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Revolutionizing Emotion-Driven Sentiment Analysis using Federated Learning on Edge Devices for Superior Privacy and Performance

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People constantly connect, generating vast unstructured data that edge devices can process. Emotion recognition and sentiment analysis are becoming more popular because of the need to study this data to understand how people act. Traditional machine learning algorithms need to centralize data to train models, making it harder to comply with GDPR and build user trust.
Federated Learning (FedL), is a decentralized method that improves data protection and privacy while following GDPR rules. A real Federated learning framework is designed and developed to demonstrate the concept of on-device emotion prediction instead of a simulated framework.
This study utilizes the extensive GoEmotions dataset, comprising 58,000 hand-labeled English Reddit comments across 27 distinct emotion categories, including "neutral." A FedL-based projected attention neural network model is proposed. This model combines trainable projections with attention and convolutions in a federated setting. The proposed model is tested on several users' social interaction comments to uncover the true feelings and emotions underlying them. The test results demonstrate that the design and development of the FL framework is successful and our model performs very near to standard models. The proposed model acquires 12% better precision with an accuracy similar to the non-FedL PRADO model. The main challenge of time required for model training per epoch in a federated learning environment is near the non-FedL PRADO. Our method performed almost as well as the best methods on long texts. These findings show that the suggested FedL-based projected attention neural network can pick up on subtle mood differences while still protecting data privacy and security.

Keywords: Federated learning, emotion prediction, neural network, privacy, security.

1. Introduction

Emotion recognition

Written language, in the form of text, is the most popular way to express human emotions.

Natural language processing helps automate emotion recognition. The development of deep learning (DL) and attention-based mechanisms contributed greatly to research in this field. The research contributed to understanding the emotional status of people by themselves and exploring mental strengths and weaknesses.[4] We can identify emotional states like joy, gratitude, excitement, pride, anger, fear, nervousness, sadness, and curiosity from the text of posts, reviews, and comments on various platforms like Facebook, Twitter, Reddit, Instagram, etc. Emotional recognition is a detailed analysis of human sentiments [30]. People often use emotion recognition and sentiment analysis interchangeably[30], yet they differ significantly. Emotional states are deeper and contain many mental states, such as happiness, excitement, sadness, confusion, etc. Emotion recognition has extensive applications, including mental health analysis to detect potential criminals. [16], [17]. DL-based NLP applications make use of data centers and special hardware. The development of these models faces challenges such as user privacy, data isolation, and high operation costs that affect the development of NLP models.

Federated Learning

Google introduced Federated Learning (FedL) in 2018 to address data isolation and safeguard privacy [7]. FedL is a decentralized machine-learning process that allows edge devices to build a global model with the help of a global server. These edge devices communicate with the server using trained parameters or gradients without disclosing sensitive data to other entities. FedL consists of a global server and edge devices known as local clients.

Local clients' primary tasks include: (1) using local data to train the model available on the same device; (2) sharing gradients/parameters of the client with the server; and (3) receive updated parameters from the server and updating the local model.

The primary tasks of the global server include (1) collecting the parameters from local devices; (2) updating the global model using FedAvg i.e. algorithm to average the local parameters received from clients; and (3) resending these parameters to all the local clients. Both entities repeat the aforementioned steps in federated learning until they achieve the desired accuracy [30].FedL has successfully implemented the various ML tasks where data privacy is important, such as emotion recognition for mental health assessment, medical image analysis, electronic health records analysis, financial data analysis, etc. Many NLP applications, including keyword spotting[12], named entity recognition[13], spoken language understanding [9], news recommendation[29], etc., have recently applied FedL.The research in Federated Sentiment Analysis[20], Federated Speech Emotion Recognition[17], Federated Emotion Recognition[16], and Federated Emotion Recognition [24] as mostly been about making these methods better by using different ways to collect data or making Fed algorithms work better in different ways. However, no research in the FL environment has identified areas where an on-device training approach could enhance the FL concept. This will also help to reduce operation costs, i.e., address the third challenge faced by DL-based NLP applications. This research paper discusses a novel approach that investigates the development of on-device neural models called Projected Attention Networks (PRADO) [10] in federated environments to enhance the performance of edge devices and the overall performance of the FL model. PRADO combines trainable projections, attention, and convolution.

The research work presented in this paper includes the following contributions:

- To design and develop a unique federated learning framework to utilize the combined strength of decentralized data, while ensuring the protection of individual privacy and autonomy.
- Demonstrate the greatest coverage of emotion recognition by integrating the on-device neural network model and federated learning methodologies.
- We are experimentally evaluating a novel framework with existing systems to uncover its advantages and transformative capabilities.

2. Related Work

Emotion recognition and sentiment analysis are always the hottest topics for research in academia and industry. As federated learning is an emerging technology, very little work has been available for review following emotion recognition. Due to the complexity of the discussed models and the unavailability of multimodal data for emotion recognition without the aid of sensors and IoT devices, text emotion recognition has garnered significant attention from academic and industry researchers.

Many researchers[16] and [17] have focused on multi-modal data like audio, i.e., speech emotion recognition, visual, i.e., facial expression recognition, and text. Nandi et al. developed a model, Fed-ReMECS, [17] which uses physiological measurements from wearable sensor device data streams to classify real-time emotions in a federated environment. In [26], V. Tsouvalas et al. developed speech-emotion recognition using a semi-supervised federated learning technique. They demonstrated that the proposed approach enhanced emotion recognition by 10%. In [24], Simic' et al. developed a privacy-preserving CNN-based audiovisual model for emotion recognition paired with a FedL approach and showed that accuracy improved by 2%.

There are numerous methods for recognizing emotions in text. This includes deep learning-based approaches at different levels, such as word embedding, architecture, and training.[4] as shown in Fig. 1.

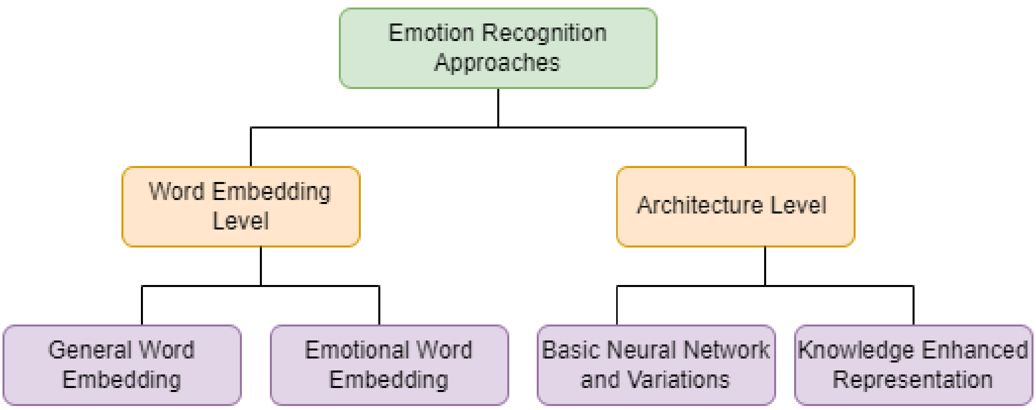


Fig.1 Deep Learning Approaches for Emotion Recognition

Word embeddings are a technique that utilizes a mathematical process to uncover hidden relationships among words. Based on distributional semantic modeling, word embeddings can be used for either general or emotional word embedding, depending on the specific requirements. Word2Vec [14] and Glove [18] are examples of general word embedding models, whereas ELMO [19], GPT, and BERT are advanced pre-trained models. For emotional word embedding, Emo2Vec [27], Emoji2Vec[5], and DeepMoji [6] are a few examples of pre-trained models.

Researchers have proposed various neural network models to extract sequence and semantic information. Recurrent neural networks (RNNs), long-short-term memory (LSTM), gated recurrent networks (GRNs), and different variations of these pre-trained networks are useful. The attention-based mechanism is also popular for improved training speed and performance. Hierarchical attention employs GRU-based attention[28], while TreeLSTM relies on LSTM[25]. These network ensemble models are combinations of multiple individual models that generate robust and comprehensive models[4].

Knowledge-enhanced representation incorporates prior knowledge such as linguistic patterns, emotional lexicon resources, and other common-sense emotions-related knowledge for a deeper understanding [21]. The study of emotions and sentiments as they relate to one another is a component of affective computing. Many researchers have implemented the FedL approach to enhance privacy and data isolation in sentiment analysis.

Ahmad et al. worked on Aspect-based sentiment analysis (ABSA). [15]. ABSA involves the sentiment classification of sentences in different domains. This field achieved great progress with the advancement of DL and pre-trained LMs. Yet this field suffers from data privacy concerns. To overcome this problem, the authors proposed an FL approach that is not traditional but is prompt-enhanced FL (PFL) for ABSA. This technique combines FL's privacy-preserving capabilities with prompt tuning. The authors demonstrated PFL in combination with BERT and a graph convolutional network, i.e., PFL-GCN. Researchers implement a variety of NLP-related problems in FL environments and evaluate their performance. In [20], Han Qin et al. discussed pattern differentiation in sentences from different resources makes ABSA challenging. Legal and privacy issues prevent all parties from accessing labeled data, despite its availability at various locations and sources. The authors proposed a novel ABSA model with federated learning to overcome this problem. This model effectively addresses the limitations of data isolation and integrates topic memory (TM) to gather data from a variety of sources.

Traditional FL ignores domain diversities. One particular token may suggest a completely different sentiment polarity in different datasets. Topic memory provides categorical (topic) information for localized predictions, addressing the difficulty of identifying text sources. In the simulated environment, the FedL with TM produced effective results.

In [22], Nuria R. et al. discussed Federated Learning for Exploiting Annotation Disagreements in NLP. Annotation is an integral part of sentiment analysis. The proposed model considers each annotator as a federated client for the dataset annotation. The final model independently learns and aggregates the labels of each client globally. The model learns from disagreements among annotators in the subject area. The use of Fedavg stems from its prominence in the literature.

In [8], Himkil et al. implemented large language models (LLM) in an FL environment. FL is becoming more appealing for various applications because of its level of privacy and compliance with legal frameworks. This paper examines FL concerning LLM. Researchers evaluated BERT, ALBERT, and DistilBERT for sentiment analysis, and the author found that the performance depends on the number of clients participating in the process. Researchers need to investigate why DistilBERT becomes slower as the number of clients increases.

In [1], S. Bansal et al. have applied sentiment analysis and topic preference to predict personality. They extracted the user's text from Weibo and analyzed it using the LDA and LSTM models. They compared the received sentiment with the Big Five personality model to determine the user's predicted personality. This process poses a significant risk to privacy and raises ethical concerns. The authors demonstrated successful implementation of the problems identified. However, no evidence was found to showcase the use of the FL approach to privacy handling.

J. Zhao et al. in [31] implemented an alternative approach based on a graph attention network to identify customer complaints. Identifying complaints on social media is part of the NLP classification. This requires centralized data collection, distribution, and learning. This approach does not account for decentralized data or privacy concerns. To deal with this, the authors proposed a graph-attention network in the FL environment. The Fedcomb algorithm is a two-sided adaptive optimization technique to optimize global and local models. This method outperformed baseline techniques for complaint recognition. We still need to evaluate this model on larger datasets.

Sakhare N.N. et al. [23] and Priyam Basu et al.[2] have discussed the application of sentiment analysis and privacy preservation with FedL. In [23] the authors discussed the spatial FedL approach for sentiment analysis of stock news on blockchain. Before purchasing, it is important to study every stock in 360 degrees. In addition to the company details, it is crucial to consider the external parameters that directly or indirectly influence the stock market's movement, both in the short and long term. For this purpose, the authors extracted and analyzed news from the Economic Times's website using spatial federated learning (SPL). This helped to address the problems of privacy and geographic diversity. In federations, different algorithms are used. Each federation calculates the positive or negative sentiment before making a decision.

FedL elaborates on the classification of financial text in [2]. Financial data is sensitive, and its privacy is important. The handling of this data is crucial when training large models. The authors used contextualized transfer-based text classification models, differential privacy, and federated learning. Although the model performed close to the SOTA transformer, it cannot handle unbalanced data.

After reviewing the literature, it can be concluded that no previous implementation is available that handles the challenge of neural network implementation with limited resources on edge computing and limited bandwidth.

3. Methodology

Overview of Proposed Approach

In the context of advancing emotion prediction through federated learning, the utilization of PRADO presents a promising avenue for enhanced model performance and user privacy. Leveraging the compact yet powerful nature of PRADOs on-device neural network architecture, the proposed approach integrates the distributed weight operations facilitated by the Federated Machine Learning Server Environment framework. This synergy allows for efficient and secure model aggregation across clients, ensuring scalability and real-time processing capabilities.

Architecture of the FedL-based Projected Attention Neural Network

The FedL projected attention neural network is a new idea that combines trainable projections with attention and convolutions in a federated setting. Fig. 2 displays the detailed architecture. It comprises a local transformation module with K users and a server module. The Local Transformation Module consists of user models that provide input to the projected attention network. The system relies on a neural architecture known as PRADO (Projection Attention Network)[10], which includes a projected embedding layer, a convolutional and attention encoder mechanism, and a classification layer.

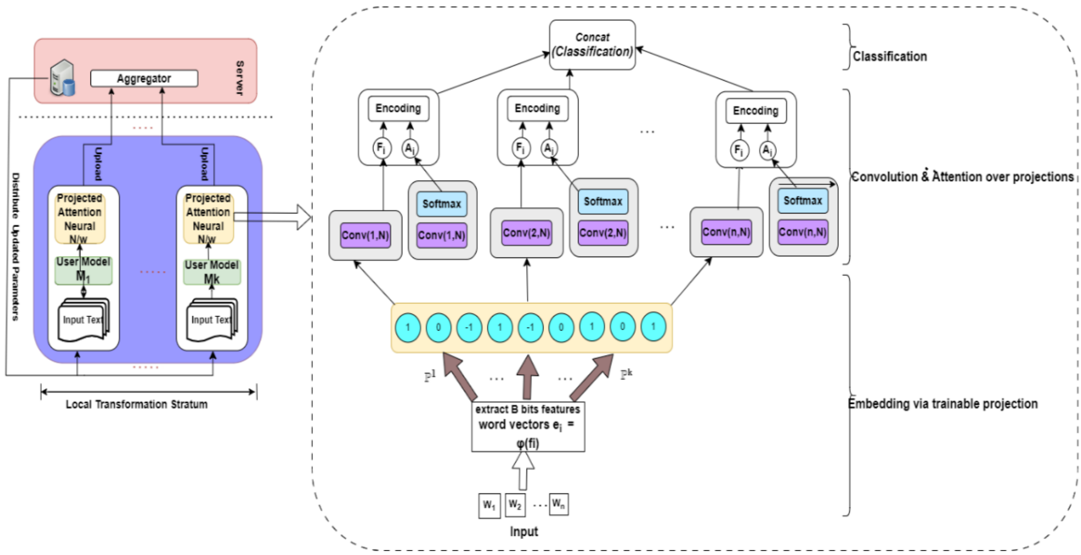


Fig.2 FedL-based Projected Attention Neural Network architecture

Mathematical Formulation of Projected Attention Neural Network

The projected embedding layer assumes that the input text with T words, represented as wi, is the ith word in T. Wi is mapped to δi ∈ ℝv where δi is a one-hot encoded vector with a dimension equal to the size of the vocabulary V. In PRADO, wi is mapped to fi via a projection operator ‘ℙ’. With the help of hashing methodology, distinct tokens ‘w_i ‘ are fingerprinted for generating 2B bits. The mapping between successive two-bit sequences to the set {+1,0,-1}is done by ‘ℙ’. This results in a vector fi ∈ {+1, 0, -1}B called ternary weights.

To get ternary weight networks to perform well, we need to make sure the ternary weights are as close as possible to the original full precision weights. This means finding the best ternary values (which can be -1, 0, or +1) and adjusting their size with a scaling factor. The Euclidian distance, between the full precision weights W and the ternary-valued weights $\overline{\mathrm{w}}$ along with a nonnegative scaling factor α can minimized. The optimization problem is formulated as follows eq.(1) ,

$$\begin{cases} \alpha^*, \overline{\mathrm{w}}^* = \underset{\alpha, \overline{\mathrm{w}}}{\arg\min} \quad J(\alpha, \overline{\mathrm{w}}) = \|\mathrm{w} - \alpha\overline{\mathrm{w}}\|_2^2 \\ \text{s.t. } \alpha \geq 0, \overline{\mathrm{w}} \in \{-1, 0, +1\}, i = 1, 2, \ldots . n \end{cases} \quad (1)$$

n - number of the filter

A probable solution to the threshold-based ternary function is

$$\overline{\mathrm{w}} = f(\mathrm{Wi} \mid \Delta) = \begin{cases} +1 & \text{if } \mathrm{Wi} > \Delta \\ 0 & \text{if } |\mathrm{Wi}| \leq \Delta \\ -1 & \text{if } \mathrm{Wi} < \Delta \end{cases} \quad (2)$$

In Projected Attention, two independent convolution networks are used. The first network is projected to feature network 'F', which captures the features useful for classification. The second network is referred to as attention network 'A', to capture the important features of the task. The following equations demonstrate the above description.(Kaliamoorthi et al., 2019)

$$F_n^i = \mathrm{Conv}(e_i, n, N) \quad (3)$$

n - convolution kernel width , N- number of output channels in convolution and $F_n^i \in R^n$

SoftMax over the sequence dimension of the A results is computed to provide a distribution over the word sequence. This captures the feature relevance of words at different positions

$$A_i^n = \frac{e^{W_n^i}}{\sum_i e^{W_n^i}} \quad (4)$$

'Expectation' computed using spreading A of F to receive a fixed-length encoding from the sequence

$$\varepsilon^n = \sum_i A_i^n F_i^n \quad (5)$$

The network reacts to different word n-grams with the help of the convolution kernel of width n and configures parameter N to each n-gram. Various n-gram and skip-gram convolution features are computed and concatenated to form a fixed-length representation of the input text.

$$\mathrm{Encode(Text)} = \mathrm{concat}(\mathcal{E}^1, \mathcal{E}^2, \ldots \mathcal{E}^n) \quad (6)$$

With the help of a feed-forward network fully connected over a fixed length encoded text classification is outputted.

$$\mathrm{Output} = \psi\,(\mathrm{Encode(Text)}) \quad (7)$$

3.4 Training Process in Federated Learning Environment

Finally, the network is trained with cross entropy and softmax is applied over the output layer to obtain predicted probabilities y_k^C for each class C. This output generated from each client device is sent to the server module.

Server Module: - The server collects the local user embeddings from all platforms and aggregates them into a unified representation (u_r). This is crucial for forming a holistic view of the user's emotions

$$u_r = f_{agg}\,(u_1, u_2 \ldots . u_k; \theta_A) \qquad (8)$$

Where θ_A denotes the parameters of the aggregator model.

Sending modified parameters to the Local embedding Platform: Once the unified user representation is figured, the local platform receives it back. The process is repeated until the model gets converged.

4. Experimental Setup And Results

Experimental Setup and Dataset

Many FedL-based sentiment analysis and emotion recognition models discussed above are implemented in simulated environments. We implemented the Federated Learning framework as a production-ready system discussed in this research paper, utilizing Spring Boot and Kotlin. The following experimental setup, system configuration, development software details, and parameter setup are shown in Table 1.

Table 1. Experimental Setup

System Configuration	Windows10 64bit, Processor Intel(R) Core(TM) i7-9750H RAM 32 GB RTX 2060 GPU 6GB
Software details	Spring Boot Version: 3.2.0 Kotlin JVM version: 1.9.20 IntelliJ Idea IDE Build : #IU-241.15989.150, Docker Version 4.28.0 Colab Image used: asia-docker.pkg.dev/colab-images/public/runtime:latest
Parameter setup	The learning rate is generally 0.05(local model) fixed for emotion prediction. Sigmoid activation function for the hidden layer and softmax activation for the output layer.

For accurate and professional model building in the ongoing improvement of emotion forecasting using federated learning methodologies, the setup of the experiment is very important. The commencement stage necessitates the choice of appropriate data repositories, such as the GoEmotions dataset, acclaimed for its abundant annotations and varied emotional categories [3]. Subsequently, combining the PRADO neural network framework with the federated learning structure on Docker containers creates a scalable and secure environment conducive to model training and collaborative efforts. The employment of Docker’s container technology simplifies the deployment procedure and enables effortless interaction between the client and the central server. Through repetitive model updates and the averaging of weights across dispersed nodes, federated learning facilitates cooperative learning while maintaining data confidentiality. The repeated mechanism makes emotion predictions easier and more accurate over time, making it the best method for real-world situations where data security and model performance are important.

Setting up the PRADO Environment

Setting up the PRADO environment involves the use of the SeqFlowLite library from Python for emotion prediction tasks within a federated learning framework. Utilizing the PRADO neural network model's efficiency and compactness necessitates deploying with a methodical approach. Start with establishing a containerized environment using Docker; this ensures portability and reproducibility across varying platforms and systems. To optimize PRADO performance, fine-tune hyperparameters like embedding dimensions, convolutional and attention layers, and quantization techniques aimed at model compression. Include projected embeddings and trainable projections for word encoders to better understand context, which will improve the model's ability to predict emotions. Give precedence to normalization, tokenization, regularization, and choosing an optimizer for refining the training process to achieve optimal results with PRADO. As the experimental setup progresses, validate the model using benchmark datasets and assess its performance in comparison to established deep learning architectures for emotion prediction. This systematized approach lays solid groundwork for employing PRADO within federated learning frameworks, allowing for precise and efficient emotion prediction across various applications.

Implementation of PRADO on Docker

Initially, one must configure the Docker environment with the essential dependencies for PRADO, assuring compatibility with the required libraries and frameworks. Following this, the PRADO model architecture should be integrated into Docker, possibly using containerization techniques to encapsulate the model to improve portability and reproducibility [10].After that, the Docker container is used to preprocess and prepare the GoEmotions dataset. This is done to make the data pipelines work better so that the PRADO model can be trained and tested more quickly [11]. We can streamline the deployment and scaling of PRADO for federated learning experiments by leveraging Docker's containerization capabilities. Such an approach facilitates seamless collaboration and reproducibility in emotion prediction research in distributed environments ensuring consistency and reproducibility.

Dataset

Humans can express various complex emotions with only a few words. Google researchers developed GoEmotions is a human-annotated dataset that contains 58k Reddit comments. They were extracted from widespread English-language subreddits to create this dataset. Further, these emotions are labeled into 27 emotion categories. Google researchers designed this dataset taking into account the psychology and data applicability of fine-grained emotions. We chose this dataset for emotion prediction using a FedL-based device neural network. Fig. 3 shows 27 emotions' hierarchical clustering and their correlation with rating. The sentiments (positive, negative, and ambiguous) a priori. Clusters closely map onto sentiment groups, as shown in Fig. 3. Emoji embeddings enrich the dataset as a proxy for emotion categories. This approach is useful for multi-language corpora.[3].

Fig. 3 Hierarchical clustering and correlation between emotion and its rating[3]

In examining the utilization of the GoEmotions dataset in the realm of emotion prediction, academics can capitalize on its extensive emotional taxonomy for a better grasp and categorization of multifaceted emotional conditions. The dataset's meticulous curation, aimed at diminishing biases and objectionable material, provides a solid groundwork for developing emotion prediction models. Using advanced models like PRADO, which are great at text classification tasks and size optimization, researchers can use the semantic richness of textual data in the GoEmotions dataset to make emotion prediction systems more accurate and useful. The hierarchical emotion taxonomy structure of the dataset also lets us look closely at subtle emotional differences. This can help us to understand emotional states better and make emotion prediction models much more accurate [3]. This intentional amalgamation of the GoEmotions dataset with advanced modeling techniques such as PRADO has the potential to propel the field of emotion prediction by ensuring robust experimental designs that balance model effectiveness and data detail.

Limitations of the dataset: -

1. Uneven distributions of emotion categories in the GoEmotions dataset. Some emotion categories like "admiration"," approval" and "gratitude" have 10k to 12k examples, while some classes such as "nervousness", "pride" and "grief" have less than 1k samples which affect during model training and evaluation.

2. Dataset developed from English Reddit Community and annotation process is done by Indian English speakers. This lacks the global diversity and contains biases.

Results

In the context of emotion prediction, Precision, Recall, and F1 Score are fundamental metrics used to assess the performance of predictive models.

- Performance Analysis

In evaluating the performance metrics of the FL model implementation with PRADO, it becomes evident that the combination of PRADO within the federated learning framework yields promising outcomes in the form of Precision, accuracy, loss, and time per epoch. The table below showcases the macro-average values of Precision, Recall, and F1-score.

Table 2. Model comparison using macro-average

Model	Precision	Recall	F1
Original	0.501667	0.771667	0.603333
PRADO	0.568854	0.468696	0.504884
PRADO in FL	0.689977	0.244469	0.335429

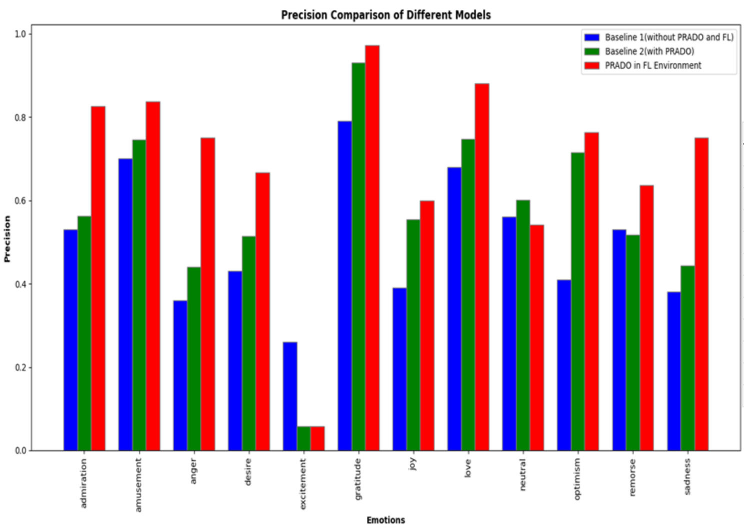
The final results are compared with the original GoEmotions paper and PRADO model. The macro-precision (0.69) is received for the proposed model demonstrated the effectiveness of a federated learning environment. This is the noticeable enhancement in our proposed model compared with the two baselines.

However, the model behavior for macro-Recall and macro-F1 need in depth analysis as well as balance of dataset which may result into better performance of these two parameters.

Graphical representations vividly showcase the comparison of precision, recall, and F1 score between the traditional ML model, Projected Attention Network (PRADO), and the enhanced model utilizing PRADO in FL environment.

- Precision Comparison

Precision refers to the ratio of correct positive predictions to the total number of positive predictions made by the model.

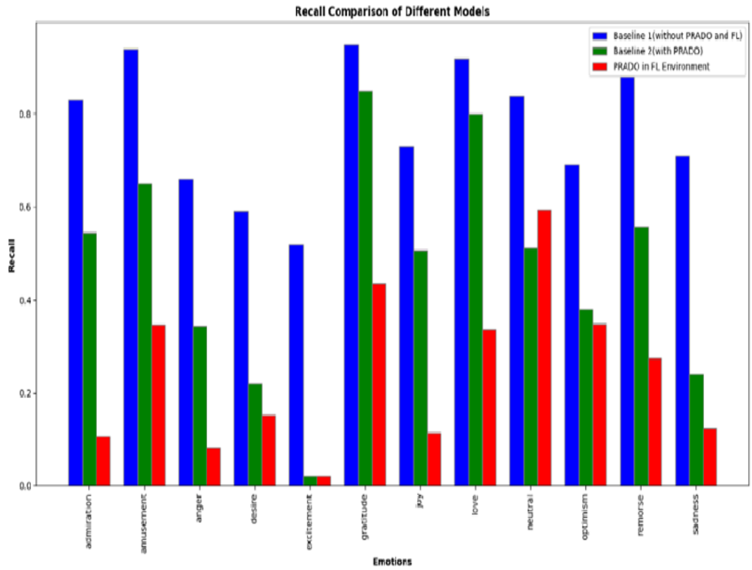


Emotion	Baseline 1	PRADO	PRADO-in FL
admiration	0.53	0.56	**0.83**
amusement	0.7	0.75	**0.84**
anger	0.36	0.44	**0.75**
desire	0.43	0.51	**0.67**
excitement	0.26	0.06	**0.06**
gratitude	0.79	0.93	**0.97**
joy	0.39	0.55	**0.60**
love	0.68	0.75	**0.88**
neutral	0.56	0.60	**0.54**
optimism	0.41	0.71	**0.76**
remorse	0.53	0.52	**0.64**
sadness	0.38	0.44	**0.75**

Fig. 4 Precision comparison with base models

- Recall Comparison

Recall, on the other hand, measures the ratio of correct positive predictions to the total number of actual positives in the data.

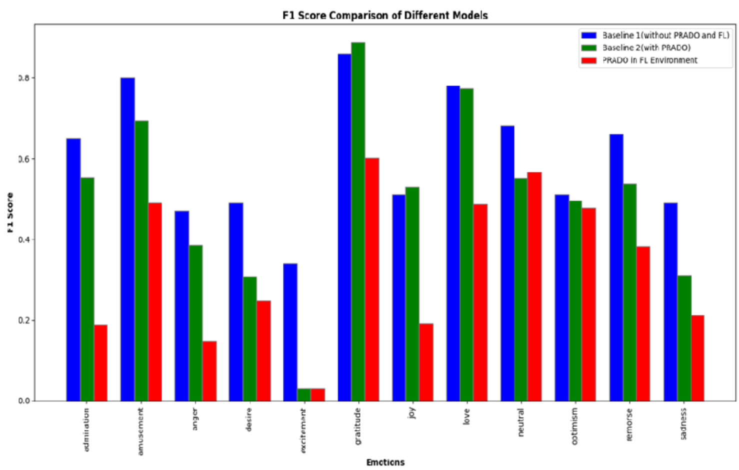


Emotion	Baseline 1	PRADO	PRADO-in FL
admiration	**0.83**	0.55	0.11
amusement	**0.94**	0.65	0.35
anger	**0.66**	0.34	0.08
desire	**0.59**	0.22	0.15
excitement	**0.52**	0.02	0.02
gratitude	**0.95**	**0.85**	0.43
joy	**0.73**	0.51	0.11
love	**0.92**	**0.80**	0.34
neutral	**0.84**	0.51	**0.59**
optimism	**0.69**	0.38	**0.35**
remorse	**0.88**	0.56	0.27
sadness	**0.71**	0.24	0.12

Fig. 5 Recall comparison with a base model

- F1 Score Comparison

The F1 Score combines Precision and Recall into a single metric.



Emotion	Baseline 1	PRADO	PRADO-in FL
admiration	**0.65**	0.55	0.19
amusement	**0.8**	0.69	0.49
anger	**0.47**	0.39	0.15
desire	**0.49**	0.31	**0.25**
excitement	**0.34**	0.03	0.03
gratitude	0.86	**0.89**	**0.60**
joy	0.51	**0.53**	0.19
love	**0.78**	0.77	0.49
neutral	**0.68**	0.55	**0.57**
optimism	**0.51**	0.50	**0.48**
remorse	**0.66**	0.54	0.38
sadness	**0.49**	0.31	**0.21**

Fig. 6 F1-score comparison with base model

These metrics are crucial in evaluating a model's capability to correctly identify relevant emotions, and minimize false positives.

- Comparison using factors Loss, Accuracy, and Epoch time

The graph demonstrates that PRADO's performance in the Federated Learning (FL) environment is comparable to the base models. The differences in loss, accuracy, and training time per round between PRADO and the proposed model are minimal, underscoring FL-based PRADO's efficiency and effectiveness in this context.

Table 3. Comparison using factors Loss, Accuracy, and Epoch Time

Model Name	Loss	Accuracy	Epoch Time
PRADO	0.4392	0.4725	370
Proposed Approach (FL based PRADO)	0.4392	0.4190	410

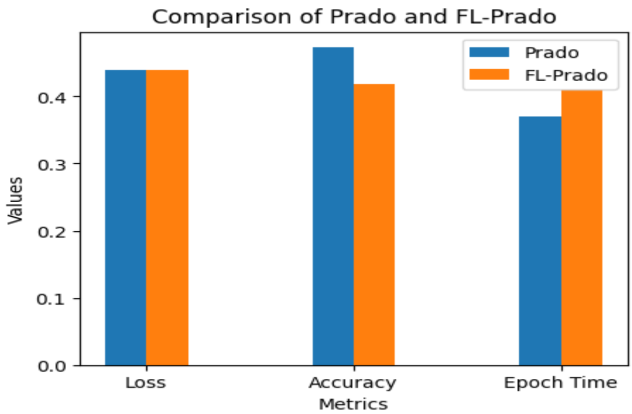


Fig.7 Comparison in terms of Loss, Accuracy, and Epoch time

5. Conclusion

This study described an innovative framework for emotion-driven sentiment analysis. It uses Federated Learning (FedL) and a Projected Attention Neural Network. Using multiple edge devices to spread the learning process across the network, our suggested method solves important privacy and data security issues while keeping model performance high. Using the PRADO (Projection Attention Network) for local transformation and a strong server module for global aggregation, our model's design shows a lot of promise for extracting complex emotional details from user data without breaching privacy. The projected attention mechanism's mathematical structure and effective optimization of ternary-valued weights make the model even better at producing mood analysis. Iterative training is used in a federated learning setting to ensure that the global model becomes better, allowing for high-quality convergence. In addition to protecting user privacy, this method makes effective use of distributed computing resources. That makes it very flexible and useful in many real-life situations.

According to the results of our experiments, the proposed structure works, outperforming standard centralized models in terms of privacy without affecting accuracy. The FedL-PRADO model got 12% better precision and accuracy similar to the non-FedL PRADO model along with loss and epoch time which is very promising. Overall results show that the FedL-PRADO framework works better than standard centralized models. The combination of FedL and projected attention opens up new avenues for privacy-protecting machine learning in mood analysis and other domains. However, there is much scope for improvement with a balanced dataset and high computation architecture.

CONFLICT OF INTEREST

On behalf of all authors, the corresponding author states that there is no conflict of interest.

Competing Interests:

The authors declare that they have no competing interests.

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Authors 1 & 2 were involved in the study and design of the research.

Data Availability Statement:

The data supporting this study's findings are available from the corresponding author upon reasonable request.

Research Involving Human and/or Animals:

Not Applicable.

Informed Consent:

Not Applicable

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