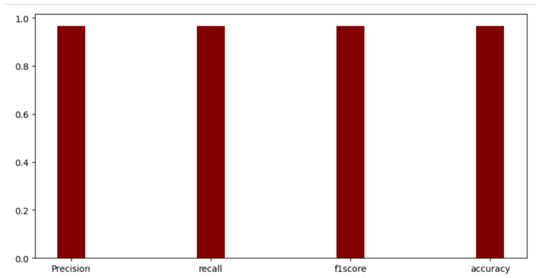


Fig. 7. Metrics obtained for SGD Algorithm

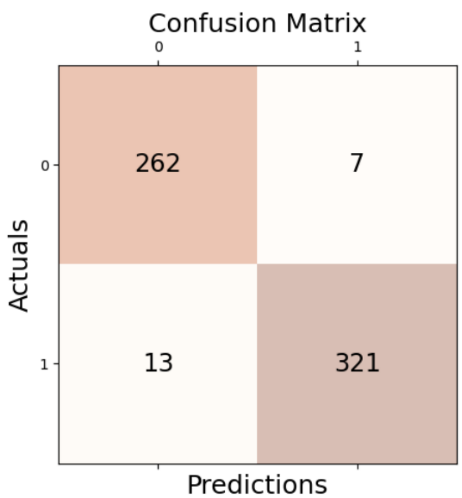


Fig. 8. Confusion Matrix obtained for SGD Algorithm

D. Bidirectional Encoder Representations from Transformers (BERT):

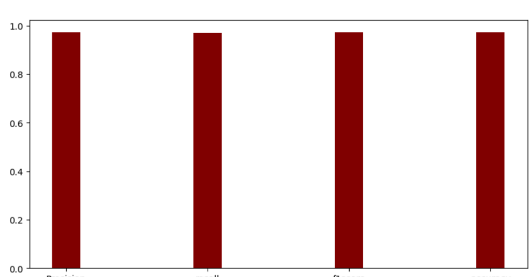


Fig. 9. Metrics obtained for BERT Algorithm

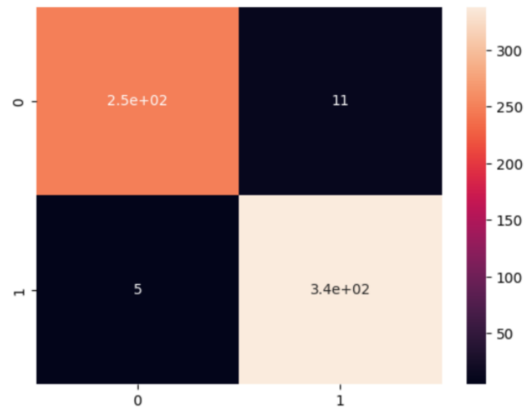


Fig. 10. Confusion Matrix obtained for BERT Algorithm

Algorithms	Precision			Recall		
	0	1	WA	0	1	WA
BERT	0.98	0.97	0.97	0.96	0.99	0.97
SGD	0.95	0.98	0.97	0.97	0.96	0.97
XGBoost	0.93	0.98	0.95	0.97	0.94	0.95
LSTM	0.96	0.96	0.96	0.94	0.97	0.96

Fig. 11. Metrics of different algorithms based on Precision and Recall

Algorithms	F1 - Score			Support		
	0	1	WA	0	1	WA
BERT	0.97	0.98	0.97	260	343	603
SGD	0.96	0.97	0.97	269	334	603
XGBoost	0.95	0.96	0.95	268	335	603
LSTM	0.95	0.96	0.96	265	338	603

Fig. 12. Metrics of different algorithms based on f1 - Score and Support

VI. DIFFERENT ALGORITHMS WITH RESULTS

A. Long short-term memory (LSTM):

Long Short-Term Memory (LSTM) networks are recurrent neural networks that can learn order dependence in sequence prediction problems. This is a necessary behavior in complex problem domains such as machine translation, speech recognition, and others. The previous step's output is used as input in the current step of RNN. Before being used in the real world, LSTM models must be trained using a training dataset. It is widely used in language translation, which entails translating a sequence from one language to a similar sequence in another. An encoder-decoder LSTM model can encode input sequences and then translate the translated version.

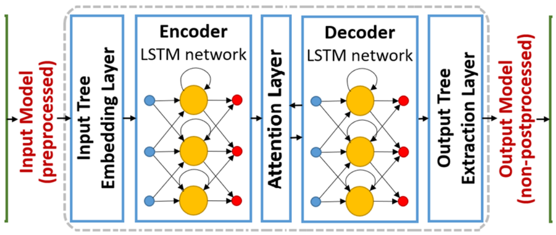


Fig. 13. Working of LSTM

B. XGBoost:

Gradient Boosted decision trees are implemented in XGBoost. This algorithm generates decision trees in a sequential fashion. Weights are very important in XGBoost. All of the independent variables are given weights, which are then fed into the decision tree, which predicts results. The weight of variables that the tree predicted incorrectly is increased, and these variables are then fed into the second decision tree. These individual classifiers/predictors are then combined to form a more powerful and precise model. It can solve problems involving regression, classification, ranking, and user-defined prediction. XGBoost improves upon the base gradient boosting framework through systems optimization and algorithmic enhancements, such as hardware optimization, efficient handling of missing data, parallelized tree building, and tree pruning using a 'depth-first' approach.

Fig. 14. MWorking of XGBoost

C. Stochastic Gradient Descent (SGD)

Gradient Boosted decision trees are applied in XGBoost. This algorithm generates decision trees in a successional fashion. Weights are really important in XGBoost. All of the independent variables are given weights, which are further fed into the decision tree, which predicts results. The weight of variables that the tree prophesied faultily is increased, and these variables are further fed into the alternate decision tree. These individual classifiers predictors are further combined to form a more important and precise model. It can crack problems involving regression, classification, ranking, and user- defined prediction. XGBoost improves upon the base gradient boosting framework through systems optimization and algorithmic advancements, similar as hardware optimization, effective conduct of missing data, parallelized tree structuring, and tree pruning using a' depth-first' approach.

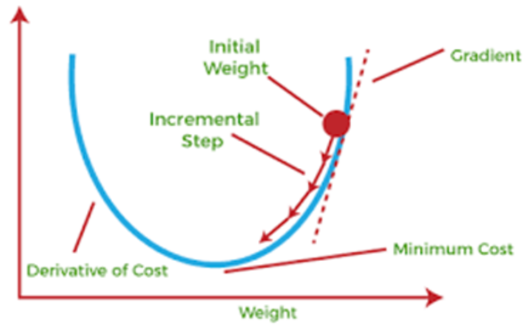


Fig. 15. Working of SGD

D. BERT (Bidirectional Encoder Representations from Transformers)

Researchers from Google Research proposed the BERT natural language processing model in 2018. Semi-Supervised Learning was one of the primary factors in BERT's successful completion of several NLP tasks. This indicates that the model has been trained for a particular task that enables it to comprehend the linguistic patterns. Once trained, the model (BERT) has the ability to process language, which can be used to strengthen other models that we create and train using supervised learning. BERT makes use of Transformer, an attention mechanism that learns contextual relations [1] [5]

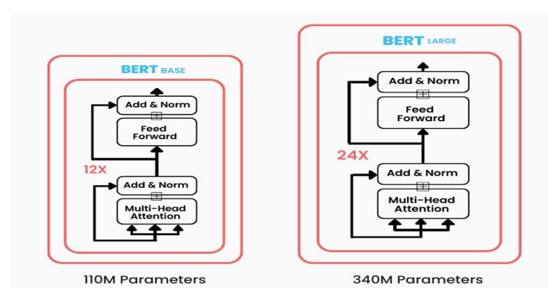


Fig. 16. Working of BERT

E. Comparison of algorithms

Here is a comparative analysis of the above four algorithms in terms of Precision, F1 Score, Recall and Support:

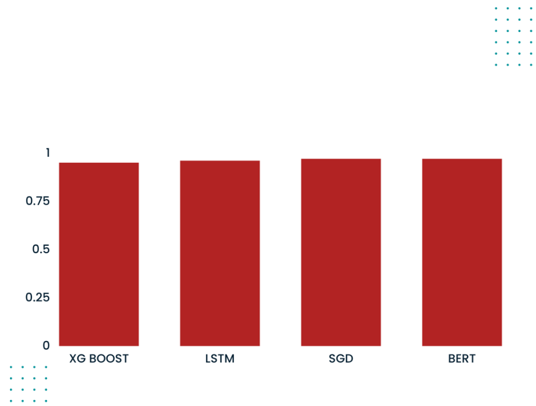


Fig. 17. Comparison of algorithms in terms of Precision

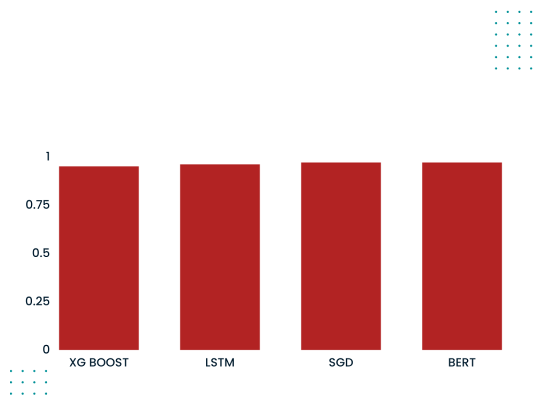


Fig. 18. Comparison of algorithms in terms of F1 Score

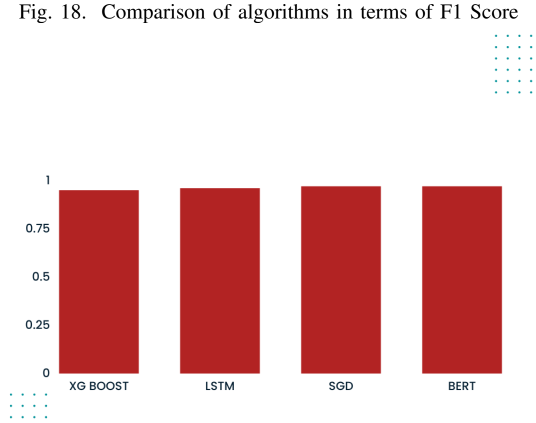


Fig. 19. Comparison of algorithms in terms of Recall

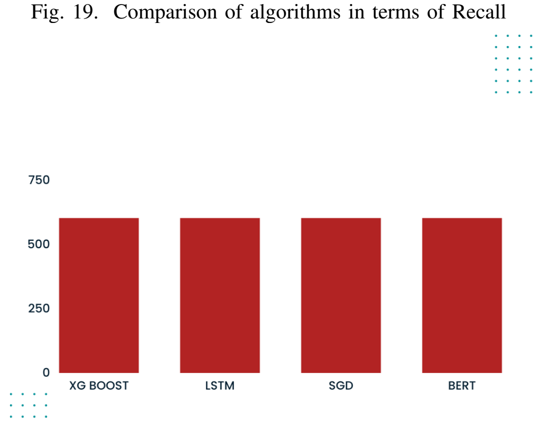


Fig. 20. Comparison of algorithms in terms of Support

VII. Results and Discussions

In the comparative study of sentiment analysis using SGD, XGBoost, LSTM, and BERT models, we analyzed their performance and effectiveness in predicting sentiment from text data.

Initially, we implemented the SGDClassifier, a linear classifier, for sentiment analysis. Despite its simplicity, it provided decent accuracy in classifying sentiments. The model showed promising results, especially considering its computational efficiency and ease of implementation. Next, we explored XGBoost, a gradient boosting algorithm known for its strong predictive power. XGBoost outperformed the SGDClassifier, achieving higher accuracy and better handling of complex relationships in the data. It demonstrated superior performance by leveraging the strengths of ensemble learning and gradient boosting techniques. Moving on to LSTM, a type of recurrent neural network (RNN), we witnessed a significant improvement in sentiment analysis accuracy. LSTM models have the advantage of capturing sequential information in text data and effectively handling long-term dependencies. This allowed the LSTM model to better understand the context and nuances of the text, resulting in improved sentiment classification.

Finally, we utilized BERT, a state-of-the-art transformer-based model, which demonstrated remarkable performance in sentiment analysis. BERT leverages a deep bidirectional architecture and pretraining on large-scale corpora, enabling it to capture intricate patterns and semantic relationships within the text. This led to highly accurate sentiment predictions and better comprehension of sentiment nuances. BERT (Bidirectional Encoder Representations from Transformers) can be concluded to be superior to other algorithms in sentiment analysis due to its unique working mechanism. Here's a detailed explanation of why BERT outperforms other algorithms:

- **Pretraining with Unsupervised Learning:** BERT is pretrained using unsupervised learning on a large corpus of text, such as Wikipedia. This pretraining process enables BERT to learn rich representations of words and sentences, capturing intricate language patterns and semantics. It learns to predict missing words in a sentence, making it capable of understanding context and relationships between words.
- **Transformer Architecture:** BERT employs a transformer architecture, which allows it to handle long-range dependencies and capture global context efficiently. Transformers use self-attention mechanisms to process words in parallel, considering their relationships with other words in the sentence. This enables BERT to capture dependencies between words regardless of their relative positions, enhancing its ability to comprehend sentiment nuances.
- **Bidirectional Contextual Understanding:** Unlike traditional models like SGD, XGBoost, and LSTM, which process text in a sequential manner, BERT performs bidirectional learning. It considers both left and right contexts when encoding each word, enabling a deep

understanding of the dependencies and contextual cues present in the sentence. This allows BERT to capture complex sentiment patterns and dependencies that may span across long distances in the text.
- **Fine-Tuning for Task-Specific Sentiment Analysis:** After pretraining, BERT is fine-tuned on task-specific labeled data, such as sentiment analysis datasets. During fine-tuning, BERT learns to map the input text to sentiment labels. Fine-tuning enables BERT to adapt its learned representations to the specific sentiment analysis task, optimizing its performance and making it highly accurate in sentiment classification.[11]
- **Contextual Word Embeddings:** BERT generates contextualized word embeddings, meaning that the representation of a word can vary depending on its context in the sentence. This contextual understanding allows BERT to capture subtle changes in word meaning based on the overall sentence sentiment. For example, the word "good" in the context of a positive sentence carries a different sentiment compared to the same word in a negative sentence. BERT's contextual embeddings capture this distinction, leading to more accurate sentiment predictions.[3]
- **Transfer Learning and Generalization:** BERT's pretraining on a large corpus and subsequent fine-tuning make it a powerful transfer learning model. It can leverage its pretrained knowledge to adapt to different sentiment analysis tasks, even with limited labeled data. This capability enhances its generalization and enables it to perform well on various sentiment analysis scenarios.

In summary, BERT's working mechanism, including its pretraining, transformer architecture, bidirectional contextual understanding, fine-tuning, contextual word embeddings, and transfer learning, collectively contribute to its superior performance in sentiment analysis. BERT's ability to capture complex language patterns, understand context, and adapt to specific sentiment analysis tasks make it a highly effective and accurate algorithm in this domain.

VIII. Conclusion

The methodology proposed for the detection of foodborne illness outbreaks using Twitter and BERT model can significantly improve the public health surveillance activities. The approach of collecting data from Twitter and processing it through various data cleaning and sentiment analysis techniques can provide quick and reliable information on potential outbreaks.

The future plans, as mentioned above, for using the collected feedback data to develop a restaurant management system and improving the sensitivity and specificity of the text mining algorithm can further enhance the accuracy of the system. The development of a web page to promote the restaurant feedback system can help to spread awareness among the general public about the importance of reporting incidents of foodborne illnesses.

Sharing this system with other health departments can enable them to incorporate Twitter in their outbreak detecction and public health surveillance activities, thus promoting the collaborative effort of the healthcare sector in addressing the issue of foodborne illnesses. Overall, this methodology can play a significant role in improving the efficiency and effectiveness of public health surveillance systems, leading to better management and prevention of foodborne illness outbreaks.

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