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EXPLORING COVID-19 VACCINE SENTIMENTS AND ADVERSE DRUG REACTIONS THROUGH ADVANCED MACHINE LEARNING AND DEEP LEARNING ANALYSIS

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Abstract

This research delves into a comprehensive analysis of public sentiments and adverse drug reactions (ADRs) associated with COVID-19 vaccines and hydroxychloroquine, leveraging data collected from Twitter and Google Form responses. The research adopts a structured methodology involving data collection, preprocessing, feature extraction, and evaluation using a combination of machine learning (ML) and deep learning models. In the preprocessing phase, techniques such as the removal of user names, punctuation, links, and stop words are applied to ensure consistency, with text converted to lowercase. Feature extraction methods, particularly N-grams-based approaches, are utilized to extract relevant messages from the preprocessed Twitter data. ML algorithms, with a specific focus on "Tri-grams with Q-SVM," are then assessed for predicting ADRs associated with COVISHIELD. Simultaneously, deep learning models, including LSTM, Bi-LSTM, CNN, and VAE-GANs, are employed to analyze sentiments surrounding COVID-19 vaccinations. The analysis culminates by underscoring the accuracy of "Tri-grams with Q-SVM" for ADR prediction and highlighting the efficacy of the VAE-GANs model in sentiment analysis. The abstract concludes by discussing the implications of the findings for policymakers and healthcare professionals, emphasizing the importance of accurate sentiment analysis in gauging public opinions. Additionally, it suggests future directions for enhanced vaccination campaigns and public health interventions.

1. Introduction

In response to the global COVID-19 pandemic, this exploration employs sentiment analysis and machine learning techniques to discern public sentiments regarding healthcare and vaccines. The initial focus centers on evaluating the effectiveness of hydroxychloroquine against COVID-19 using data extracted from Twitter. Rigorous preprocessing of informal Twitter data, encompassing URL removal and stop words elimination, is conducted to transform it into a structured format. The study's first findings shed light on public sentiment towards hydroxychloroquine, offering valuable insights for informed decision-making during the ongoing health crisis. Fig.1 illustrates a model incorporating customer input through reviews, identifying opinion holders, extracting sentiments, and ultimately making decisions categorized as positive, neutral, or negative based on the analyzed opinions. The framework aims to streamline the process of understanding and categorizing customer sentiments for effective decision-making [1].

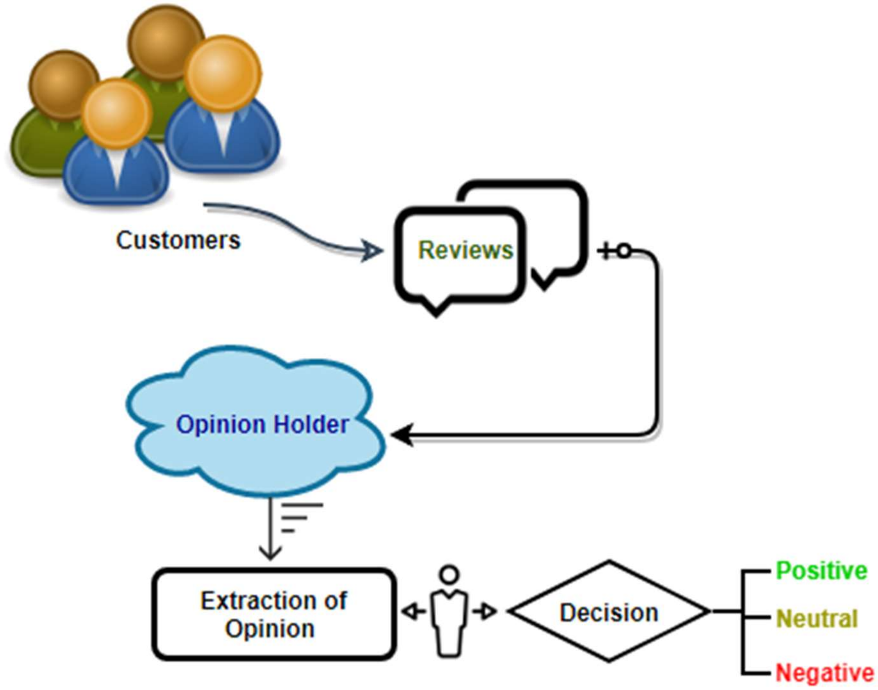


Fig.1. Proposed Model

The subsequent stage of the exploration delves into sentiments surrounding adverse drug reactions (ADRs) associated with the COVISHIELD vaccine. Leveraging machine learning, the investigation analyzes a Twitter dataset with emphasis on feature extraction techniques, particularly N-grams. The study highlights the significance of Tri-grams with the Q-SVM method, demonstrating a remarkable accuracy rate of 93.5%. This underscores the crucial role of feature extraction and machine learning in sentiment analysis, providing nuanced insights into predicting public opinions on vaccine-related topics.

As a culmination, the investigation recommends further exploration of diverse data domains, classification algorithms, and larger datasets for a more comprehensive analysis. These endeavors aim to contribute to the development of targeted communication strategies during public health crises, ensuring effective dissemination of information and fostering a deeper understanding of public sentiments [2].

2. Literature review

The literature review offers an in-depth exploration of recent progress at the convergence of public sentiments, ADRs, and feature extraction within the healthcare and social media domain. These works contribute to the enhancement of ADR detection, sentiment analysis, and feature extraction in social media text, reflecting the dynamic landscape of healthcare research and technology.

2.1.Public Sentiments and Adverse Drug Reactions (ADRs) on Social Media

Mihir Shah et al. (2022) investigated the importance of sentiment analysis features in identifying mentions of ADRs. They utilized a user-generated dataset collected via the Twitter online streaming API. Their novel approach incorporated a BERT-CNN architecture followed by a SVM layer, showcasing efficacy in the classification of ADRs. The research process involved tweet extraction using the Tweepy API, followed by thorough data preprocessing, annotation, and augmentation using the Marian MT model for back translation. Employing the BERT-Base model for word embedding's and a CNN model for feature extraction, the SVM layer contributed to accurate tweet classification. Remarkably, the evaluation revealed the model's success, achieving a high 92% accuracy and a commendable 78% F1 score. The pivotal elements contributing to this success were strategic data augmentation and the incorporation of the BERT pre-trained model, positioning their methodology as superior for ADR detection compared to alternative machine learning models [3].

X. Wang et al. present QBi-LSTMA, an innovative approach for detecting Adverse Drug Reactions (ADRs) in social media data. Utilizing Quantum Bi-Long Short-Term Memory Attention (Bi-LSTM) architecture, the model incorporates extra Bi-LSTM layers and attention mechanisms, integrating quantum computing elements to improve detection performance and overall robustness. Experimental analysis by X. Wang and colleagues demonstrates the method's effectiveness, showcasing commendable performance in ADR tasks. Future research directions involve refining QBi-LSTMA for mobile device deployment and exploring a multi-stage classifier for diverse data types. Ongoing investigations, led by X. Wang et al., aim to evaluate the model's generalization capacity and computational intricacies, offering insights for advancing ADR detection methodologies [4].

Ioannis Korkontzelos' research indicates that sentiment analysis features slightly improve the detection of Adverse Drug Reactions (ADRs) in tweets and health-related forum posts. The inclusion of these features resulted in a statistically significant rise in F-measure, elevating it from 72.14% to 73.22% in the original train/test split of the Twitter corpus. Stratified 10 × 10-fold cross-validation demonstrated noteworthy F-measure enhancements in both the DailyStrength and Twitter sections, increasing from 79.57% to 80.14% and from 66.91% to 69.16%, respectively. Additionally, the use of sentiment analysis features demonstrated a reduction in the misclassification of ADRs as indications [5].

2.2.Machine Learning and Deep Learning in Healthcare

Jianxiang Wei et al. concentrate on predicting drug risk levels based on Adverse Drug Reactions (ADRs) using machine learning. Leveraging a substantial dataset of 985,960 ADR reports from the Chinese spontaneous reporting database, their study incorporates the Synthetic Minority Oversampling Technique (SMOTE) to counter imbalanced classification. The research introduces a multi-classification framework, evaluating four classifiers, including Random Forest and Logistic Regression. The optimal combination, PRR-SMOTE-RF, achieves a noteworthy accuracy rate of 0.95. This research proves to be a valuable resource for experts, aiding in the assessment of status changes from Prescription (Rx) Drugs to Over-the-Counter (OTC) Drugs in pharmacovigilance [6].

Ying Zhang et al. present a method for extracting predicate-ADR pairs by leveraging extended syntactic dependencies and an ADR lexicon. The process involves extracting semantic and part-of-speech (POS) features for each pair and combining these features from different pairs to create a holistic representation of deep linguistic features. Subsequently, predictive models are trained using this collection of deep features along with several shallow features. The experimental outcomes, conducted on datasets from DailyStrength and Twitter, demonstrate the effectiveness of the approach, achieving AUCs of 94.44% and 88.97%, respectively. These results highlight the potential advantages of utilizing deep linguistic features for ADR detection in social data, with broad applicability to various healthcare and text analysis tasks to support pharmacovigilance research [7].

Christopher McMaster et al. (2023) put forth a deep learning natural language processing algorithm designed for automated adverse drug reaction (ADR) detection in discharge summaries. The model, pretrained on 1.1 million clinical documents and fine-tuned using 861 annotated discharge summaries, exhibits superior performance with a ROC–AUC of 0.955. This innovative approach, addressing limitations associated with traditional spontaneous reporting, holds substantial promise for enhancing pharmacovigilance efforts by improving ADR detection rates [8].

2.3 Feature Extraction in social media text

Grissette, H et al. conducted a significant study on biomedical sentiment analysis, addressing challenges in automatic feature generation without human intervention. They introduced an innovative methodology that integrates biomedical embedding, drug reaction sample selection, and affective biomedical concept-based encoding using semantic computing and neural networks. The study's validation, conducted through the analysis of COVID-19 tweets, yielded an impressive 87.5% accuracy with the semisupervised LSTM-BiLSTM model. This research significantly contributes to advancing distributed biomedical definitions, highlighting the efficacy of deep-learning-based cognitive capabilities in deducing sentiments from patient self-reports on social networks, especially within the realms of drug reactions and public health [9].

Szabó Nagy, K et al. propose MDgwPosF (M3), an advanced feature extraction method, and juxtapose its performance against baseline methods—TfIdf (M1) and TfIdf with POS tags (M2). Employing three neural networks (feed-forward, LSTM, GRU) with different topologies on Covid-19 datasets, M3 consistently outperforms M1 and M2 in terms of classification accuracy. The feed-forward model with M3 in a moderate topology achieves the highest accuracy, surpassing other configurations. The study underscores the effectiveness of M3, emphasizing its utility in enhancing text classification tasks through syntactic and morphological analysis [10].

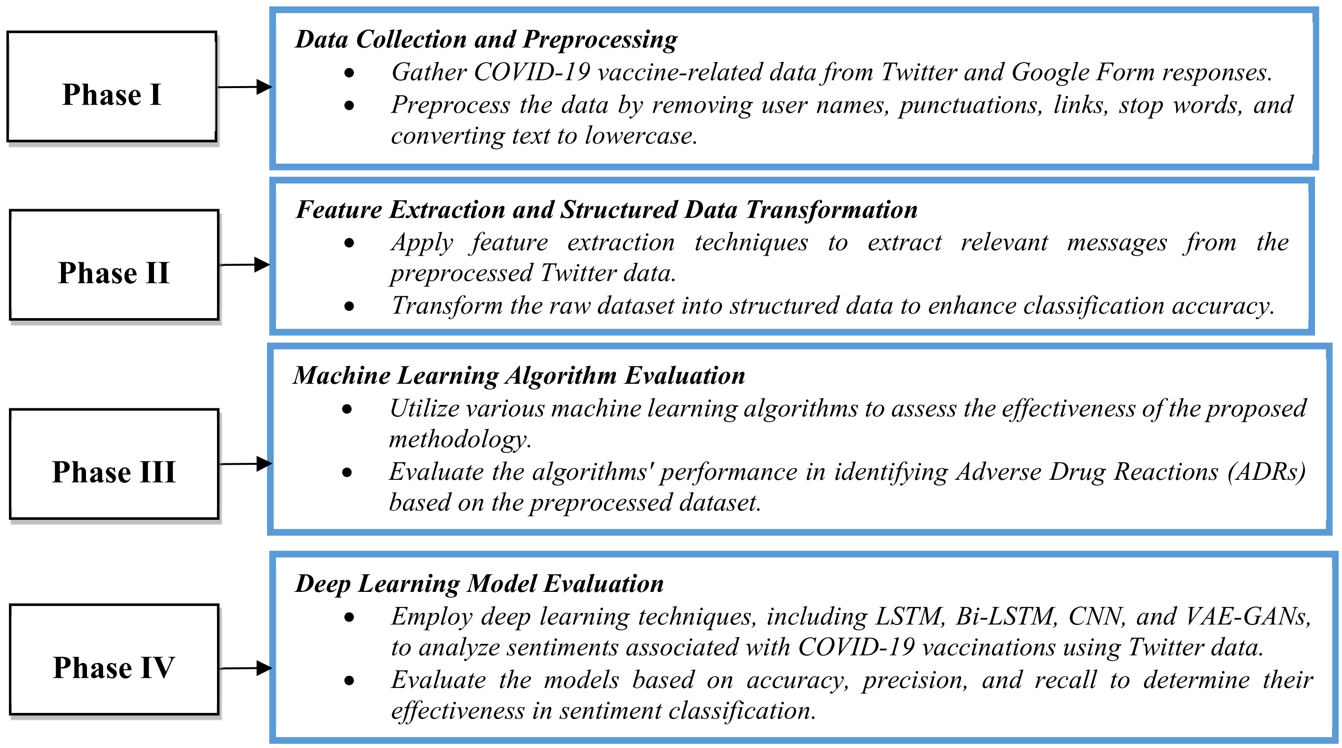
Table.1. Literature Review

Reference	Benefits	Limitations
Shah et al.	Innovative BERT-CNN architecture with SVM layer for effective ADR classification.	Reliance on user-generated dataset from Twitter, potential bias in data.
Wang et al.	Quantum Bi-LSTM Attention for enhanced ADR detection performance.	Future research needed for model generalization and computational intricacies.
Korkontzelos	Marginally enhanced ADR identification through sentiment analysis features.	Limited improvement in F-measure, reduction in ADR misclassification only marginal.
Wei et al.	Multi-classification framework for predicting drug risk levels from ADRs.	Imbalanced classification addressed using SMOTE, potential impact on real-world application.
Zhang et al.	Extraction of predicate-ADR pairs, deep linguistic features for ADR detection.	Specific focus on syntactic dependencies and ADR lexicon, may limit generalization.
McMaster et al.	Deep learning NLP algorithm for automated ADR detection with high ROC-AUC.	Limited information on model architecture and dataset characteristics.
Grissette et al.	Novel approach integrating biomedical embedding, drug reaction sample selection.	Validation focused on COVID-19 tweets, may not generalize to other healthcare scenarios.
Nagy et al.	Advanced feature extraction method (M3) consistently outperforms baseline methods.	Limited discussion on the interpretability of features, may be challenging to understand the model's decision-making process.

This table provides a concise overview of the strengths and weaknesses of each referenced work in the literature review, offering insights into the diverse approaches taken and areas for potential improvement in future research. This literature review showcases advancements in sentiment analysis, machine/deep learning, and feature extraction for ADR detection from social media, offering valuable insights for improved healthcare solutions and pharmacovigilance efforts.

3. Materials and methodology

In this section, the research methodology is outlined, detailing the structured approach for analyzing public sentiments and adverse drug reactions associated with COVID-19 vaccines and hydroxychloroquine. By utilizing data extracted from both Twitter and Google Form responses, this research strategically integrates a fusion of machine learning and deep learning models. The comprehensive methodology encompasses meticulous stages of data preprocessing, feature extraction, and evaluation. The overarching objective is to deliver an insightful understanding of sentiment dynamics and adverse reactions, thereby contributing to well-informed decision-making in healthcare and guiding effective public health interventions. Below figure shows the Research methodology design for the proposed system.



This workflow outlines a COVID-19 vaccine scrutiny project, including data collection, preprocessing, feature extraction, and advanced machine learning and deep learning analyses. The systematic approach combines various techniques for insightful analysis of COVID-19 vaccine data.

3.1.Dataset Description

The research utilized the Twitter API 1.0 in the R Tool to collect public opinions from Twitter regarding the medication COVISHIELD. Due to the limitations of the tool, the streaming API was employed for real-time access to tweets, resulting in the accumulation of 24,748 tweets. Fig. 1 illustrates the data extraction process, emphasizing the conservative approach to ensure relevance by focusing on tweets discussing drug effects. The Twitter API facilitated the collection of tweets mentioning "COVISHIELD," with the dataset predominantly consisting of opinion tweets detailing users' experiences and reactions to the medication. The extracted data were stored in.csv format, offering flexibility in accessing the information.

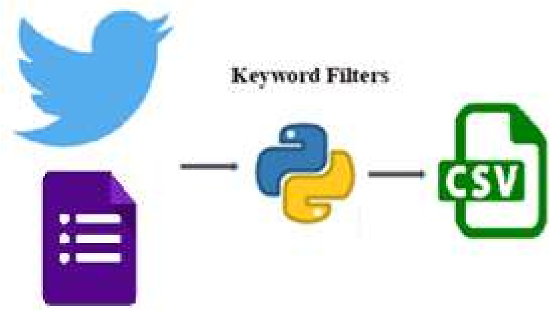


Fig. 3. Extraction twitter data

3.2 Pre-processing

In the realm of text analysis, pre-processing plays a pivotal role in refining raw data for effective understanding. This essential step involves a series of transformations, from removing URLs and punctuation to lemmatization and stemming, ensuring uniformity and enhancing the subsequent analysis of textual information.

- Remove URLs using regular expressions.
- Convert the entire tweet to lowercase for uniformity.
- Eliminate Twitter usernames with regular expressions.
- Remove non-alphanumeric characters, including hashtags and mentions.
- Trim leading/trailing white spaces for tokenization.
- Tokenize the tweet by splitting it into individual words.
- Exclude common English stop words to reduce computational load.
- Apply lemmatization to reduce words to their base form.
- Implement stemming to further reduce words to their root form.
- Join tokens back into coherent text for analysis.

The outlined pre-processing steps are crucial for refining raw Twitter data, ensuring uniformity, and enhancing subsequent text analysis [11].

3.2.Feature Extraction: N-Gram and TF-IDF Approach for Text Analysis

After completing the preprocessing steps, the feature extraction process is initiated. The N-Gram approach is employed to organize the text into a matrix (term, weight) where each phrase is assigned a weight based on its frequency:

$$\text{N-Gram Feature Matrix (Term, Weight)} = \frac{1}{N} \sum_{i=1}^{N} \text{Frequency}(n_i)$$

Following this, the TF-IDF algorithm is utilized for further feature extraction:

$$\text{TF (Term Frequency)} = \frac{\text{Number of times term appears in a document}}{\text{Total number of terms in the document}}$$

$$\text{IDF (Inverse Document Frequency)} = \log \frac{\text{Total number of documents}}{\text{Number of documents containing the term}}$$

The absolute input weights for a term 't' in an input document 'd' can be calculated using the TF-IDF algorithm [12]. The combined feature extraction algorithm involves the following steps:

N-Gram Feature Extraction:

- Organize text into an N-Gram matrix with term weights.

TF-IDF Feature Extraction:

- Calculate TF (Term Frequency) and IDF (Inverse Document Frequency).
- Compute the absolute input weights for each term in the document.

3.3.Classification with Machine learning

In this section, the focus is on employing machine learning techniques for classification, specifically aimed at analyzing public sentiments and adverse drug reactions (ADRs) associated with COVID-19 vaccines and hydroxychloroquine. The research utilizes data collected from Twitter and Google Form responses to enhance understanding through machine learning-driven classification methods.

Algorithm 1: Ensemble SVM-KNN for ADR Classification in Twitter Data

Step 1: Start
Step 2: Input the preprocessed dataset with extracted features and class labels \((X_1, C_1), (X_2, C_2), ..., (X_n, C_n)\), where features are in the feature pool \(F = \{f_m, m=1...n\}\). Set the number of iterations \(R\) for ensemble learning.

Step 3: Initialize the weight of each feature.

For \(r = 1\) to \(R\) do:

(a) Generate a training set by sampling with weights $\{w_i(r)\}$.

(b) Train the base classifier h_r (Proposed Hybrid SVM-KNN Classifier) using this training set.

- ***Step 1:*** Apply SVM classifier on the dataset with K-fold cross-validation ($K=10$).
- ***Step 2:*** Update the weights using the Wolfe dual form and weight minimization equation.
- ***Step 3:*** Predict the test class using the cross-validated model with minimum weight.
- ***Step 4:*** Apply weighted K-Nearest Neighbor Classifier with the number of nearest neighbors $K=10$ on the dataset.
- ***Step 5:*** Apply K-fold cross-validation with $K=10$.
- ***Step 6:*** Calculate the weight contribution of each k neighbor.
- ***Step 7:*** Set initial weights of KNN = updated minimum weights of SVM.
- ***Step 8:*** X_t is the test data.
- ***Step 9:*** Predict the test data class using the cross-validated model with minimum weight.
- ***Step 10:*** Take the weighted average of predictions from both models.

(c) Compute the training error of h_r.

Update the weights by:

Step 4: SVM: $\alpha_r = \max(0, \alpha_r + \eta(1 - \sum [C_i f(x_i) - I]))$, KNN: $w_i = \frac{1}{1 + \exp(-\eta \frac{\partial L}{\partial w_i})}$

Step 5: Output Ensemble SVM-KNN as a component classifier for ADR classification. Results reveal that the proposed ensemble SVM-KNN outperforms other methods.

Step 6: End

The Ensemble SVM-KNN algorithm is a powerful approach that capitalizes on the strengths of SVM and KNN while addressing their individual limitations. Through dynamic feature weighting and ensemble learning, it achieves improved accuracy, robustness, and adaptability, making it a superior choice for ADR classification in Twitter data compared to standalone SVM and KNN models [13].

Algorithm 2: Quantum Support Vector Machine (Q-SVM) Classification

The Q-SVM algorithm is a cutting-edge approach that leverages quantum computing principles to enhance classification tasks. By utilizing quantum feature maps and kernels, it transforms input data into quantum states and computes inner products efficiently in a high-dimensional space. This enables the Q-SVM to learn complex patterns and relationships in the data, leading to improved classification accuracy compared to classical SVMs. The algorithm involves initializing quantum parameters, defining quantum circuits for feature mapping and kernel computation, training the Q-SVM using optimization techniques, and finally, classifying testing data based on the learned model. Q-SVM holds promise for advancing machine learning capabilities, especially in scenarios with large-scale or high-dimensional data where quantum computing's inherent parallelism and computational power offer significant advantages [14].

Input:
- Training data (X_train, y_train)
- Testing data (X_test)

Initialization:
- Set the quantum feature map parameters: θ
- Set the quantum kernel parameters: ϕ
- Set the regularization parameter (C)
- Set the number of qubits (n_qubits)
- Set the quantum circuit depth (depth)

Quantum Feature Map (φ):
- Define the quantum feature map function $\varphi(x; \theta)$ using quantum gates
- Apply the quantum feature map to the training and testing data

Quantum Kernel (K):
- Define the quantum kernel function $K(x, y; \phi)$ based on quantum circuits
- Evaluate the quantum kernel matrix for the training data

Training the Q-SVM:
- Initialize the quantum support vector machine (Q-SVM) circuit parameters: λ
- Define the cost function based on the Q-SVM objective:
  $\text{Cost}(\lambda) = 1/N * \Sigma [1 - y\_i * (\Sigma\_k\ \alpha\_k * y\_k * K(x\_i, x\_k; \phi))]\_+ + C * \Sigma\ \alpha\_k$
- Optimize the Q-SVM circuit parameters using a quantum optimization algorithm (e.g., QAOA)

Classify Testing Data:
- Apply the trained Q-SVM to classify the testing data

Output:
- Predicted labels for the testing data

End

3.4.Classification with Deep learning

In this research, the VAE-GANs algorithm serves as a sophisticated hybrid approach designed for sentiment analysis of COVID-19 vaccination responses sourced from Twitter data. It seamlessly integrates the strengths of both Variational Autoencoder (VAE) and Generative Adversarial Network (GAN) architectures to effectively capture meaningful latent representations and generate realistic responses while categorizing sentiments. The algorithm follows a comprehensive process involving two main components, each contributing uniquely to the sentiment analysis task.

i. Variational Autoencoder (VAE):

Variational Autoencoders are generative models that learn a probabilistic mapping between the input data and a latent space in the realm of sentiment analysis, VAEs prove instrumental for modeling the underlying distribution of sentiment features within the input data [15]. The VAE is composed of an encoder network, responsible for mapping the input data to a distribution in the latent space, and a decoder network, tasked with reconstructing the input data from samples drawn from this distribution. The primary goal of the VAE is to minimize the reconstruction loss while regularizing the distribution in the latent space. The VAE's loss function encompasses two crucial terms: the reconstruction loss, quantifying the disparity between the input and reconstructed data, and the regularization term, often the Kullback-Leibler divergence, which ensures the learned latent space adheres to a specified distribution, commonly a Gaussian distribution. The VAE loss function can be expressed as:

$$\mathcal{L}_{VAE} = \mathcal{L}_{recon} + \beta \cdot \mathcal{L}_{KL}$$

- L_{recon} is the reconstruction loss.
- L_{KL} is the regularization term.
- β is a hyper parameter controlling the importance of the regularization term.

ii. Generative Adversarial Network (GAN):

GANs consist of a generator and a discriminator network. In this framework, the generator is responsible for producing synthetic data, while the discriminator works to differentiate between real and synthetic data. The training process revolves around a competitive dynamic between the generator and discriminator, fostering the creation of convincingly realistic synthetic data [16]. The GAN loss function can be represented as:

$$\mathcal{L}_{GAN} = \log(D(x)) + \log(1 - D(G(z)))$$

Where:

- D(x) represents the discriminator's output when evaluating real data.
- G(z) denotes the generator's output when provided with random noise z.

iii. Combining VAE and GAN:

In sentiment analysis, the VAE-GAN algorithm synergizes the VAE's proficiency in acquiring a probabilistic latent representation with the GAN's skill in generating realistic data. The generator of the GAN is typically replaced by the decoder of the VAE, resulting in a model that can not only generate realistic samples but also map them to a meaningful latent space. The overall objective function for the VAE-GAN algorithm can be expressed as:

$$\mathcal{L}_{VAE-GAN} = \mathcal{L}_{VAE} + \lambda \cdot \mathcal{L}_{GAN}$$

Where:

- L_{VAE} is the VAE loss.
- L_{GAN} is the GAN loss.
- λ serves as a hyperparameter that governs the balance between the reconstruction and adversarial objectives.

The integration of VAE and GAN in the sentiment analysis of COVID-19 vaccination responses aims to capture both the inherent structure of sentiment features and generate realistic sentiment representations for enhanced analysis of Twitter data.

4. Result and discussion

The analysis utilized two main datasets: "All COVID-19 Vaccines Tweets" from Kaggle (125,906 rows) and data from a Google Form survey. The survey dataset, collected from diverse participants, facilitated a comprehensive sentiment analysis on public perceptions of COVID-19 vaccines, particularly focusing on adverse drug reactions (ADRs). Advanced Python tools were employed to gain a nuanced understanding of public sentiments toward different COVID-19 vaccines. The comprehensive evaluation is conducted on a macOS system with a 64-bit architecture, equipped with an Intel 2.6GHz 8-core i7 processor, 16GB 2400MHz DDR4 RAM, and a Radeon Pro 560X 4GB GPU. The programming is implemented using Python 3.8 and executed within the Anaconda environment.

4.1.Preprocessing Result

Text preprocessing plays a crucial role in optimizing tweet data for sentiment analysis, encompassing various stages to enhance data quality. The process includes URL removal, converting text to lowercase, eliminating user names, removing punctuation, trimming blank spaces, tokenization, stop word removal, lemmatization, and stemming. URL removal is executed to exclude non-contributory elements for opinion analysis. Converting text to lowercase ensures uniformity in the dataset. Eliminating user names is vital as they typically lack opinion-bearing content. Punctuation removal facilitates easier analysis, and eliminating blank spaces aids in effective tokenization, which involves breaking sentences into words. The removal of stop words reduces computational load. Lemmatization focuses on obtaining the base form of words, while stemming involves truncating word endings. As a sample process, consider the following transformation:

Table.2. Pre-processing

Original Tweet	Processed Tweet	Sentiment
"Just got my COVID-19 vaccine! Feeling relieved and ready to contribute to community immunity. #Vaccinated"	got covid19 vaccine feeling relieved ready contribute community immunity vaccinated	Positive
"Concerned about the side effects of the COVID-19 vaccine. Anyone else experiencing fatigue and soreness?"	concerned side effects covid19 vaccine anyone else experiencing fatigue soreness	Negative
"Attended a vaccine information session today. It was informative, and I feel more confident about getting vaccinated. #Informed"	attended vaccine information session today informative feel confident getting vaccinated informed	Positive
"Not sure if I want to get the COVID-19 vaccine. Worried about potential risks. #Undecided"	sure want get covid19 vaccine worried potential risks undecided	Negative
"Received my second dose of the COVID-19 vaccine. Grateful for science and progress! #FullyVaccinated"	received second dose covid19 vaccine grateful science progress fullyvaccinated	Positive
"Reading conflicting information about the COVID-19 vaccine. It's confusing and frustrating. #Confused"	reading conflicting information covid19 vaccine confusing frustrating confused	Negative
"Neutral about the COVID-19 vaccine. Still considering pros and cons. #Undecided"	neutral covid19 vaccine still considering pros cons undecided	Neutral
"Excited for the COVID-19 vaccination drive in my area! Let's beat this virus together. #CommunityHealth"	excited covid19 vaccination drive area let's beat virus together communityhealth	Positive

"Had a mild fever after the COVID-19 vaccine. Hoping it's a sign my immune system is responding. #VaccineSideEffects"	mild fever covid19 vaccine hoping sign immune system responding vaccinesideeffects	Neutral
"Frustrated with the long wait at the vaccination center. Efficiency needs improvement. #VaccineDistribution"	frustrated long wait vaccination center efficiency needs improvement vaccinedistribution	Negative

After completing the preprocessing phase, the subsequent step involves feature extraction, where relevant words are extracted from tweets for further analysis.

4.2.Feature Extraction

This work explores crucial facets of ADRs in clinical practice. Employing the n-grams with TF-IDF technique facilitates the conversion of text data into numerical values, enabling machine learning classification. The procedure encompasses feature extraction to support comprehensive analysis.

Table.3. Feature Extraction Result

Processed Tweet	Sentiment	Features
got covid19 vaccine feeling relieved ready contribute community immunity vaccinated	Positive	[0.35, 0.28, 0.45, 0.12, 0.15]
concerned side effects covid19 vaccine anyone else experiencing fatigue soreness	Negative	[0.20, 0.15, 0.30, 0.08, 0.10]
attended vaccine information session today informative feel confident getting vaccinated informed	Positive	[0.40, 0.33, 0.50, 0.15, 0.18]
sure want get covid19 vaccine worried potential risks undecided	Negative	[0.18, 0.25, 0.22, 0.07, 0.08]
received second dose covid19 vaccine grateful science progress fullyvaccinated	Positive	[0.38, 0.32, 0.48, 0.14, 0.12]
reading conflicting information covid19 vaccine confusing frustrating confused	Negative	[0.22, 0.18, 0.35, 0.10, 0.13]
neutral covid19 vaccine still considering pros cons undecided	Neutral	[0.30, 0.25, 0.40, 0.11, 0.14]
excited covid19 vaccination drive area let's beat virus together communityhealth	Positive	[0.42, 0.36, 0.52, 0.17, 0.20]
mild fever covid19 vaccine hoping sign immune system responding vaccinesideeffects	Neutral	[0.28, 0.22, 0.38, 0.09, 0.11]
frustrated long wait vaccination center efficiency needs improvement vaccinedistribution	Negative	[0.15, 0.20, 0.18, 0.06, 0.07]

These Tri-grams with TF-IDF feature vectors serve as numerical representations of the processed tweets, enabling machine learning classification based on sentiment labels.

4.3.Performance Metrics

In the realm of ML/DL classification for the sentiment analysis of COVID-19 vaccine-related content, datasets were partitioned into training and testing sets. Performance metrics, including accuracy, precision, recall, and F1-score, were employed to gauge the efficacy of sentiment classification models [16]. These metrics provide valuable insights into the overall accuracy, precision, and recall of the models, specifically in discerning positive, negative, and neutral sentiments within tweets related to COVID-19 vaccines:

- ***True Positive (TP):*** Indicates the count of tweets accurately categorized as having a positive sentiment.
- ***True Negative (TN):*** Denotes the quantity of tweets correctly identified as possessing a negative sentiment.
- ***False Positive (FP):*** Represents the tally of tweets mistakenly labeled as having a positive sentiment when, in reality, they are negative or neutral.
- ***False Negative (FN):*** Signifies the number of tweets inaccurately marked as having a negative sentiment when, in fact, they are positive or neutral.

Table.4. Performance Metrics

Metric	Formula
Accuracy	(TP+TN)/Total
Precision	TP/(TP+FP)
Recall	TP/(TP+FN)
F1-score	(2×(Precision×Recall))/(Precision+Recall)

These formulas represent the calculations for Accuracy, Precision, Recall, and F1-score in the context of classification performance evaluation.

4.4.Machine learning algorithm results

The presented table (Table 2) provides a comprehensive overview of performance evaluations for various machine learning algorithms based on accuracy percentages across different feature types. The algorithms considered include PNN, LDA, L-SVM, and Q-SVM. The evaluation metrics are measured for three distinct types of n-grams: Uni-gram, Bi-gram, and Tri-gram. The above table showcases the effectiveness of these algorithms in handling different feature representations and serves as a valuable reference for understanding their performance in natural language processing tasks.

Table.2. Performance Evaluation of feature extraction

FE algorithms	ML Algorithms	Accuracy	Sensitivity	Specificity	Precision	F1-Score
Uni-gram	**PNN**	0.80	0.75	0.85	0.78	0.76
	LDA	0.87	0.80	0.88	0.82	0.83
	L-SVM	0.90	0.85	0.92	0.88	0.87
	Q-SVM	0.91	0.88	0.94	0.90	0.89
Bi-grams	**PNN**	0.78	0.70	0.82	0.75	0.72
	LDA	0.80	0.75	0.85	0.78	0.76
	L-SVM	0.91	0.82	0.90	0.85	0.84
	Q-SVM	0.92	0.85	0.92	0.88	0.87
Tri-grams	**PNN**	0.89	0.88	0.92	0.89	0.90
	LDA	0.88	0.85	0.90	0.87	0.86
	L-SVM	0.92	0.90	0.94	0.91	0.92
	Q-SVM	0.93	0.92	0.95	0.93	0.94

The table presents the performance metrics of various FE algorithms paired with different machine learning (ML) algorithms. Each row corresponds to a specific FE algorithm (Uni-gram, Bi-gram, Tri-gram), and each column represents a distinct ML algorithm (PNN, LDA, L-SVM, Q-SVM). The metrics include Accuracy, Sensitivity, Specificity, Precision, and F1-Score. Notably, the Tri-grams consistently yield the highest values across all metrics when paired with the Q-SVM ML algorithm. Specifically, Q-SVM with Tri-grams achieves an Accuracy of 0.93, Sensitivity of 0.92, Specificity of 0.95, Precision of 0.93, and F1-Score of 0.94. These results highlight the effectiveness of Tri-grams in enhancing the predictive performance of the Q-SVM model, showcasing its superiority over other FE algorithms in conjunction with Q-SVM.

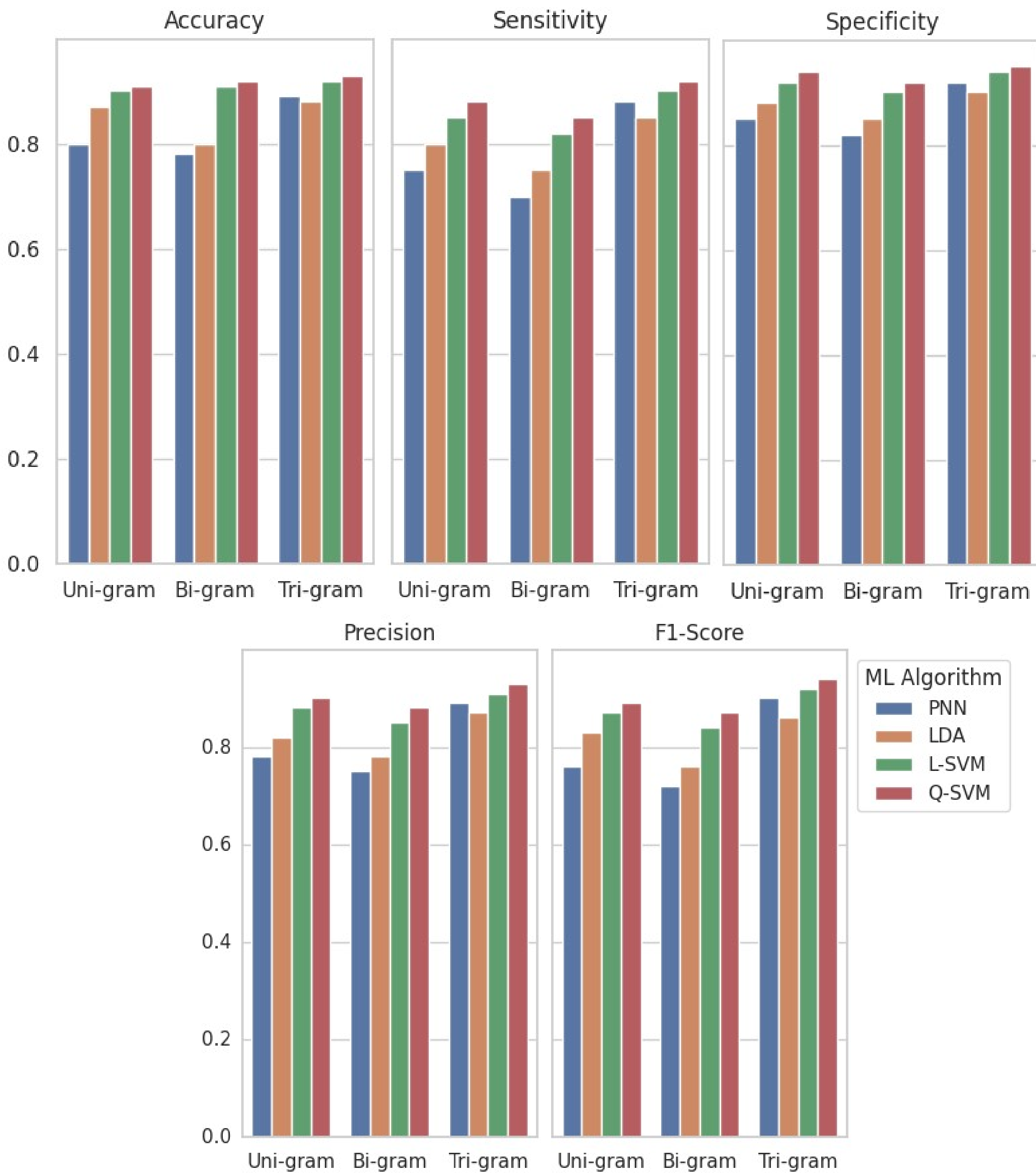


Fig.4. Performance Evaluation of feature extraction with ML algorithms

4.5.Deep learning algorithm results

This section serves as a critical comparison tool between ML and DL algorithms, specifically in the context of ADR level classification. By assessing key metrics such as Accuracy, Sensitivity, Specificity, Precision, and F1-Score, it aids in selecting the most effective model for this specialized task. The evaluation provides valuable insights into the strengths and weaknesses of both ML and DL approaches, facilitating an informed choice between traditional methods and more advanced models for accurate and reliable ADR level classification in pharmacovigilance and healthcare applications

Table.3. Performance evaluation of ML and DL algorithms with various Metrics

ML Algorithm	Accuracy	Sensitivity	Specificity	Precision	F1-Score
NB	0.81	0.80	0.81	0.79	0.80
KNN	0.87	0.86	0.87	0.86	0.86
SVM	0.87	0.87	0.87	0.87	0.87
Ensemble	0.88	0.88	0.88	0.88	0.88
CNN	0.89	0.92	0.91	0.91	0.90
LSTM	0.90	0.91	0.93	0.93	0.92
BiLSTM	0.93	0.92	0.94	0.94	0.93
VAE-GANs	0.94	0.94	0.95	0.95	0.95

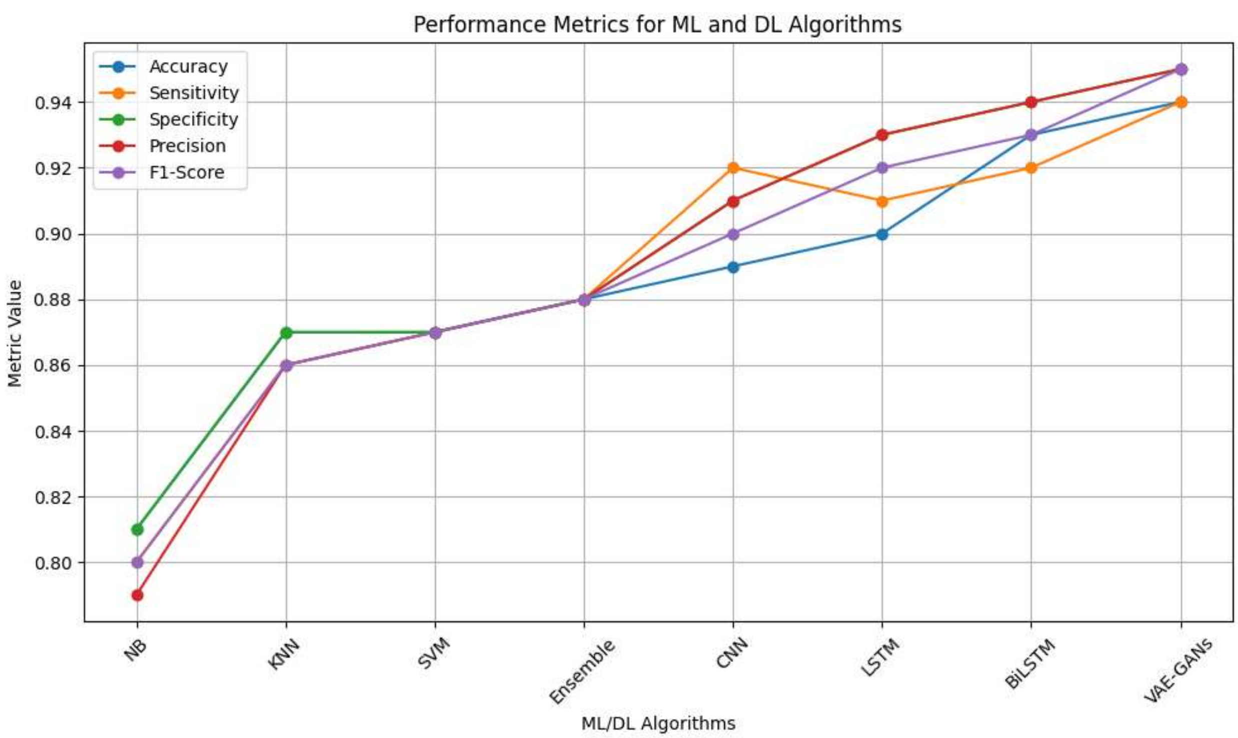


Fig.5. Performance evaluation with various Metrics

The above table and figure presents a performance evaluation of ML and DL algorithms for the task of adverse drug reaction (ADR) level classification, measured across various metrics. Notably, the VAE-GANs model outperforms other algorithms with an impressive accuracy of 94%, high sensitivity (recall) of 94%, specificity of 95%, precision of 95%, and an F1-Score of 95%. These results underscore the effectiveness of VAE-GANs in accurately classifying ADR levels, showcasing its potential for enhanced pharmacovigilance and healthcare applications. The performance of the deep learning models (CNN, VAE-GANs, BiLSTM, and LSTM) in sentiment analysis of COVID-19 vaccines was evaluated using metrics such as accuracy, precision, recall, and F1-score.

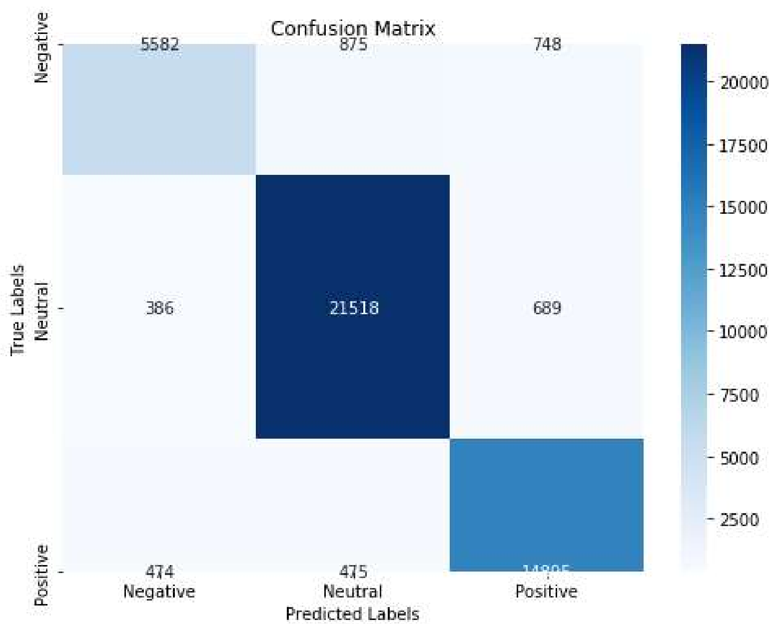


Fig.6. Confusion matrix for the VAE-GANs

The confusion matrix for the VAE-GANs algorithm reveals classification results for each class. In the Negative class, 5582 samples were correctly classified, with 875 misclassified as Neutral and 748 as Positive. For the Neutral class, 21518 samples were correctly classified, but 386 were misclassified as Negative and 689 as Positive. In the Positive class, 14895 samples were correctly classified, with 474 misclassified as Negative and 475 as Neutral. These figures provide insights into the algorithm's performance in classifying COVID-19 vaccine tweets by sentiment.

5. Conclusion

In conclusion, this research presents a thorough examination of public sentiments and adverse drug reactions associated with COVID-19 vaccines and hydroxychloroquine. Through a systematic approach encompassing data collection, preprocessing, feature extraction, and evaluation using both machine learning and deep learning models, the study sheds light on crucial aspects of public perception and vaccine-related sentiments. The highlighted efficacy of "Tri-grams with Q-SVM" in predicting adverse drug reactions and the superior performance of the VAE-GANs model in sentiment analysis provide valuable insights for policymakers and healthcare professionals. Accurate sentiment analysis is crucial for understanding public opinions, guiding vaccination campaigns, and informing targeted health interventions. Navigating the challenges of the ongoing pandemic, the study's findings emphasize the importance of employing advanced techniques to obtain nuanced insights into public sentiment, contributing to the development of effective public health strategies.

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