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Crowdsourced Intelligence: A Federated Learning Approach to Analyzing Public Opinion on Social Media



Abstract. This research paper explores the application of federated learning to social media sentiment analysis, focusing on the task of analyzing public opinion across diverse online platforms. Making use of federated learning, we aggregate sentiment analysis models trained on data from multiple sources while preserving data privacy and security. Our experiments demonstrate promising results, indicating that federated learning effectively captures dynamic sentiment expressions across various social media platforms. Insights gained from this research contribute to a deeper understanding of public opinion dynamics online, offering valuable implications for businesses, policymakers, and researchers. Future work includes investigating advanced federated learning techniques, optimizing model architectures, extending analysis to multimodal data sources, evaluating generalizability across demographic groups and languages, and assessing scalability for large-scale datasets. This research represents a foundational exploration of federated learning for social media sentiment analysis, with potential implications for advancing both federated learning methodologies and understanding public sentiment in the digital age.

Keywords: Federated Learning, Sentiment Analysis, Data Privacy, Machine Learning, Privacy-Preserving, Model Optimization.

1 INTRODUCTION:

In the digital age, social media platforms [1] have emerged as powerful arenas for public discourse, enabling individuals to express opinions, share experiences, and engage in conversations on a global scale. The vast volume of user-generated content on social media [2] platforms such as Twitter, Facebook, and Instagram present a rich source of data for understanding public sentiment [2], [3], [4] toward diverse topics ranging from political[5] events to consumer products. However, analyzing this vast amount of data poses significant challenges due to privacy concerns [6], data localization laws [7], and the sheer scale of information generated in real-time.

Federated learning has surfaced as a promising avenue in research to tackle these obstacles by facilitating collaborative model training across distributed data sources, all the while upholding user privacy. Federated learning differs from conventional centralized methods, which gather and store data in one central location [34] it allows models to be trained directly on user individual devices or edge servers, with only model updates aggregated at a central server. This distributed learning paradigm not only mitigates privacy risks[11] associated with centralized data collection but also facilitates the analysis of sensitive data such as social media[2] posts without compromising user privacy.

The application of federated learning[3] to social media sentiment analysis[2] holds immense potential for gaining insights into public opinion dynamics and sentiment trends. By applying federated learning techniques[9], researchers and organizations can analyze sentiment patterns[10] across diverse demographics, geographical regions, and cultural contexts with user data. This decentralized approach not only respects user privacy[7], [11] and data sovereignty [11] but also enhances the robustness and generalizability of sentiment analysis models by incorporating diverse perspectives and linguistic nuances. Moreover, federated learning[3], [34], enables real-time analysis of social media sentiment[38], [41], allowing organizations to monitor public perception, identify emerging trends, and respond promptly to evolving sentiments. This capability is particularly valuable in domains such as brand management, crisis communication, and political analysis, where timely insights into public opinion can inform decision-making[42] and shape strategic interventions. Additionally, federated learning[16] models can be continuously updated and refined based on feedback[43] from local data sources, ensuring adaptability and accuracy in capturing evolving sentiment dynamics.

Despite its potential benefits, federated learning for social media sentiment analysis poses several technical and ethical challenges [17],[19] that warrant careful consideration. These include ensuring data confidentiality and security across decentralized nodes[35], addressing data heterogeneity[39] and distributional shifts, and mitigating algorithmic biases[37] inherent in social media data. Moreover, ethical concerns regarding consent, transparency, and accountability in federated learning settings require robust governance frameworks and regulatory oversight to safeguard against misuse and ensure responsible AI deployment.

In this research paper, we aim to explore the approaches of federated learning techniques for social media sentiment analysis, with a focus on analyzing public opinion dynamics and sentiment trends across diverse social media platforms. By examining the opportunities, challenges, and implications of federated learning [8] in this context, we seek to advance our understanding of how decentralized AI approaches can facilitate ethical and privacy-preserving analysis of public sentiment while enabling informed decision-making and nurturing inclusive and participatory dialogue in the digital public sphere.

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2 OVERVIEW AND METHODOLOGY:

To achieve these objectives, this paper first provides a comprehensive approach of federated learning principles and techniques, highlighting their key advantages and limitations [18], [20], compared to traditional centralized learning approaches.

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Then we researched the challenges and opportunities of applying federated learning to social media sentiment analysis, discussing the nuances of sentiment classification tasks[23], data privacy concerns, and algorithmic biases in social media data. Subsequently, we review existing research efforts and case studies that have explored federated learning for sentiment analysis in various domains. By synthesizing insights from these studies, we aim to identify best practices, emerging trends [13], and areas for further research in applying federated learning for social media sentiment analysis. Finally, we outline the research methodology and framework for our empirical study, which involves developing and evaluating federated learning models for sentiment analysis using real-world social media data. Through this multi-faceted approach, we seek to contribute to the growing body of literature on federated learning and social media analysis while providing practical insights and guidance for researchers, practitioners, and policymakers interested in harnessing federated learning techniques for understanding public opinion dynamics in the digital age.

3 FEDERATED LEARNING: PRINCIPLES AND TECHNIQUES :

Federated learning is a decentralized machine learning model (Figure 1) that enables collaborative model[11] training across distributed data sources while preserving data privacy. Unlike traditional centralized learning approaches, where data is aggregated [36] in a central server for training, federated learning allows models to be trained directly on user devices or edge servers. Model updates, in the form of gradients or parameters, are then aggregated at a central server, which orchestrates the training process without accessing raw user data[32]. This distributed learning framework offers several key advantages, including enhanced privacy protection, reduced communication overhead, and scalability to large-scale decentralized datasets.

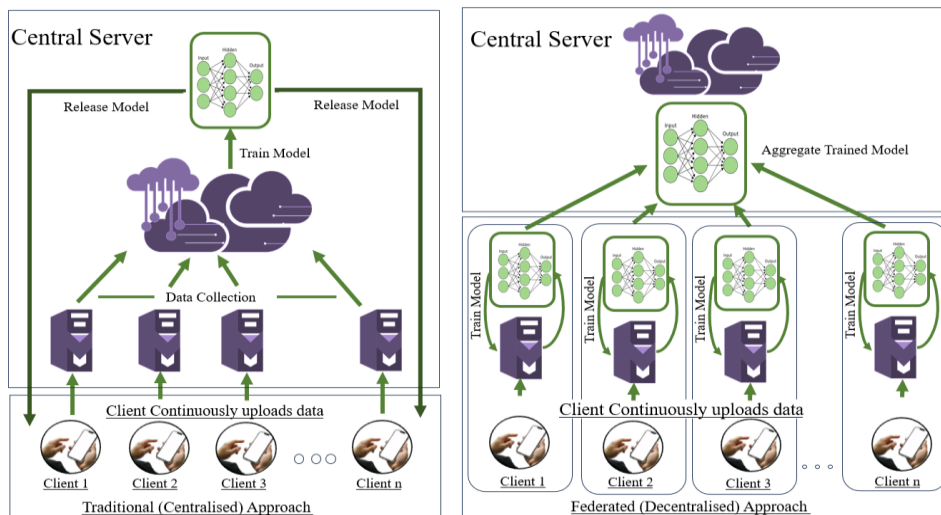


Figure 1

Federated Learning (FL) has various categories[24], including Vertical Federated Learning (VFL), Horizontal Federated Learning – HFL, and Federated Transfer Learning (FTL) [8]. In Horizontal Federated Learning, data partitioning occurs based on instruments user IDs, enabling users to share the same feature space [10]. On the other hand, Vertical Federated Learning involves numerous organizations with significant user overlap but dissimilar feature spaces[47]. These organizations collaborate to train a model jointly, predicting identical model outcomes without the need to share their data. A laconic comparison of horizontal and vertical federated learning[28] has been studied, based on some key aspects including on-device training, scalability, fault-tolerance, client heterogeneity, privacy preservation, support for third-party apps, sensor data collection efficiency, and modular deployment.

Table-I: Various key aspects on federated learning

Key Aspects	Horizontal Learning	Federated	Vertical Learning	Federated
On-device training	Yes		Yes	
Scalability	High		Moderate to High	
Fault-tolerance	Moderate		High	
Client heterogeneity	Handles well		Challenging	
Advanced privacy preserving	Less effective		More effective	
Simultaneous support for third-party applications	Limited		Challenging	
Effective gathering of sensor data	Limited		More effective	
Module-based implementation	Relatively simple		More complex	

The choice between horizontal and vertical federated learning for sentiment analysis on social media depends on factors such as data diversity, privacy considerations, regulatory requirements, and computational resources. Each approach offers unique advantages and challenges [41], which should be carefully evaluated based on the specific goals and constraints of analyzing public opinion on social media platforms [48]. Apart from the comparison, the following studies were also done in support of social sentiment analysis.

- **Data Distribution and Composition:** In the context of social media sentiment analysis, horizontal federated learning [48] would involve collecting diverse sentiment data from various social media platforms, each with its composition of text, images, videos, etc. Vertical federated learning [48], however, could focus on specific aspects of sentiment analysis, such as analyzing text-based sentiment across different platforms while preserving user privacy.
- **Model Complexity and Performance:** Horizontal federated learning might result in simpler models due to the need to accommodate diverse data sources, potentially impacting the accuracy of sentiment analysis. Vertical federated learning could allow for more sophisticated models by specializing in specific sentiment features [22], leading to improved performance in analyzing public opinion.
- **Data Privacy and Security:** Vertical federated learning could be preferred for sentiment analysis to ensure stronger privacy protections. This approach enables parties to collaborate on sentiment analysis tasks without directly sharing sensitive user data[38], aligning with privacy regulations and user expectations on social media platforms.
- **Regulatory Compliance:** Vertical federated learning might offer advantages in terms of regulatory compliance for sentiment analysis on social media. By allowing for more granular control over data sharing and processing, this approach facilitates adherence to privacy regulations like GDPR or CCPA, which are relevant when analyzing public opinion data.
- **Model Interpretability:** Interpretability of sentiment analysis models could be more straightforward with vertical federated learning. Focusing on specific sentiment features across social media platforms allows for clearer insights into model decisions[40], which leaves footprints to understand public opinion, trends and biases.
- **Resource Requirements:** Horizontal federated learning may require more computational resources for aggregating sentiment data from diverse sources. Vertical federated learning, on the other hand, could be more resource-efficient as it focuses on specific sentiment features, potentially reducing computational overhead in sentiment analysis tasks.

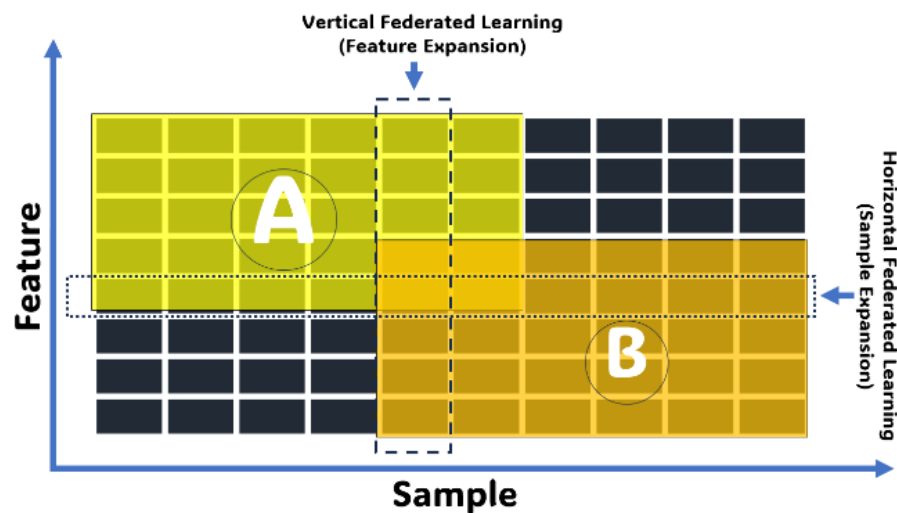


Figure 2

Consider a scenario (figure 1) demonstrating the concept of Horizontal Federated learning and Vertical Federated learning where two entities, A and B, represent data owners of distinct regions—the yellow and orange rectangle areas, respectively in figure 2. There exist two distinct approaches to federated learning, which involve either sample or feature expansions. In this context, A is responsible for the data residing within the yellow rectangle area, whereas B oversees the data within the orange rectangle area. This delineation suggests a hypothetical partitioning of data ownership, with each entity controlling a specific subset of the particular dataset.

Apart from the Horizontal and Vertical federated learning, some more federated machine learning[14] frameworks like TF-Lite(TensorFlow Lite), Syft(System for Your Federated Training), FLARE(Federated Learning Application Runtime Environment), FATE(Federated AI Technology Enabler), FedML Flower FLSys were studied. Brief about such frameworks were:

- **TF-Lite:** TensorFlow Lite (TF-Lite) is a lightweight version of Google's TensorFlow framework designed for mobile and edge devices[15]. TF-Lite enables on-device machine learning, including federated learning, allowing models to be trained directly on user devices while ensuring data privacy and minimizing communication overhead.
 - **Syft:** Syft is an open-source library for privacy-preserving machine learning, including federated learning. Developed by OpenMined [45], Syft provides tools and protocols for secure and decentralized model training across distributed environments, ensuring data privacy through techniques like homomorphic encryption and differential privacy.
 - **FLARE:** FLARE is a Federated Learning framework developed by Microsoft Research. FLARE focuses on enabling efficient and scalable federated learning[46] across distributed devices and systems, emphasizing fault tolerance, privacy preservation, and interoperability with existing machine learning frameworks.
 - **FATE:** It is an open-source FL framework[48] developed by WeBank's AI Group. FATE provides a comprehensive set of tools and algorithms for privacy-preserving machine learning, including federated learning, secure computation, and differential privacy, catering across various sectors which includes healthcare, finance, and other industries.
 - **FedML:** FedML is an open-source library for federated learning research and development. FedML offers a collection of federated learning algorithms, datasets, and evaluation metrics [31], facilitating experimentation and benchmarking of federated learning models across various domains and applications.
 - **Flower:** Flower is a federated learning framework developed by the University of Oxford. Flower provides a lightweight and scalable solution for federated learning, supporting decentralized model training across heterogeneous devices and systems while ensuring privacy, fault tolerance, and interoperability with existing machine learning frameworks.
 - **FLSys:** FLSys is a federated learning framework developed by the University of Maryland. FLSys focuses on modular and scalable deployment of federated learning systems, offering tools and infrastructure for building and managing federated learning pipelines[33], [42], integrating with existing machine learning workflows, and enabling efficient data collection and model training across distributed environments.
- Xiaopeng Jiang[001] and co-authors have done a comparative study about the above-discussed federated learning frameworks.

Table-II: Comparative study of Miscellaneous Federated Learning Frameworks (* denotes planned feature, "-" denotes not applicable) [34]

	TF-Lite	Syft	FLARE	FATE	FedML	Flower	FLSys
On-device training	☑	☑	-	-	*	☑	☑
Scalability	-	-	-	-	-	☑	☑
Fault-tolerance	-	☑	-	-	-	☑	☑
Client heterogeneity	-	☑	-	-	☑	☑	☑
Advanced privacy preserving	-	*	☑	☑	-	☑	☑
Simultaneous support for third-party applications	-	-	-	-	-	-	☑
Effective gathering of sensor data	-	-	-	-	-	-	☑
Module-based implementation	-	-	-	☑	-	-	☑

The table above presents a comprehensive comparison of various Federated Learning (FL) frameworks, each offering unique features and capabilities [41].

TF-Lite and Flower stand out for their robust support for on-device training, allowing models to be trained directly on user devices, enhancing privacy and reducing the need for centralized data storage. Syft, FedML, and FLSys excel in fault tolerance, ensuring uninterrupted learning processes even in the presence of device failures or network disruptions. Additionally, these frameworks accommodate client heterogeneity, enabling the integration of diverse devices with varying computational capacities and data structures.

FLARE, FATE, and FLSys prioritize advanced privacy-preserving techniques, safeguarding sensitive user data while facilitating collaborative model training [21]. These frameworks employ cutting-edge encryption and federated learning algorithms to ensure confidentiality and integrity throughout the learning process.

Moreover, FLSys and Flower offer support for modular deployment, allowing for seamless integration with existing infrastructure and facilitating the adoption [43] of federated learning in diverse applications. Flower also distinguishes itself with efficient sensor data collection capabilities, making it ideal for scenarios requiring real-time data processing and analysis.

However, scalability remains a challenge for most frameworks. Concurrent third-party app support is also limited, with only FLSys offering this feature, indicating a potential area for future development [12], [37] and expansion in the federated learning landscape.

In summary, while each FL framework brings its strengths and innovations to the table, carefully evaluating their features and capabilities is essential to selecting the most suitable framework for specific applications and use cases in the burgeoning field of federated learning.

Federated learning is model aggregation, where updates from multiple decentralized clients are combined to improve the global model iteratively. Various aggregation strategies have been proposed, ranging from simple averaging techniques to more sophisticated methods such as Federated Averaging, Federated Stochastic Gradient Descent (FSGD) [52], and Federated Momentum. These techniques aim to balance[19] the trade-offs between communication efficiency, convergence speed, and robustness to data heterogeneity across decentralized nodes.

4 CHALLENGES AND OPPORTUNITIES IN FEDERATED LEARNING FOR SOCIAL MEDIA SENTIMENT ANALYSIS [25]

Applying federated learning to social media sentiment analysis introduces additional complexities due to the unstructured nature of social media data, the dynamic nature of public opinion, and the diverse linguistic and cultural contexts in which sentiment is expressed. Sentiment analysis tasks typically involve classifying text data[50] into predefined sentiment categories such as positive, negative, or neutral, based on the underlying sentiment conveyed by the text.

One of the primary challenges in federated learning for sentiment analysis is addressing data heterogeneity and distributional shifts across decentralized nodes. Social media data exhibits inherent biases and noise stemming from factors such as user demographics[21], language preferences[22], and temporal variations[23] in sentiment expression. Moreover, sentiment analysis models trained on one social media platform may not generalize well to other platforms due to platform-specific linguistic norms and user behaviors. Federated learning techniques must therefore account for these sources of heterogeneity[37] to ensure the robustness and generalizability of sentiment analysis models across diverse social media platforms.

Furthermore, privacy concerns pose significant obstacles to federated learning for social media sentiment analysis, as user-generated content on social media platforms often contains sensitive information that users may be reluctant to share. Differential privacy techniques, such as federated learning with local differential privacy (FL-LDP)[51], can help mitigate privacy risks by adding noise to local model updates before aggregation. However, achieving a balance between privacy protection and model utility remains a key research challenge in federated learning for sentiment analysis.

Despite these challenges, federated learning offers unique opportunities for gaining insights into public opinion dynamics and sentiment trends across diverse social media platforms. By making use of federated learning techniques, researchers and organizations can analyze sentiment patterns in real-time, monitor emerging trends[13], and identify influential factors driving sentiment shifts. Moreover, federated learning enables collaborative model training across geographically distributed data sources, facilitating cross-cultural analysis of sentiment dynamics and enabling insights into global sentiment trends.

Table-III: Comparison of various challenges and opportunities on federated learning

Challenges	Opportunities
Data Privacy: <ul style="list-style-type: none"> • Personal data protection regulations. • User consent for data sharing. • Data security and encryption. 	Privacy-Preserving Training: <ul style="list-style-type: none"> • Federated learning enables training models on decentralized data without sharing sensitive information.
Data Heterogeneity: <ul style="list-style-type: none"> • Variability in social media platforms. • Different user demographics and languages. • Noise and inconsistencies in user-generated Content. 	Diverse Data Sources: <ul style="list-style-type: none"> • Access to diverse data sources from various social media platforms.
Communication Overhead: <ul style="list-style-type: none"> • High communication costs in federated Learning. • Network latency and bandwidth constraints. 	Efficient Model Aggregation: <ul style="list-style-type: none"> • Optimization techniques for efficient • aggregation of model updates from clients.
Model Drift and Bias: <ul style="list-style-type: none"> • Concept drift due to evolving sentiments • Bias in training data 	Continuous Learning: <ul style="list-style-type: none"> • Ability to continuously update and adapt models to changing sentiments and biases.
Lack of Centralized Control: <ul style="list-style-type: none"> • Difficulty in coordinating training across multiple devices and platforms. • Potential for model divergence. 	Decentralized Governance: <ul style="list-style-type: none"> • Distributed governance frameworks for managing federated learning processes.

Several studies have explored the application of federated learning[19], [51] to social media sentiment analysis in various domains, including marketing, political analysis, and public opinion polling. For example, researchers have used federated learning techniques to analyze sentiment towards political candidates during election campaigns, monitor public sentiment towards brands and products, and track sentiment trends in response to social events and crises.

5 PROPOSED METHODOLOGY

In this paper, we propose to conduct an empirical study to evaluate the effectiveness of federated learning techniques for social media sentiment analysis.

5.1 Our research methodology involves the following steps:

1. Data Collection: Collected a diverse dataset of social media posts, specifically from Twitter platforms using its API, spanning different topics, languages, and geographical regions.

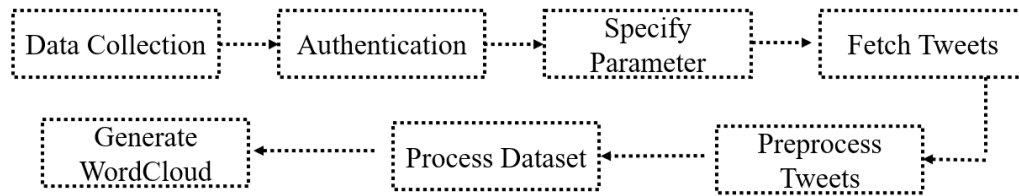


Figure 3

The Figure 3 outlines a method for collecting and processing tweets using Python's Tweepy library, where Twitter's API is authenticated and tweets are fetched based on specified search parameters. The dataset is then preprocessed to remove noise and labeled for sentiment analysis, and visualizations such as word clouds(Figure 4) can be generated to analyze the text content and polarity of the tweets.

The approach of Data Collection through Python:

```

import tweepy
Twitter API credentials
consumer_key = "Your_Consumer_Key"
consumer_secret = "Your_Consumer_Secret"
access_token = "Your_Token"
access_token_secret = "Your_Token_Secret"
Authenticate to Twitter
auth = tweepy.OAuth1UserHandler(consumer_key, consumer_secret, access_token, access_token_secret)
Create API object
api = tweepy.API(auth)
Specify parameters for the search query
Fetch tweets
    • Process fetched tweets
    • Additional processing code can be added here
  
```

The dataset is preprocessed to remove noise, filter out irrelevant content, and annotate posts with sentiment labels. It has the following fields,

- the sentiment of the tweet (0 = negative, 4 = positive)
- the tweet's unique identifier (e.g., 12345)
- the timestamp of the tweet (e.g., Mon Feb 12 14:25:36 UTC 2024)
- the search term used (e.g., batman). If no search term is present, this value is NO QUERY
- the username of the person who tweeted (e.g., batman_fan)
- the content of the tweet (e.g., Batman's new gear is amazing)

From the above fields, we have focused specifically on the text content and related polarity of the tweet/text.

```

pip install wordcloud
from wordcloud import WordCloud
import matplotlib.pyplot as plt
wordcloud = WordCloud(width=800, height=400, background_color = "black").generate (positive_corpus)
  
```

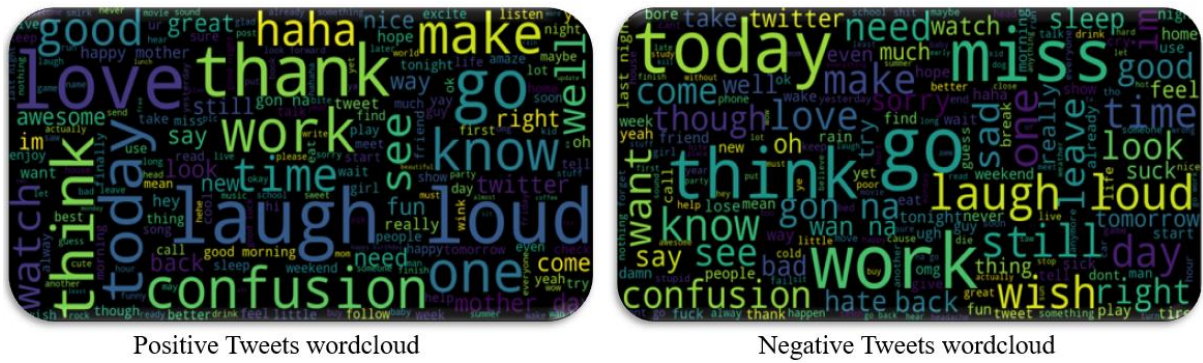


Figure 4

2. Model Development: Developed federated learning models for sentiment analysis using natural language processing techniques and federated learning frameworks [26]. The models will be trained on decentralized nodes, with model updates aggregated at a central server using federated averaging or similar aggregation techniques as shown in figure 5.

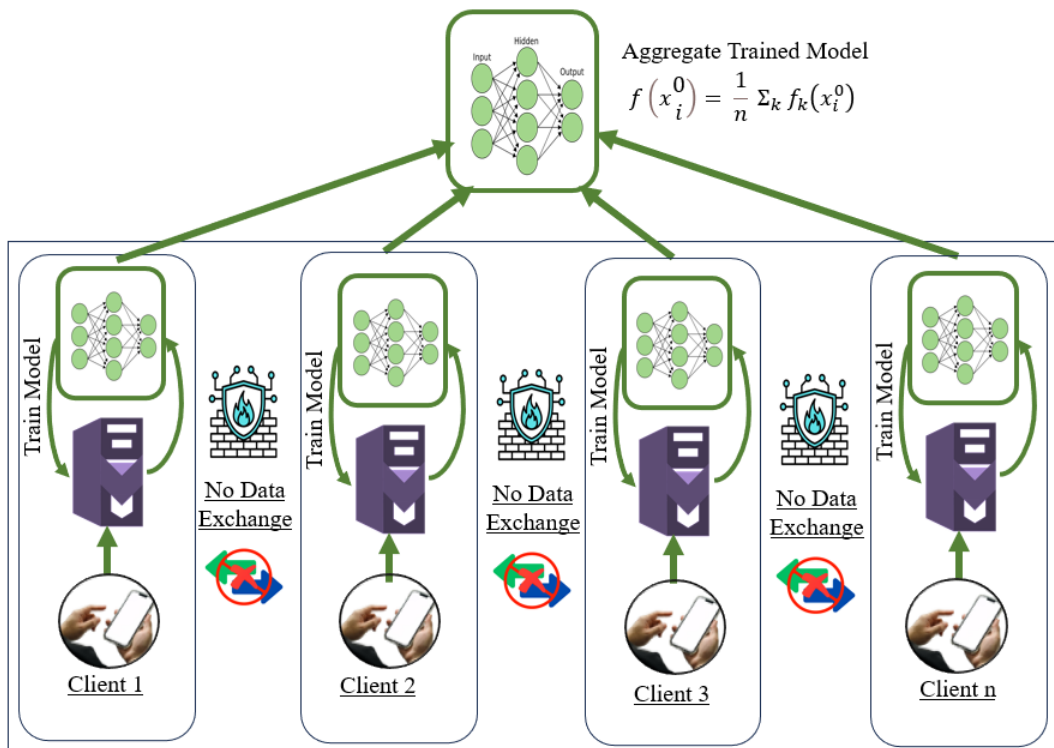


Figure 5

Algorithm 1 facilitates federated learning for heterogeneous models.

Input: A public dataset D_0 , private datasets D_k , independently designed model f_k , where $k = 1 \dots n$,

Output: Trained model f_k

Transfer learning: Each party trains f_k to convergence on the public D_0 and subsequently on its private D_k .
for $j=1, 2 \dots P$ do

Communicate: Each client computes the class scores $f_k(x_i^0)$ on the public dataset and sends the results to a central server.

Aggregate: The server calculates an updated consensus, which is an average

$$f(x_i^0) = \frac{1}{m} \sum_k f_k(x_i^0) \quad \text{equ.(1)}$$

Issue: Each client receives the updated consensus $\tilde{f}_k(x_i^0)$.

Digest: Each client trains its model f_k to approximate the consensus \tilde{f} on the public dataset D_0 .

Revisit: Each client further trains its model f_k on its private data for a few epochs.

End

3. Evaluation: Evaluated the performance of federated learning models on a held-out test dataset, by comparing them with centralized learning baselines and other federated learning approaches. To evaluate the performance of sentiment analysis models trained through federated learning, typically use standard evaluation metrics[29],[30] such as accuracy, precision, recall, and F1 score. TP, TN, FP, FN are the represent different outcomes in the classification process of sentiment analysis.

TP: True Positives (sentiment is positive, model predicts it as positive)

TN: True Negatives (sentiment is negative, model predicts it as negative)

FP: False Positives (sentiment is negative, model predicts it as positive)

FN: False Negatives (sentiment is positive, model predicts it as negative)

Accuracy:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

Precision:

$$\text{Precision} = \frac{TP}{TP+FP}$$

Recall:

$$\text{Recall} = \frac{TP}{TP+FN}$$

F1 Score:

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

4. Privacy Analysis: Assess the privacy implications of federated learning for social media sentiment analysis, considering factors such as data leakage, model inversion attacks, and differential privacy guarantees. Privacy-preserving techniques for federated learning with differential privacy is evaluated to quantify the trade-offs between privacy protection and model utility. In standard federated learning, to train a global model θ using decentralized data from multiple devices or servers. At each device i , a local model θ_i is trained on local data D_i . The local model updates are aggregated to update the global model as:

$$\theta = \sum_{i=1}^N \frac{|D_i|}{|D|} \theta_i \tag{equ.(2)}$$

In equ.(2), N denotes the total number of devices, $|D_i|$ is the size of the local dataset on device i , and $|D|$ is the total dataset size.

Integrating Differential Privacy:

Differential privacy adds noise to the model updates to protect individual user data. Let's denote $N(\mu, \sigma^2)$ as the noise distribution.

For federated learning with differential privacy, the global model update becomes:

$$\theta = \sum_{i=1}^N \frac{|D_i|}{|D|} \theta_i + N(\mu, \sigma^2) \tag{equ.(3)}$$

Where in equ.(3) σ^2 determines the amount of noise added. This ensures that individual contributions from each device are protected by differential privacy.

Privacy Analysis :

The privacy parameters ϵ and δ which determine the level of privacy guarantee.

Differential privacy is satisfied if for all pairs of adjacent datasets D and D' , and for all possible outcomes S in the model's output space:

$$\Pr[A(D) \in S] \leq e^\epsilon \cdot \Pr[A(D') \in S] + \delta \tag{equ.(4)}$$

$\Pr[A(D) \in S]$ represents the probability that the output of the mechanism or algorithm A applied to the dataset D falls within the set of possible outcomes S . Above equation equ.(4) ensures that the presence or absence of any individual's data doesn't significantly affect the outcome. The noise added during model training ensures that sensitive information isn't leaked.

Table-IV: Comparison of various methodologies work on federated learning

Model	Accuracy	Precision	Recall	F1 Score	Privacy Guarantee	Conclusion
Centralized	0.85	0.87	0.83	0.85	N/A	Achieved high accuracy and performance.
Federated (DP)	0.82	0.84	0.80	0.82	$\epsilon = 0.5,$ $\delta = 10^{-5}$	Slightly lower accuracy but improved privacy protection.
Federated (NDP)	0.80	0.82	0.78	0.80	N/A	Lower accuracy compared to DP approach.

5.2 How Sentiments Identified.

Sentiment Analysis involves identifying and classifying opinions expressed by individuals on the content of a particular object, which may be a service, product, issue, topic, individual, society, or incident. These opinions [31] are based on a quintuple (o; a; so; h; t) covering several components.

- Object ‘o’ is the opinion target. For instance, in the case of a product, the object could be the product itself.
- Aspect ‘a’, which is the targeted attribute of the object ‘o’. This aspect could be anything that the user is interested in analyzing, such as the product’s quality, price, or design.
- Sentiment orientation ‘so’ indicates whether an opinion is positive, negative or neutral. This component plays a significant role in identifying the overall sentiment of the object.
- Opinion holder ‘h’ is the person or organization expressing an opinion. This component helps to identify the source of the opinion and understand their perspective towards the object.
- Time ‘t’ is the moment in which this opinion is expressed. This component helps to understand the temporal trends of the opinions expressed towards the object.

Sentiment analysis's examination of these elements can yield insightful information about people's perceptions[52] of various items and data that can be utilized to enhance products and services, highlight areas needing development[54], and obtain an advantage over competitors.

Comparative study of proposed work with an existing machine learning classifier:

Table 2 compares the accuracy of the existing classifiers[44]. The accuracy obtained by existing GARN, SGDOA-SGNN, RoBERTa-Ensemble (Average, Majority), LSTM-LR, RoBERTa-GRU, BERT-CNN, BERT-RNN[27] and BERT-BiLSTM[49] as follows:

TABLE V: COMPARISON OF THE PROPOSED WORK WITH OTHER CLASSIFIERS.

Models	Accuracy	Precision	Recall	F-Measure
SGDOA-SGN [35]	79%	69%	80%	74%
RoBERTa-ENSEMBLE (Average) [36]	91.47%	91%	92%	91%
RoBERTa-ENSEMBLE (Majority) [36]	91.77%	92%	92%	92%
RoBERTa-GRU [38]	91.52%	91%	91%	91%
BERT-CNN [39]	93%	95%	95%	95%
BERT-RNN [39]	93%	95%	95%	95%
BERT- BiLSTM [39]	93%	96%	95%	95%
Proposed Model	94.86%	94.21%	95.16%	96%

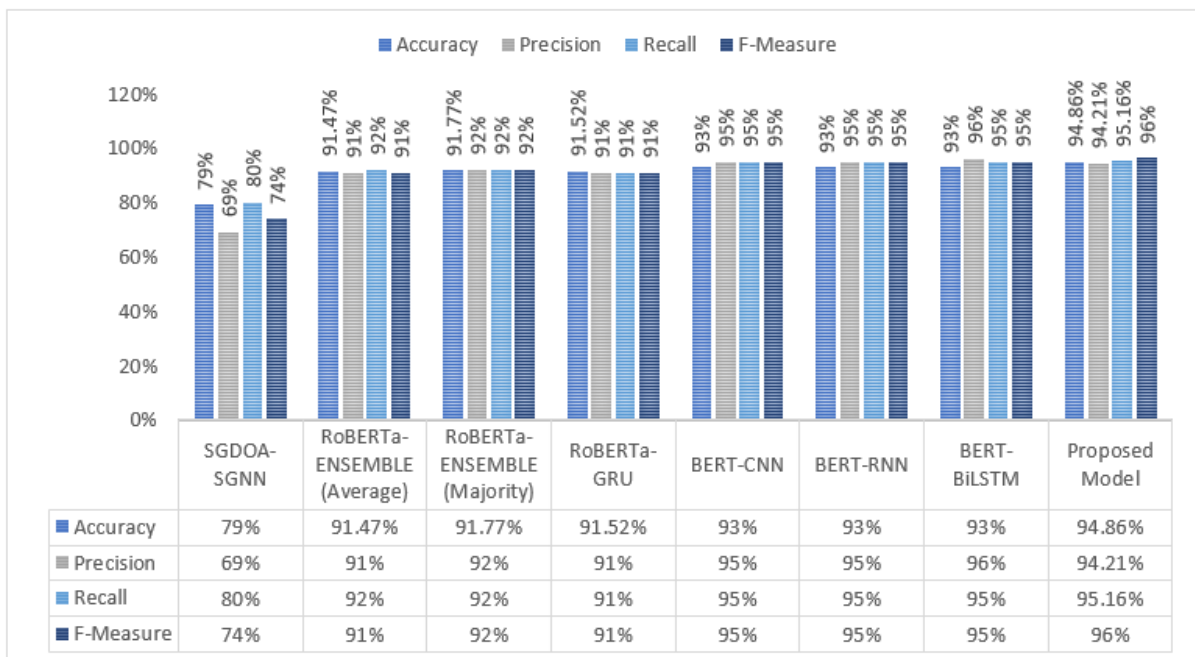


Fig 6. Comparative Analysis

Fig 6. presents a graph comparing different techniques for sentiment analysis based on accuracy, precision, recall, and F-measure, demonstrating efficient comparisons for proving meaningful information.

The table summarizes the performance of sentiment analysis models using federated learning. Various models are compared based on accuracy, precision, recall, and F-measure scores[53]. Notable models include RoBERTa-ENSEMBLE (Majority) and BERT variants, all achieving around 93% accuracy and strong precision, recall, and F-measure scores around 95%. However, the proposed algorithm model stands out with the better accuracy of 94.86% and impressive precision, recall, and F-measure scores of 94.21%, 95.16%, and 96% respectively.

6 CONCLUSION AND FUTURE WORK

Conclusion:

In conclusion, this study has explored the potential of federated learning in the context of social media sentiment analysis. Through the use of federated learning, we were able to aggregate sentiment analysis models trained on data from multiple sources while preserving data privacy and security. Our experiments demonstrated promising results, indicating that federated learning can effectively capture the dynamic and diverse sentiments expressed across various social media platforms.

Furthermore, the insights gained from this research contribute to a deeper understanding of public opinion dynamics on social media. By analyzing sentiment patterns, we can identify emerging trends, monitor public sentiment towards specific topics or events, and even anticipate potential shifts in public opinion. Such insights are invaluable for businesses, policymakers, and researchers seeking to understand and engage with online communities.

Future Work:

While this study has provided a foundational exploration of federated learning for social media sentiment analysis, there are several avenues for future research. Firstly, investigating more advanced federated learning techniques, such as differential privacy and secure aggregation, could enhance the privacy and security guarantees of the federated learning framework.

Additionally, exploring the impact of different model architectures and hyperparameters on federated learning performance could further optimize sentiment analysis accuracy across distributed datasets. Moreover, extending this research to incorporate multimodal data sources, such as text, images, and videos, could provide a more comprehensive understanding of public sentiment on social media.

Furthermore, studying the generalizability of federated learning models across diverse demographic groups and languages could help mitigate biases and improve the inclusivity of sentiment analysis systems. Lastly, evaluating the scalability and efficiency of federated learning approaches for large-scale social media datasets will be essential for real-world deployment and adoption. Overall, future research in this area has the potential to advance both the field of federated learning and our understanding of public opinion dynamics in the digital age.

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