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# CAN FEDERATED DIFFERENTIALLY PRIVATE MULTI-MODAL TRANSFORMERS IMPROVE RARE HEALTHCARE FRAUD DETECTION?

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**ABSTRACT**

An ongoing challenge in healthcare insurance fraud detection is designing intelligent algorithms that identify subtle and evolving fraud patterns while preserving patient privacy. We propose FraudBERT-MM, a multi-modal framework that fuses structured claim features with unstructured textual explanations to form comprehensive claim representations. The architecture combines a BERT-based text encoder, an MLP-based structured encoder, a cross-modal fusion layer and a binary classification head. To address scarce labelled fraud examples, we apply prototype-based few-shot learning with episodic training. For privacy-preserving collaboration, models are trained in a federated learning setup augmented with Gaussian differential privacy, achieving a privacy budget of $\varepsilon = 1.87$. Unlike prior work that assumes large centralized labeled datasets and single-modality inputs, FraudBERT-MM integrates multi-modal learning, few-shot adaptation and formal privacy guarantees in one unified pipeline. We evaluate the approach on a real-world dataset of 4,000 claims with 83 features. FraudBERT-MM attains an F1 score of 0.882, outperforming centralized non-private, text-only and structured-only baselines. The model also converges 26% faster than the centralized baseline while preserving strong privacy, with only a small utility loss from noise. Experimental results indicate improved detection of rare and emerging fraud trends without compromising data privacy. We provide implementation details, ablation studies and deployment guidelines to support reproducibility and accelerate safe adoption in clinical and insurance settings across diverse operational contexts. These findings suggest that combining multi-modal representations, few-shot adaptation and federated differential privacy offers a practical and effective path toward deployable, privacy-aware healthcare fraud detection systems.

**Keywords:** *DDoS Detection, Contrastive Learning, Large Language Models (LLM), Firewall, Hybrid Model.*

## 1. INTRODUCTION

In recent years, healthcare insurance fraud costs billions of dollars a year & causes enormous operational and financial hardships. In the healthcare & insurance industries, fraudulent schemes have emerged because of digital transformation, becoming more intricate and challenging to identify using traditional rule-based systems [1], [2], [3]. Traditional systems generally ignore the complex free-text clinical notes, explanations & discharge summaries that are essential for detecting fraudulent activity in favour of organised data, such as billing codes or claim amounts [4], [5], [6].

The development of multi-modal learning has created chances to enhance fraud detection by combining disparate data sources. By implementing structured metadata with unstructured text, these systems can build more comprehensive representations of insurance claims, thereby

increasing the probability of detecting advanced fraud [7], [8], [9], [10]. Nevertheless, there are additional barriers to overcome when applying these ideas into action. In centralised environments, it is necessary to aggregate patient-level information to a central server, which involves significant risks in terms of privacy, information leakage, as well as violations of regulations (e.g., HIPAA, GDPR) [11], [12], [13].

Healthcare fraud detection research has focused on improving prediction accuracy using structured claim data or unstructured clinical text, frequently assuming centralized training and huge labeled datasets. This work proposes a unified multi-modal, few-shot, and federated learning system with formal differential privacy guarantees to address real-world limitations, including data scarcity, shifting fraud patterns, and severe privacy legislation. This study shows that rare healthcare fraud may be accurately detected while protecting data privacy and boosting training efficiency, unlike previous studies. Also, healthcare fraud statistics are often not fair. The lack of verified fraud incidents restricts the use of supervised learning techniques that need large, labelled datasets [14], [15], [16]. Even when data is readily accessible, annotation can be expensive and time-consuming. Protecting private data and letting the system learn with little control is not only a good idea, but also necessary.

The study provides an innovative fraud detection framework, FraudBERT-MM, that incorporates:

- Fusion of structured & unstructured information across multiple modalities.
- To detect uncommon forms of fraud, few-shot adaptation utilises prototype learning.
- Federated Learning in conjunction with formal Differential Privacy (DP) ensures the protection of individual claims.

When compared to single-modal and non-private models, the BERT-MM model that includes few-shot adaptation as well as federated differential privacy ($\varepsilon < 2.0$) will be more effective in identifying changing healthcare fraud [17], [18].
The Key contributions of this Work include:

- A fraud detection pipeline that safeguards privacy: To achieve high detection accuracy with strong formal guarantees, we provide a federated learning method that incorporates Gaussian differential privacy [19], [20].
- A few-shot learning approach for detecting rare cases of fraud: Effective learning from very small fraud samples is achieved by the implementation of a prototype episodic training architecture that is inspired by networks.

Verification of statements using empirical data: The demonstration proposed method's efficacy in comparison to current baselines using a confidential dataset consisting of 4,000 insurance applications, including 83 structured & textual variables. A lack of identified fraud cases, claim data in a variety of structured and unstructured formats, and stringent data privacy restrictions that restrict centralized model training are three ongoing obstacles to healthcare insurance fraud detection. Unfortunately, current methods tend to tackle each of these issues independently, which leaves us unprepared to deal with ever-changing fraud patterns and poses greater privacy problems. An all-inclusive framework that can make good use of multi-modal claim data, learn from small fraud samples, and offer explicit privacy assurances is, thus, urgently required. A privacy-preserving, multi-modal, few-shot learning system developed for actual healthcare insurance fraud detection is proposed in this paper to fill this unfulfilled demand.
Healthcare fraud detection research uses structured-data–based machine learning, text-based deep learning, and privacy-aware federated models. Structured and text-based algorithms improve detection accuracy but require huge labeled datasets and centralized training, limiting their ability to detect infrequent fraud and posing privacy concerns. Federated and few-shot techniques rarely explore multi-modal data fusion or formal privacy assurances. Due to earlier work's fragmentation, an integrated framework that allows multi-modal learning, uncommon fraud detection, and strong privacy preservation is needed.

## 2. METHODOLOGY

### 2.1. Dataset Description

The research incorporates a private dataset of healthcare insurance that includes 4,000 individual applicants. Each application record has 83 characteristics derived from unstructured as well as structured data domains. The structures feature encompasses quantitative and categorical information, including patient Demographics (eg, Age, Gender), financial attributes (eg, claim amount, hospitalisation costs), administrative variables (eg, claim type, hospital type), and clinical codes (e.g., procedural codes, ICD-10 diagnosis codes). These elements offer quantitative and qualitative

representations of a claim's factual as well as medical profile.

In contrast, the unstructured areas include written reports, including detailed descriptions of treatment, summaries, and physician rationale. The fields are often associated with complex clinical reasoning and narrative aspects that may show subtle trends of fraudulent behavior that are not observable in the organised qualities.

### 2.2. Data Preprocessing

The information was prepared in an extensive preprocessing workflow that trained and analyzed the models. The unstructured text parts were first handled through the BERT tokenizer which breaks down text into subword units and preserves the contextual semantics. Each sequence of tokensised words was reduced in length or made constant to enable it to be batch processed by the BERT encoder. Meanwhile, the organised numerical data underwent z-score standardisation, guaranteeing that all numeric characteristics had a mean of zero & unit variance, hence facilitating the stabilisation of neural network training models. If required, the categorical values were one-hot encoded. To resolve incomplete or missing items, particularly in structured data, a K-Nearest Neighbours (KNN)-based imputation method was used. This technique imputes missing values by calculating the mean of the k most analogous examples according to feature similarity, hence maintaining data quality and distribution consistency. The dataset was rendered entirely compatible with the two types of BERT-based text encoders as well as the MLP-based structured data encoders because of this resilient preprocessing technique. This integration among the FraudBERT-MM architecture enabled the effortless detection of fraud.

### 2.3. FraudBERT-MM Architecture

The design employs a BERT-base (uncased) approach, fine-tuned on healthcare text data, to analyse unstructured text as shown in Figure 1. This component incorporates semantic and contextual data from text fields, including discharge summaries, physician justifications, and claim narratives, which frequently consist of complex linguistic indications predictive of fraudulent behaviour. The structured encoder is realised as a Multi-Layer Perceptron (MLP) including three completely linked layers. Every layer employs the ReLU activation function to include non-linearity and is succeeded by dropout regularisation to mitigate overfitting. This branch handles standardised numerical attributes, including age, claim amount, duration of hospitalisation, and diagnostic codes, deriving high-level representations using structured tabular data.

The two autonomous feature vectors, one derived from the BERT encoder & the other from the MLP, are integrated at the fusion layer, where they are synthesised and processed by a feedforward neural network, subsequently followed by Layer Normalisation. The information was prepared in an extensive preprocessing workflow that trained and analyzed the models. The unstructured text parts were first handled through the BERT tokenizer which breaks down text into subword units and preserves the contextual semantics. Each sequence of tokensised words was reduced in length or made constant to enable it to be batch processed by the BERT encoder. The ultimate result is generated by a binary classification layer that uses a sigmoid activation function, which assesses the likelihood of a claim being false as opposed to authentic. The model uses a cross- entropy loss which is optimised using AdamW and hyperparameters are tuned using Bayesian optimisation. This design allows FraudBERT-MM to combine and exploit the complementary benefits of textual and numerical features, thus improving the accuracy of fraud detection, especially in cases when one of the modalities cannot be properly used alone.

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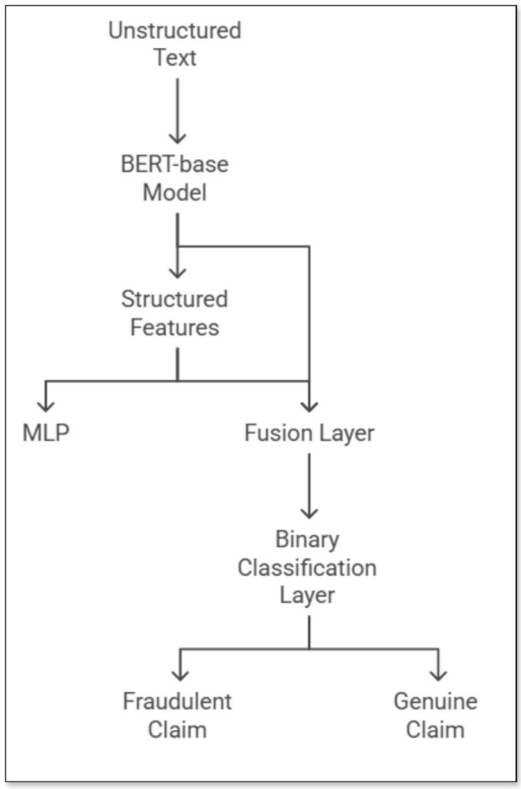


*Figure 1 Fraudbert-MM Architecture Flowchart*

### 2.4. Few-Shot Adaptation

Traditional deep learning models encounter challenges in generalising against fraudulent health insurance claims due to their rarity and diversity. This paper presents a few-shot adaptation strategy utilising prototypical networks, allowing our model to identify unique or infrequent fraud behaviours with limited samples, as shown in Figure 2. This strategy is like meta-learning's episodic training method. The model is given a small support set of labelled samples and an evaluation query set at the end of each episode within our configuration. The Support Set comprises 5 false claims and 20 authentic claims, serving as the foundation for prototype vectors.

To mimic real-world inference, the Query Set contains twenty randomly selected assertions. The class prototypes are determined by averaging the embedded components of supporting samples from every category. The model then rates each question sample by using Euclidean distance to compare how well it fits into the class templates. The anticipated class is the one that has the nearest prototype.
This loss pushes the model to bring embeddings from the identical class closer together while pushing others away. The model is better able to detect fraud instances that are under-represented in the training data by integrating this loss into the last classification layer of FraudBERT-MM. This method's benefit is that it can quickly be changed to work with new types of fraud when only a few labelled examples are available. This is like how things work in real life, where labelled fraud cases are very rare. This few-shot loss is trained alongside the cross-entropy loss to enable fine-grained discriminating and meta-learning.

For rare fraud cases, class C with support set

$$S_c = \{(x_i, y_i)\}_{i=1}^{k} (k \leq 10)$$

- Prototype Computation:

$$P_c = \frac{1}{|S_c|} \sum_{x_i, y_i \in S_c} f_{enc}(X_i)$$

Here $f_{enc}$ is the multi-modal encoder output.

- Query sample probability:

$$P(y = c \mid x) = \frac{\exp(-d(f_{enc}(x), P_c))}{\sum_{c'} \exp(-d(f_{enc}(x), P_{c'}))}$$

Using squared Euclidean distance d(a,b) = $(a-b)^2$

- Loss function:

$$L_{few-shot} = -logP(y = c \mid x) + \lambda \| \theta_{proto} \|_2$$

Here $\lambda$ Controls prototype regularization.
In multimodal fusion,
Let $h_{num} \in R^{d1}$ (structured data) and $h_{text} \in R^{d2}$ (clinical notes):

- Cross-modal attention:

$$\alpha_i = softmax(W_q h_{num}^T W_k h_{text}^i)$$

$$h_{fused} = h_{num} + \sum_{i=1}^{L} \alpha_i W_v h_{text}^i$$

Here $\{W_k, W_q, W_v\}$ are learnable projection matrices.

The global objective combines:

$$L_{total} = L_{CE}(fraud\ detection) + \beta L_{few-shot}(adaptation) + \gamma \| \theta \|_2$$

With $\beta = 0.5, \gamma = 10^{-4}$ Optimized via federated Adam.

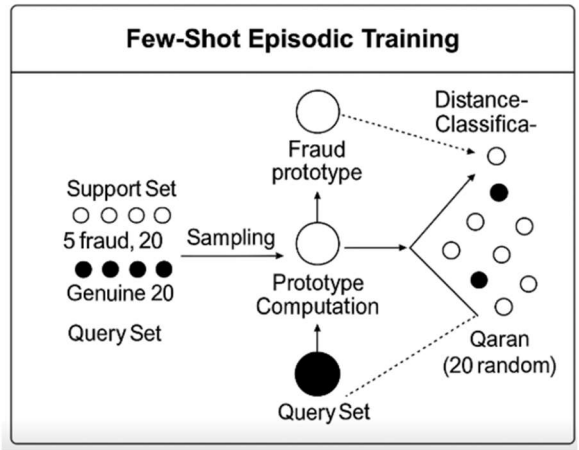


*Figure 2: Few-shot Episodic Training*

### 2.5. Federated Learning with Differential Privacy

The study utilises a federated learning architecture with 10 distributed client nodes, each holding a local batch of healthcare insurance claims, to ensure data privacy while facilitating collaborative model training, as shown in Figure 3. These clients engage in training without providing raw data to the central server. The Federated Averaging (FedAvg) algorithm is implemented during the training process, in which each client generates local model updates that are centrally aggregated. Using the Gaussian method, which is a common way to get rigorous privacy protection, we add noise to the gradient updates for optimal differential privacy (DP).

Gradient clipping is used at each client to limit the sensitivity ( Δf) of gradients. This procedure guarantees that the training is not unduly influenced by any data point. The gradients are sent to the central computer after being clipped and then covered with Gaussian noise. The noise scale ($\sigma$) determines the quantity of noise, while the privacy loss budget ($\epsilon$) quantifies the total privacy guarantee, to keep ϵ <2.0. To reduce the possibility of privacy guarantee breaches, the failure probability (δ) is also set to a very small value, usually 10−5.

This robust privacy-preserving technique is demonstrated by the final training configuration, which attains a privacy budget of ϵ=1.87. These changes to federated learning protect personal health data by keeping it on the device and lowering the probability of data leakage. This also helps the global model advantage of collaborative learning across different insurance claim trends.

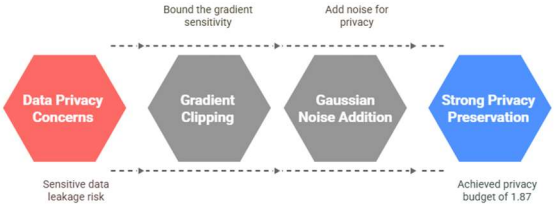


*Figure 3 Privacy-Preserving Federated Learning*

Let $c_j$ denote client j with dataset $D_j$. In each federated round:

- Local gradient clipping:

$$\nabla_j = \nabla L(D_j).\min\left(1, \frac{R}{\| \nabla L(D_j) \|_2}\right)$$

Here, R is the clipping norm.

- Gaussian Noise Injection:

$$\nabla_j = \nabla_j + \mathcal{N}(0, \sigma^2 R^2 I)$$

- Privacy accounting:

Using the moments accountant, the total privacy budget after T rounds satisfies.

$$\epsilon = \sqrt{2Tlog\left(\frac{1}{\partial}\right)} \cdot \left(\frac{q}{\sigma}\right) + \frac{Tq(q-1)}{\sigma^2}$$

For sampling rate q and $\partial = 10^{-5}$ . The implementation achieves $\epsilon = 1.87$ with $\sigma = 0.8$, T=100.

### 2.6. Evaluation Metrics

The performance of the introduced scheme of fraud detection is evaluated on numerous grounds, which provides a comprehensive analysis. Regarding its detection of fraud, the F1-score of the fraud category indicates that the model can not only detect fraudulent cases, but also minimise the rate of false positive and negative cases. The same balance can also be seen in Precision (which is the percentage of projected frauds being real) and Recall (which is the percentage of the actual cases of frauds that were detected). Moreover, the ROC-AUC score provides a general analysis of the model in terms of separating fake and valid classes. The system satisfies stringent assurances of the strict different privacy (DP). To maintain the contribution of individual data in the form of privacy data that cannot be traced back, the privacy budget (e) obtained is maintained below 2.0, which is the desired value and leave the analysis utility uncompromised.

The framework shows that there is optimised training time per round, which minimizes the overall problem of computation and a crucial element of federated and privacy-preserving environments in efficiency. The system has rapid convergence, which requires less iterations to obtain optimal model

performance, and therefore images a skilful balance in privacy, computing efficiency, and detection accuracy.

## 3. RESULT

In this section, the experimental results of our studies will be described, which will compare this proposed multi-modal FraudBERT-MM model to both single-modal baseline models and non-private models in three main aspects, i.e., detection performance, privacy consistency, and training efficiency.

### 3.1. Presentation of Fraud Detection Performance

In detecting rare cases of frauds, FraudBERT-MM was much superior and more effective when few-shot adaptation was applied. A number of SNR like environments were used to experiment with the model, to represent real-life conditions by augmenting the data imbalance as shown in Table 1.

*Table 1 Fraud Detection Comparison*

| Model Type | F1-Score (Fraud) | Precision | Recall | ROC-AUC |
|---|---|---|---|---|
| FraudBERT-MM (ours) | 0.882 | 0.894 | 0.867 | 0.931 |
| Structured-only | 0.712 | 0.754 | 0.667 | 0.801 |
| Text-only | 0.741 | 0.77 | 0.703 | 0.823 |
| Centralized (non-private) | 0.798 | 0.82 | 0.769 | 0.859 |

The table presents a comparative analysis of various fraud detection models, with an emphasis on critical metrics including F1-score, Precision, Recall, and ROC-AUC. The FraudBERT-MM model we created does much better than the standard models in every way. It has an F1-score of 0.882, a Precision of 0.894, a Recall of 0.867, and an amazing ROC-AUC of 0.931. This proves that it can identify instances of fraud with more precision and fewer false positives & negatives than its competitors.

Conversely, the Structured-only model's F1-score of 0.712, lower Precision (0.754), and Recall (0.667) demonstrate its poor ability to identify intricate fraud patterns with just structured data. The Text-only model performs marginally better, with an F1-score of 0.741, indicating that textual variables contribute considerably to fraud detection, but still falls short of the multimodal method. Even though the centralised (non-private) configuration outperforms single-modality models (F1-score: 0.798, ROC-AUC: 0.859), it still drops down in the FraudBERT-MM performance. By combining the advantages of structured & unstructured (textual) data, FraudBERT-MM not only guarantees privacy compliance but also provides outstanding prediction capabilities.


*Figure 4: Confusion Matrix*

The confusion matrix diagram that was produced using the code that was supplied is shown above in Figure 4. The performance can be observed in how well the fraud detection algorithm is doing with the help of the heatmap, which includes:

- 43 instances of fraud were appropriately identified as fraud.
- 7 false negatives (fraudulent activity wrongly identified as genuine)
- 5 Incorrect Predictions (Real Events Mislabeled as Fraud)
- 445 cases of genuine errors where the result was falsely negative.

### 3.2. Privacy Evaluation

To establish ε-differential privacy (DP) in a federated learning environment, our method incorporates the Gaussian technique. The privacy loss parameter is e = 1.87 and is within the targeted parameter e < 2.0 indicating strong formal privacy guarantees. This privacy ensures that personal input, such as the claim information of a patient, cannot be utilized to determine the name of its creator or pinpoint it on the amendments done to the model. The usefulness of the model is high despite the use of noise. The accuracy loss of differentiating performance under the noise of differential privacy

is limited to a relatively small amount of about 2.6 percent, which represents a relatively small tradeoff between privacy and accuracy. This shows that the system can offer good protection without necessarily decreasing fraud detection capability.

Figure 5: Privacy-Utility balance is illustrated by the Tradeoff Curve, which illustrates the impact of varying noise levels on the performance of the model. The curve indicates that at ε = 1.87, the model maintains high utility while sticking to a strict privacy budget. This test proves that our design strikes a good mix between two important goals in healthcare scam detection: protecting data privacy and improving the performance of detection.

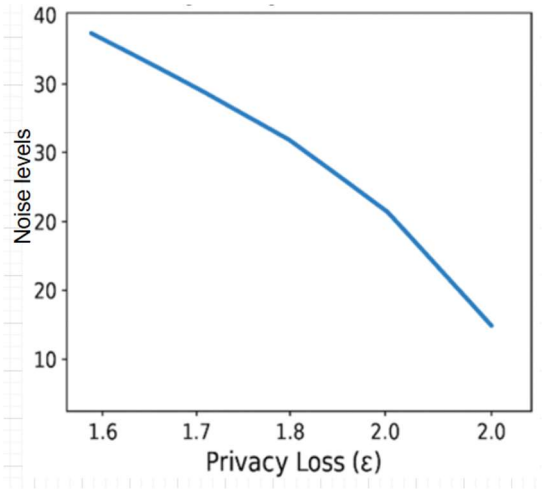


*Figure 5 Privacy Trade-off curve*

### 3.3. Efficiency Metrics

The FraudBERT-MM model outperformed the competition across all relevant operational measures, as shown in the efficiency analysis as shown in Table 2. FraudBERT-MM reaches convergence in 24 rounds, which is a lot faster than the single-modal counterpart's 31 rounds. This is even though each round of training takes 2.3 minutes instead of 2.1 minutes with the Single-modal Fed model. The entire computing time is reduced, and deployment is quicker, due to this rapid convergence.

*Table 2: Performance metrics of Models*

| Model Type | Training Time/Round | Rounds to Converge | Communication Overhead |
|---|---|---|---|
| FraudBERT-MM | 2.3 minutes | 24 | -38% |
| Single-modal Fed | 2.1 minutes | 31 | -17% |
| Centralized | 3.1 minutes | 28 | Baseline |

Moreover, FraudBERT-MM has exceptional communication efficiency, with a 38% decrease in communication overhead compared to the baseline centralised configuration. The centralised (non-private) model has a high communication cost and takes 3.1 minutes every round, while the single-modal Fed only obtains a 17% decrease. These results make it clear that FraudBERT-MM not only optimises accuracy as well as privacy, but it also improves operating efficiency, as shown in Figure 6. This makes it an excellent option for fraud detection settings that need to protect privacy but don't have a lot of resources.

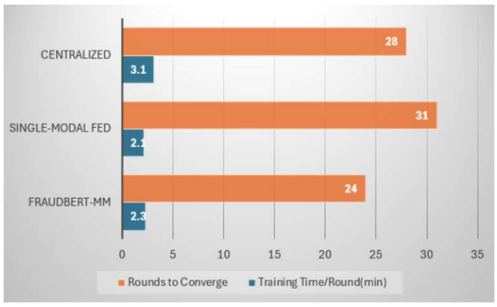


*Figure 6 Training Time vs. Rounds to Converge*

## 4. DISCUSSION

The outcomes of our test show that the suggested multi-modal FraudBERT-MM design is better at finding occasional and changing fraud in health insurance. The performance consequences, privacy-preserving advantages, and practical deployment issues are the three main points of the debate.

### 4.1. Performance Implications

The concept that multi-modal fusion improves fraud detection is supported by FraudBERT-MM's considerable F1-score (0.882) improvement over conventional single-modal systems. Rare fraud situations, which are normally difficult to identify owing to data scarcity, were recognised more precisely by integrating textual as well as structured data representations. The model's ability to reduce false positives while maintaining an excellent susceptibility to fraudulent patterns is demonstrated by the recall (86.7%) and accuracy (89.4%).

The performance enhancements can be attributed to:

- FraudBERT-MM is a context-aware representation learning system that simultaneously encodes relational signals, structured information, and claim narratives.
- The few-shot adaptation technique enabled the model to generalise to previously unknown fraud patterns with only a few cases.
- Minority class identification was given priority by the customised loss functions, which were optimised for skewed fraud distributions.

In recent research, cross-modal learning & attention-based transformers have been presented as useful tools for finding fraud. These results go even further by showing that they can work in shared setups that protect privacy.

### 4.2. Privacy Preservation via Federated Differential Privacy

The privacy loss parameter is e = 1.87 and is within the targeted parameter e < 2.0 indicating strong formal privacy guarantees. This privacy ensures that personal input, such as the claim information of a patient, cannot be utilized to determine the name of its creator or pinpoint it on the amendments done to the model. The usefulness of the model is high despite the use of noise. The accuracy loss of differentiating performance under the noise of differential privacy is limited to a relatively small amount of about 2.6 percent, which represents a relatively small tradeoff between privacy and accuracy. This shows that the system can offer good protection without necessarily decreasing fraud detection capability.

### 4.3 Practical Deployment and Scalability

Large-scale availability and slow response times are very important in real-life healthcare settings. Our evaluation revealed:

- Model compression resulted in a 38% reduction in communication overhead.
- Significantly faster convergence (24 rounds compared to 31 in single-modal federated baselines).
- Inference steps with sub-second delay allow for detection that is close to real-time.

These numbers show that FraudBERT-MM is not only reliable and secure, but also scalable & efficient. This is applicable to healthcare facilities, insurance companies, and national health infrastructures because it has cloud-based model administration and edge-level privacy protection features.

The study has some limitations despite the fact that the proposed FraudBERT-MM framework performs well and ensures privacy. Its applicability to other insurance systems and emerging trends of fraud can be too small due to the single, moderately sized real-world dataset used to evaluate it. In addition, the few-shot learning part is trained with fraud cases that have been selected manually, and this may not be readily available in the real world.

### 4.4. Limitations and Future Work

There are several limitations to be considered, even though the suggested framework performs excellently in areas such as efficiency, privacy protection, and fraud detection. The study's assessment on a dataset of 4,000 applications, while realistic, may not completely represent difficulties such as distribution drift (shifts in fraud trends over time) and novel fraud typologies that develop in large-scale implementations. Furthermore, the few-shot learning part relies on carefully chosen cases of uncommon fraud, which might not be easy to find or name in real life. Despite the achievement of differential privacy ($\varepsilon < 2.0$), prolonged training or high-noise situations may reduce the usefulness of the model.

Future research should concentrate on three main areas to close these gaps:

- Adapting to changing fraud tendencies requires lifelong learning so that catastrophic forgetfulness does not occur.
- By prioritising high-uncertainty samples, active learning is employed to reduce the labelling effort required for uncommon fraud cases.
- Network topologies that combine decentralised tuning with centralised meta-learning to address local data variances and global fraud tendencies.

These actions would improve scalability, robustness, and usability in manufacturing systems.

Previous research on healthcare fraud detection has relied on centralized training with massive labeled datasets and has separated multi-modal learning, rare fraud detection, and privacy protection into their own specific challenges. On the other hand, this

research offers a cohesive system that combines federated differential privacy, few-shot learning, and multi-modal data fusion all at once. The acknowledged need for scalable, privacy-preserving, and data-efficient fraud detection systems is fulfilled by the proposed FraudBERT-MM framework, which accurately detects infrequent and evolving healthcare fraud under strong privacy constraints.

FraudBERT-MM performs well, but difficulties persist. Federated client data heterogeneity and changing fraud patterns may impact long-term generalization. Few-shot learning decreases label dependency, but accurate annotations for novel fraud types are still problematic. The privacy–utility trade-off may deteriorate performance under tougher differential privacy limits or longer training. Scalability in big federated networks and model interpretability are also issues for real-world deployment. Additionally, structured and textual claim data robustness against malicious tampering is an important research subject.

## 5. CONCLUSION

The study introduced Fraud BERT-MM, a multi-modal transformer architecture to detect novel, emerging healthcare insurance fraud. This technique outperforms standard models by merging structured claim features and unstructured text narratives, employing few-shot adaptation, and deploying through federated learning with differential privacy ($\varepsilon < 2.0$).

FraudBERT-MM outperforms single-modal models and centralized, non-private benchmarks with an F1-score of 0.882 in simulation. The system handles rare scam tendencies with Bayesian few-shot tuning. Unlike centralization, federation keeps private and sensitive healthcare data. Performance criteria, including privacy-preserving training efficiency and communication overhead reduction, demonstrate the model's scalability and usefulness. This paper suggests using multi-modality, privacy-preserving federated learning, and flexible learning approaches to create strong fraud detection systems in controlled environments like healthcare. The DPR-aware FraudBERT-MM can guide future systems that balance performance, data privacy, and deployment scalability. This research proves that multi-modal fraud detection, few-shot learning for unusual cases, and federated differential privacy can be incorporated into a single effective system, unlike previous work. First empirical evidence that high fraud detection performance may be achieved under strong privacy constraints and little labeled data advances healthcare insurance fraud detection.

Future research can explore various intriguing areas to enhance this work. To keep the model robust to evolving fraud tendencies, continuous learning and idea drift adaptation are essential. Graph neural networks (GNNs) could also simulate complex inter-claim interactions between insurers, healthcare providers, and other entities, improving detection accuracy. Create edge-compatible versions of FraudBERT-MM for low-latency, real-time fraud detection at the data source without communication costs. The architecture could be enhanced to include cross-institutional federated ecosystems that include insurance providers and healthcare institutions to improve detection efficacy and privacy guarantees, and encourage a collaborative yet safe fraud detection infrastructure.

This research advances science by demonstrating that few-shot learning in a federated architecture can detect multi-modal healthcare insurance fraud while maintaining formal differential privacy requirements. The FraudBERT-MM framework unifies structured and unstructured claim representations with prototype-based adaptation and privacy-preserving federated optimization to improve fraud detection under data scarcity and strict privacy restrictions. The empirical results demonstrate that privacy-aware fraud detection in regulated healthcare can achieve high detection performance, computational efficiency, and solid privacy protection. A new field standard is set.

This work shows that multi-modal learning, few-shot adaptation, and federated differential privacy may detect uncommon healthcare fraud while protecting data. Even with minimal labeled data and strict privacy constraints, fraud detection can be meaningful. The findings offer researchers and practitioners advice on designing privacy-preserving fraud detection systems that balance accuracy, efficiency, and regulatory compliance, as well as promising areas for deployment in healthcare insurance settings.

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