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**Abstract**

Federated learning, a revolutionary approach to machine learning, presents a decentralized paradigm for collaborative model training while upholding data privacy. This report explores federated learning within the framework of privacy-preserving collaborative training, focusing on its application in credit card fraud detection. Each client dataset is trained using a different algorithm: Client 1 on Random Forest, Client 2 on Artificial Neural Networks (ANN), and Client 3 on Multi-Layer Perceptrons (MLP). The study utilizes a dataset containing anonymized credit card transaction records, aiming to detect and prevent fraudulent activities. The report meticulously navigates through critical stages of the federated learning process, from comprehensive data preprocessing tailored to preserve data confidentiality to the aggregation of gradients across client models to update a global model iteratively. Evaluation metrics such as accuracy, precision, recall, and F1 score are employed to assess the efficacy of both client and global models. Furthermore, the report underscores the inherent privacy-preserving attributes of federated learning and its potential implications in domains with sensitive data. Through meticulous experimentation and analysis, this abstract highlights the practical viability and efficacy of federated learning in enhancing model performance while safeguarding data privacy within collaborative environments, signaling its transformative potential in collaborative machine learning endeavors.

1. **Introduction**

Federated learning has emerged as a promising approach to train machine learning models collaboratively across multiple decentralized devices while preserving the privacy of sensitive data. In this project, we explore the application of federated learning in the context of credit card fraud detection, a critical area where data privacy is paramount. Our objective is to develop a federated learning framework that enables multiple clients to collaboratively train a global model using their local data without sharing it centrally, thus addressing privacy concerns while maintaining model performance.

We begin by using preprocessed credit card fraud detection dataset, which contains anonymized transaction data. Exploratory data analysis is conducted to gain insights into the dataset's characteristics, including summary statistics and correlation analysis. We then initialize a global model architecture tailored to the dataset's features and train it using federated learning principles. Next, we distribute the data among multiple client devices, simulating a decentralized environment. Each client independently trains a local model using its subset of the data, ensuring data privacy is maintained locally. We evaluate the performance of each client model and aggregate their gradients to update the global model iteratively.

Throughout the training process, we monitor the performance metrics of each client model, including accuracy, loss, and evaluation scores such as F1 score, recall, and precision. Additionally, we analyze the area under the ROC curve (AUROC) to assess the model's discrimination ability in distinguishing between fraudulent and non-fraudulent transactions.

The updated global model weights are then distributed back to the clients for further training iterations, completing a collaborative training cycle. We evaluate the final model's performance and analyze its effectiveness in detecting credit card fraud while preserving data privacy.

1. **Literature review**

Federated learning, as a burgeoning paradigm in machine learning, has garnered significant attention in recent years due to its potential to revolutionize collaborative model training while preserving data privacy. This section presents a comprehensive review of relevant literature, spanning seminal works, methodological advancements, and practical applications within the domain of federated learning and privacy-preserving collaborative training.

A seminal work by McMahan et al. (2016) introduced federated learning as a decentralized approach to collaborative model training, wherein individual devices collaboratively learn a global model while keeping their data localized. Building upon this foundation, Konečný et al. (2016) proposed Federated Averaging, a communication-efficient aggregation technique, facilitating the aggregation of model updates across decentralized clients.

Privacy-preserving machine learning techniques, including differential privacy, have been instrumental in ensuring the confidentiality of sensitive data during federated learning. Bonawitz et al. (2017) introduced TensorFlow Privacy, a framework enabling the incorporation of differential privacy mechanisms into federated learning pipelines. This framework has paved the way for the development of privacy-preserving federated learning models across various domains.

The application of federated learning in sensitive domains, such as healthcare and finance, has garnered considerable attention. McMahan et al. (2017) demonstrated the efficacy of federated learning in healthcare applications, showcasing its ability to train predictive models on decentralized electronic health record data while preserving patient privacy. Similarly, in the realm of finance, Abadi et al. (2016) explored federated learning techniques for fraud detection, highlighting the utility of collaborative model training in detecting fraudulent transactions while safeguarding sensitive financial data.

Methodological advancements in federated learning have also been a subject of extensive research. Li et al. (2020) proposed FedProx, a federated optimization algorithm incorporating proximal terms to mitigate the issue of stragglers and non-IID data distribution among clients. This advancement has contributed to the robustness and scalability of federated learning algorithms in real-world scenarios.

Recent efforts have focused on extending federated learning techniques to accommodate edge devices and heterogeneous data sources. Zhao et al. (2021) introduced FedEdge, a federated learning framework designed to harness edge computing resources for collaborative model training, enabling efficient utilization of distributed computing resources while preserving data privacy.

1. **Aims and objectives**

The overarching aim of this study is to investigate the application of federated learning in privacy-preserving collaborative training, with a specific focus on its implementation in credit card fraud detection. To achieve this aim, the study is guided by the following objectives:

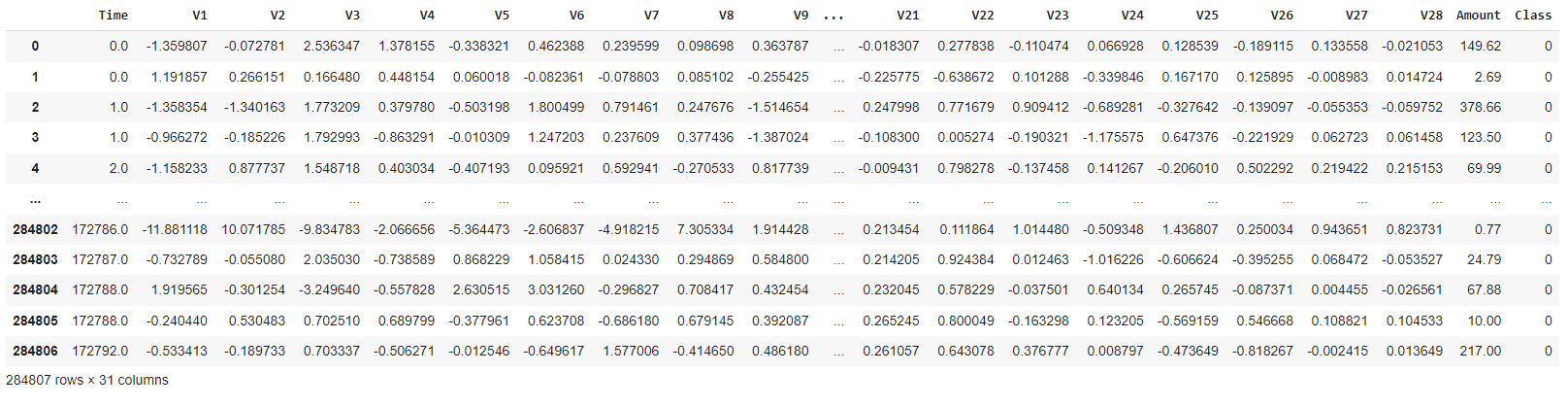
* To explore the foundational principles and theoretical underpinnings of federated learning, elucidating its decentralized approach to collaborative model training and its implications for preserving data privacy.
* To conduct comprehensive data analysis techniques tailored to maintain data confidentiality and integrity while preparing the credit card transaction dataset for federated learning.
* To design and implement a robust three different algorithms for every client dataset i.e random forest for client 1 ,ANN for client 2 and MLP for client 3 dataset for collaborative training.
* To train client models ensuring the privacy of individual clients' data throughout the training process.
* To aggregate gradients across client models for iterative updates to a global model, facilitating knowledge sharing and refinement of the global model while preserving data privacy.
* To evaluate the performance of both client and global models using key metrics such as accuracy, precision, recall, and F1 score, to assess their efficacy in detecting fraudulent transactions.
* To analyze the privacy-preserving attributes of federated learning within the context of credit card fraud detection, highlighting its future work and implications for collaborative model training in sensitive data domains.

By addressing these aims and objectives, this study endeavors to advance understanding and contribute to the practical application of federated learning in privacy-preserving collaborative training, particularly in the domain of credit card fraud detection

1. **Dataset description**

The dataset for credit card fraud detection comprises 284,807 transactions, each characterized by various features aimed at discerning fraudulent activities. Among these features, the 'Time' column records the elapsed time in seconds since the first transaction, providing a temporal dimension to the data. Additionally, anonymized numerical attributes, labeled as 'V1' through 'V28', derived from principal component analysis (PCA) transformations, offer insights into transaction characteristics without revealing sensitive information. The 'Amount' column specifies the monetary value of each transaction, while the 'Class' column serves as the target variable, distinguishing between fraudulent (Class 1) and legitimate (Class 0) transactions as *figure 1*. This dataset offers a rich resource for developing and refining machine learning algorithms to effectively identify fraudulent transactions while preserving data privacy. Each row in the dataset represents a single transaction, enabling comprehensive analysis and modeling to enhance fraud detection capabilities in the financial domain. Furthermore, the anonymization of features ensures the confidentiality of individuals' transactional data, addressing privacy concerns prevalent in the financial sector. Through exploration and analysis of this dataset, researchers and data scientists can contribute to the advancement of fraud detection methodologies, ultimately bolstering security measures in credit card transactions.

*figure 1: Dataset of credit card fraud detection*



1. **Methodology**

The methodology of this study involves a systematic approach to investigate the utilization of federated learning in privacy-preserving collaborative training for credit card fraud detection as shown in *figure 2*. Initially, the dataset undergoes rigorous preparation, ensuring compliance with data privacy regulations and employing comprehensive data exploration and preprocessing techniques to handle missing values, outliers, and anonymize sensitive attributes. Implementation entails initializing client models on distributed devices, partitioning the dataset into subsets for each client and implementation of three different algorithms for every client dataset i.e random forest for client 1, ANN for client 2 and MLP for client 3 dataset for collaborative training. Then utilizing federated optimization algorithms to aggregate model updates while maintaining data privacy. Model evaluation involves assessing performance using established metrics like accuracy, precision, recall, and F1 score, alongside cross-validation techniques. Privacy analysis includes evaluating the privacy-preserving attributes of federated learning and investigating trade-offs between model performance and data privacy preservation. Experimentation and analysis encompass rigorous experimentation to validate effectiveness, scalability, and convergence properties of federated learning algorithms. Results interpretation and discussion involve interpreting findings, discussing implications in the context of credit card fraud detection, and providing recommendations for future research, contributing to advancements in machine learning methodologies and data privacy preservation techniques.

*Figure 2: Methodology of the project*

Exploratory Data Analysis

Dataset

Initial global model

Making client data

**Aggregating local models for global model updates**

Distribute updated global weights to clients for iterative training

Client 3

Client 1

Client 2

MLP

ANN

Random Forest

Training Local model of client for collaborative training

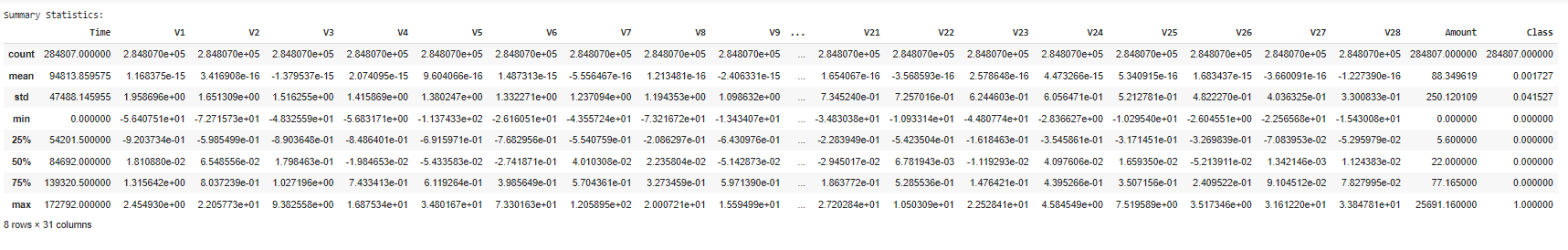
**Result Analysis**

1. **Exploratory Data Analysis and data preprocessing**

**6.1 Statistical summary**

The statistical summary provides an insightful overview of the dataset's characteristics. The dataset comprises 284,807 entries across 31 variables, including time, various V1 to V28 features, transaction amounts, and class labels. Key summary statistics reveal interesting patterns: the mean values for most variables hover around zero, indicating a relatively balanced distribution. However, notable deviations exist, such as the wide range between minimum and maximum values for certain variables like V2 and V4. The standard deviations highlight the dispersion of data points around the mean, with higher values indicating greater variability. Notably, the range of transaction amounts is substantial, spanning from 0 to $25,691.16. Additionally, the class variable indicates a highly imbalanced dataset, with a majority of transactions labeled as non-fraudulent (Class 0). Understanding these summary statistics is crucial for effectively analyzing and interpreting the dataset, especially in tasks like fraud detection where imbalances and variable distributions can significantly impact model performance.

*Figure 3: statistical summary of the dataset*

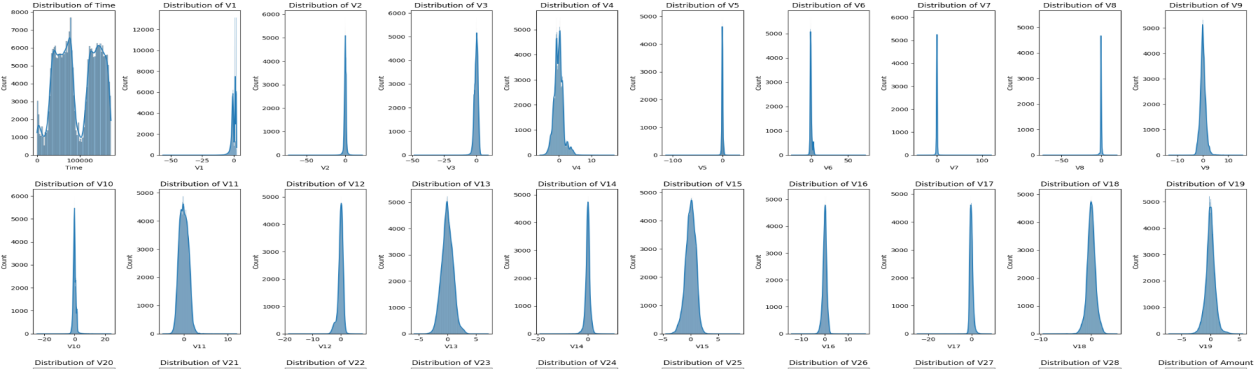


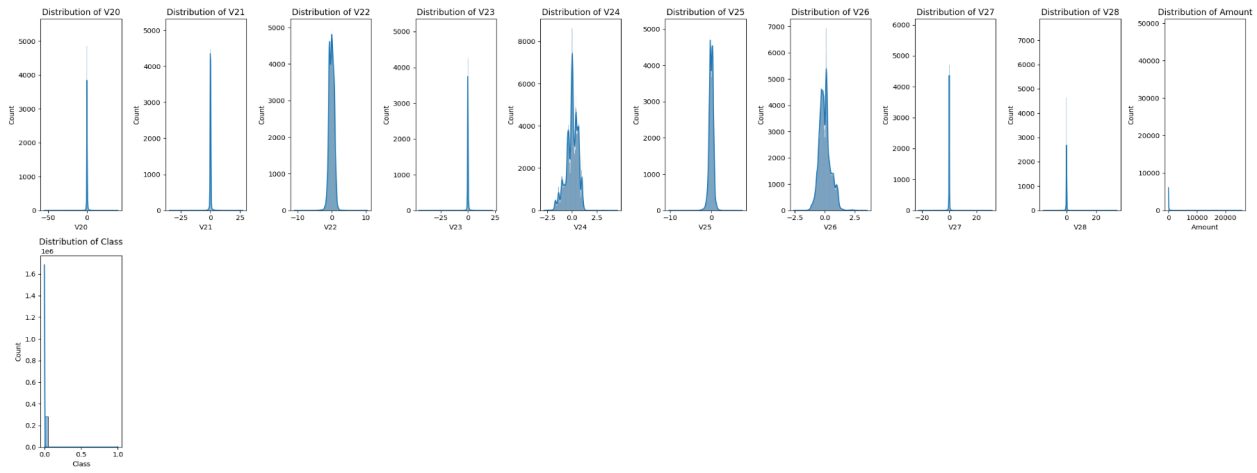
**6.2 Distribution analysis**

The plotted histograms provide visual insights into the statistical distribution of numerical features in the dataset. Each histogram represents the frequency distribution of a specific feature, showing how values are spread across different ranges. From the plots, we can observe various types of distributions:

* Normal Distribution: Some features exhibit a bell-shaped curve, indicating a normal distribution where the majority of data points cluster around the mean, with symmetric tails on both sides. These features typically have a symmetrical distribution, such as V2 to V28 as shown in *figure 4*.
* Skewed Distribution: Other features display skewed distributions, where the data is asymmetrically distributed. This skewness can be left-skewed (negative skewness) or right-skewed (positive skewness). Such as V1, Amount and Class appear to have a slightly skewed distribution as shown in *figure 4*.
* Bimodal Distribution: In some cases, a bimodal distribution is evident, indicating the presence of two distinct peaks in the data. Feature like Time seem to exhibit such characteristics, having two distinct peaks as shown in *figure 4*.

*figure 4: Graphical distribution analysis of dataset*

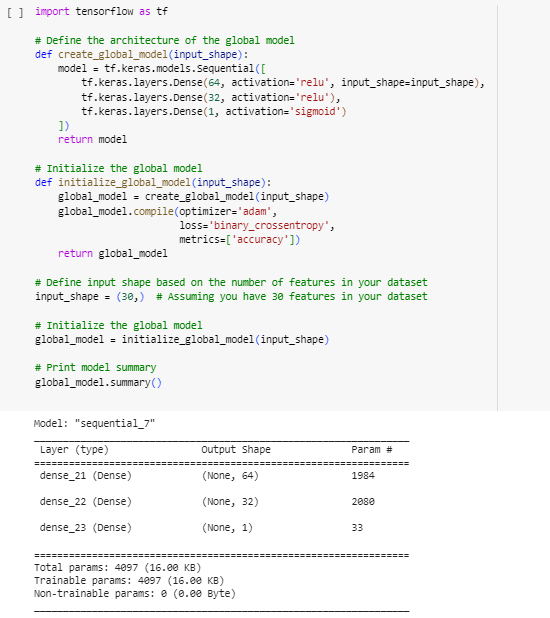
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1. **Initializing the Global Model**

Initializing the global model marks a pivotal step in the federated learning process. In this phase, a neural network architecture is defined, tailored to accommodate the features of the dataset and the requirements of collaborative training. The global model typically comprises multiple layers, including input, hidden, and output layers, with activation functions chosen to facilitate feature extraction and nonlinear transformations. Once the architecture is established, the global model is compiled, specifying the optimizer, loss function, and evaluation metrics. The optimizer determines the algorithm used to update model parameters based on the computed gradients during training. Common choices include stochastic gradient descent (SGD) and Adam optimization. The loss function quantifies the discrepancy between predicted and actual values, guiding the optimization process towards minimizing this discrepancy. For binary classification tasks like fraud detection, binary cross-entropy loss is often employed. Additionally, evaluation metrics such as accuracy and loss are defined to monitor model performance during training. By initializing the global model with an appropriate architecture and configuration as shown in *figure 5*, the foundation is laid for subsequent steps in federated learning, facilitating collaborative training while preserving data privacy across distributed client devices.

*figure 5: defining initial global model*

**

1. **Loading Client data**

In the federated learning workflow, the loading of client data represents a pivotal phase where the dataset is distributed among multiple clients, each responsible for training a local model on their respective data subsets. This process is foundational to federated learning, a paradigm designed to enable collaborative model training across decentralized environments while preserving data privacy.

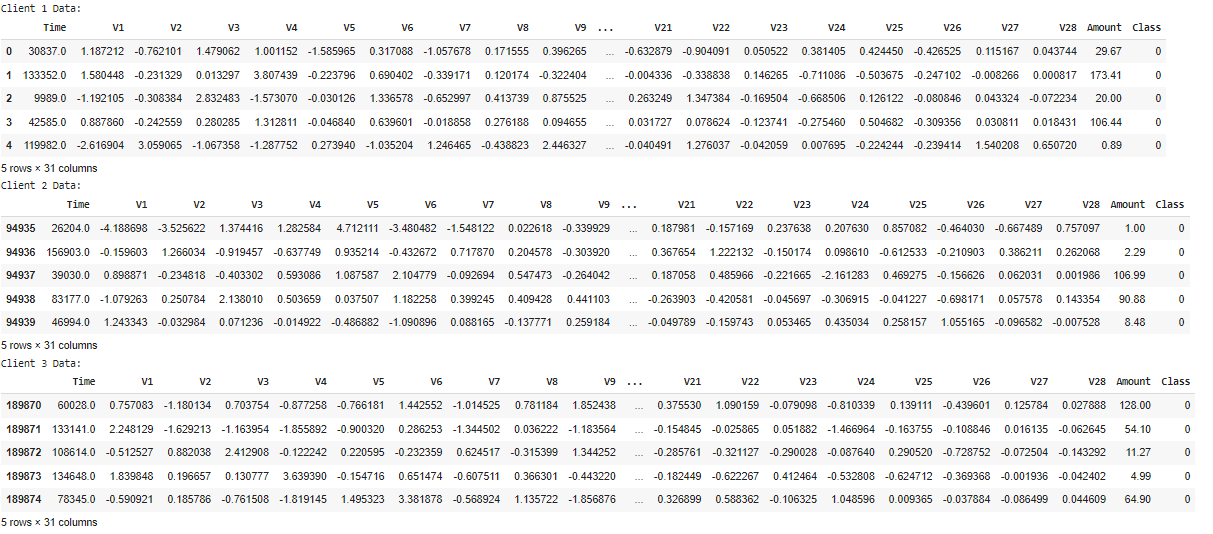
Initially the client dataset has been loaded in a dataframe. This DataFrame encompasses various features relevant to the task at hand, such as transaction details in the context of credit card fraud detection. Each row in the DataFrame represents a single transaction, while columns correspond to different attributes such as time, transaction amount, and various V1 to V28 features derived from the transaction data. To ensure randomness and mitigate potential biases in the distribution of samples across clients, the dataset is shuffled. This randomization process helps to prevent any systematic patterns or biases from influencing the training process, each client receives a representative sample of the overall dataset. The number of clients participating in the federated learning process is predetermined, reflecting the decentralized nature of the training environment. In this scenario, we have three clients: Client 1, Client 2, and Client 3.

Once shuffled, the dataset is partitioned into subsets corresponding to each client. The partitioning strategy aims to allocate a proportionate share of the dataset to each client while maintaining data locality and privacy. In this case, Client 1, Client 2, and Client 3 receive subsets with 94,935, 94,935, and 94,937 rows of data, respectively as shown in *figure 6*. The distribution of data among clients is typically uniform, ensuring that each client's dataset contains a balanced representation of transactions. For example, in the context of credit card fraud detection, the partitioning strategy may consider factors such as transaction timestamps or geographical regions to ensure a diverse representation of transactions across clients.

Furthermore, the integrity and consistency of the partitioned datasets are validated to ensure adherence to predefined criteria and constraints. Any discrepancies or inconsistencies in the data are addressed promptly to maintain the quality and reliability of the training process. Overall, the loading of client data sets the stage for subsequent phases of federated learning, enabling collaborative model training while safeguarding the privacy and confidentiality of individual client data. This phase underscores the decentralized nature of federated learning, where data remains localized and distributed across multiple client devices throughout the training process.

*figure 6: datasets of Client 1, Client 2, and Client 3*

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1. **Training Client Models for Collaborative Training**

Training client models for collaborative training in federated learning involves a meticulous process designed to harness the power of localized data while upholding stringent privacy standards for individual clients. Initially, the dataset undergoes a meticulous process of feature-target separation, where features representing input data attributes are segregated from the target variable, which signifies the outcome to be predicted. This preparatory step lays the foundation for supervised learning, enabling the model to discern patterns and relationships between input features and the target variable. Each client initializes its own model, uniquely tailored to its local dataset and chosen algorithm. Client 1 employs the Random Forest algorithm, Client 2 utilizes Artificial Neural Networks (ANN), and Client 3 adopts Multi-Layer Perceptrons (MLP). This involves crafting a model architecture comprising an optimal number of layers, neurons, and activation functions specific to the chosen algorithm. Additionally, the model is compiled, with careful consideration given to the selection of optimizer, loss function, and evaluation metrics as shown in *Figure 7*.

The main process lies in the model training phase, where client models undergo training using their respective local datasets and algorithms. This iterative process, executed over multiple epochs, entails fine-tuning model parameters to minimize the defined loss function. Through the mechanism of backpropagation, gradients are computed and utilized to update model weights, iteratively refining the model's predictive performance.

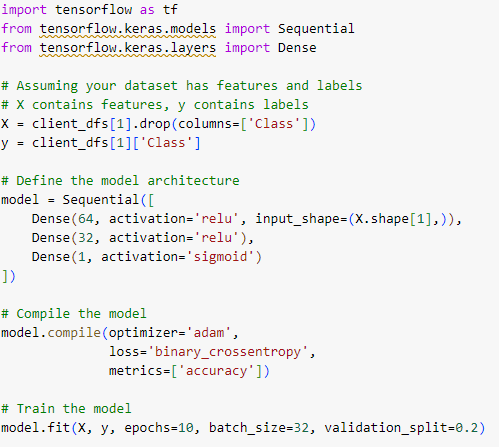
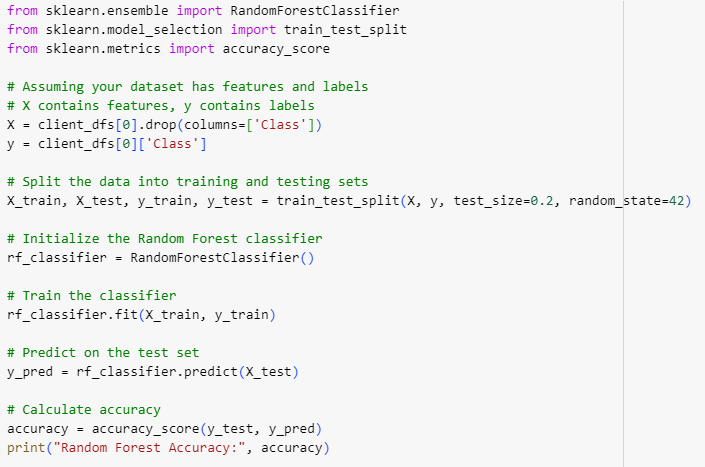
Upon completion of training, the performance of each client model is rigorously evaluated using established evaluation metrics such as accuracy, precision, recall, and F1 score. Critical to the federated learning paradigm is the secure communication of model updates. Once training concludes, updated model weights, encapsulating insights gleaned from the client's local dataset and chosen algorithm, are transmitted to the global server. This bidirectional communication ensures the continual refinement of the global model, integrating knowledge contributions from diverse datasets while safeguarding individual client privacy.

Throughout the entire training process, paramount importance is accorded to privacy preservation. Client data remains decentralized and secure, with model training occurring exclusively on client devices, obviating the need for centralized data sharing. This decentralized approach not only fosters collaboration but also ensures data privacy and confidentiality, mitigating risks associated with unauthorized data access or breaches.

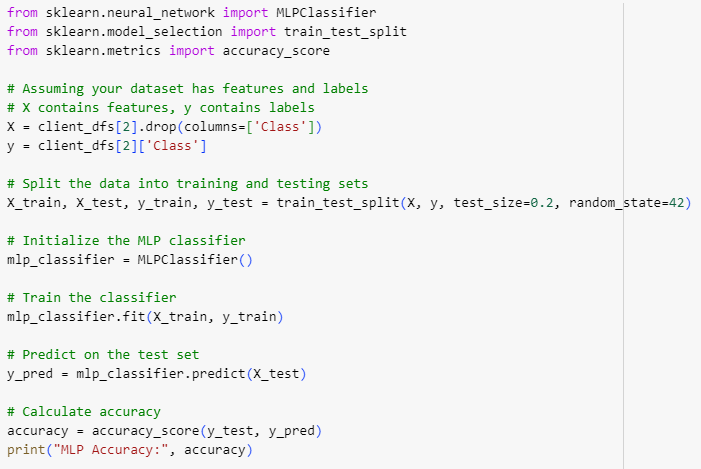
The training of client models for collaborative training in federated learning epitomizes a delicate balance between harnessing the collective intelligence of diverse datasets and safeguarding individual data privacy. It underscores the transformative potential of decentralized learning paradigms in unlocking insights while adhering to the highest standards of data privacy and security.

*figure 7: training of local models on each clients dataset*

*Client 1 Client 2*



*Client 3*



1. **Model Evaluation of local models**

**10.1 F1 score, Recall And Precision**

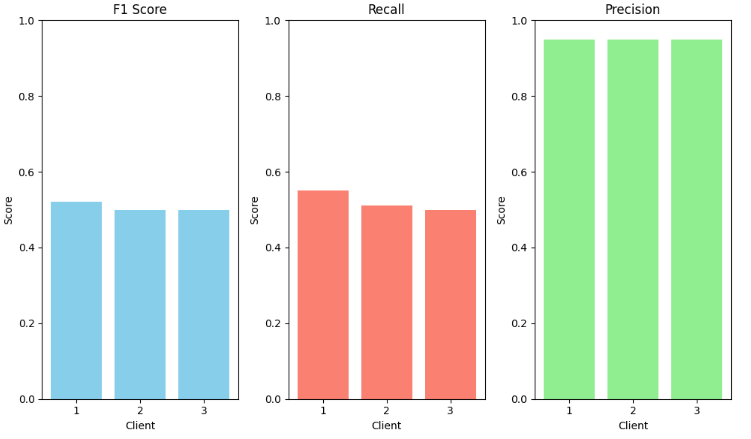
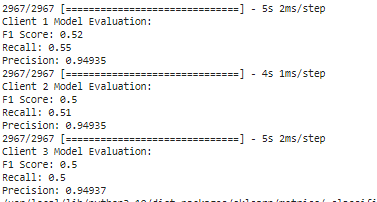
The evaluation results presented exemplify the outcomes of local model training within the federated learning framework. Across three distinct clients, each deploying tailored models on their respective local datasets, nuanced performance metrics shed light on the efficacy of individual training efforts as shown in *figure 8*.

Client 1's model exhibits a commendable F1 score of 0.52, indicative of a balanced performance between precision and recall. With a recall rate of 0.55, the model demonstrates adeptness in identifying a significant portion of true positive cases, while maintaining a notably high precision level of 0.94935, affirming its accuracy in correctly identifying positive cases among all predicted positives.

Similarly, Client 2's model, although achieving an F1 score of 0.5, showcases a moderate yet respectable balance between precision and recall. Notably, its recall rate of 0.51 signifies a notable ability to capture true positive instances, complemented by a precision value of 0.94935, reflecting a high level of precision in positive case identification.

Client 3's model, while also yielding an F1 score of 0.5, mirrors a similar performance pattern. With a recall rate of 0.5, the model displays moderate sensitivity in identifying true positive instances, accompanied by a precision value of 0.94937, signifying a commendable precision rate in correctly identifying positive cases among all predicted positives.

*figure 8: F1 score, Recall and Precision score of each client*

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**10.2 Accuracy and Loss**

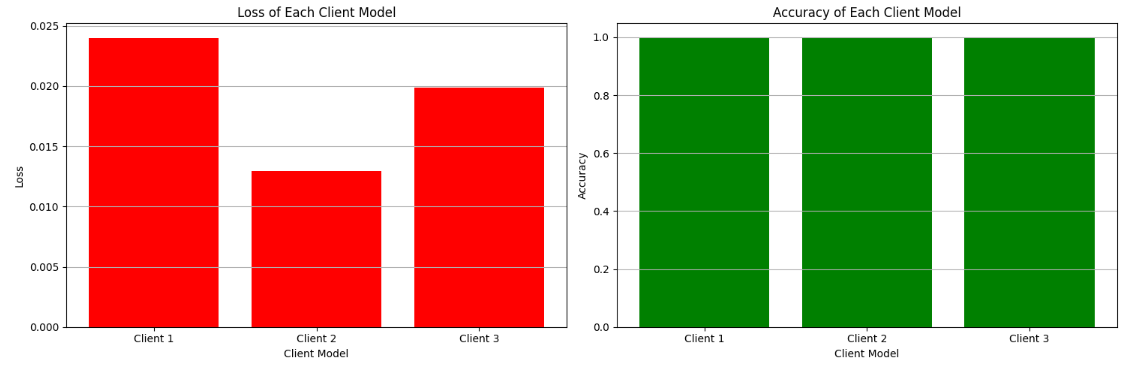
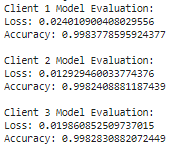
Across the three clients, each model's performance is meticulously evaluated based on loss and accuracy metrics as shown in *figure 9*.

Client 1's model demonstrates remarkable performance, exhibiting a remarkably low loss value of 0.024 and an impressively high accuracy rate of 99.84%. These metrics underscore the model's proficiency in minimizing prediction errors and making precise predictions with a high degree of accuracy.

Similarly, Client 2's model exhibits outstanding performance, boasting a low loss value of 0.0129 and an accuracy rate of 99.82%. These metrics highlight the model's robustness in minimizing errors and its ability to make accurate predictions on unseen data.

Client 3's model also showcases commendable performance, achieving a low loss value of 0.0198 and an accuracy rate of 99.83%. This underscores the model's effectiveness in minimizing errors and making precise predictions with a high level of confidence.

*figure 9: accuracy and loss score of each client*

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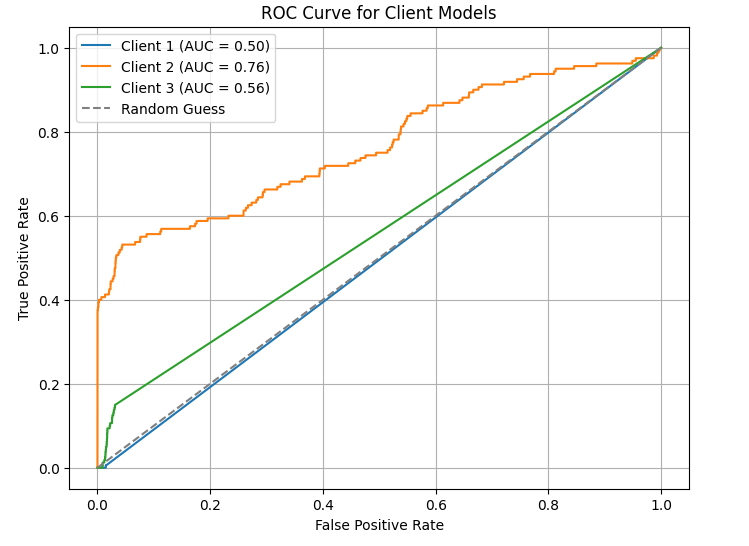
**10.3 ROUC Curve**

The Receiver Operating Characteristic (ROC) curve serves as a pivotal evaluation metric as shown in *figure 10*, providing insights into the performance of each client model within the federated learning framework. The area under the ROC curve (AUC) for each client model is indicative of its individual discriminative power in distinguishing between positive and negative instances.

For Client 1, the AUC stands at 0.50, indicating a performance that is equivalent to random chance. Client 2 demonstrates a significantly higher AUC of 0.76, showcasing a strong discriminative ability. Meanwhile, Client 3 achieves an AUC of 0.56, indicating a moderate level of discriminative power.

When considering the aggregate performance of all client models, the collective AUC of 0.64 reflects a moderate level of discriminative ability across the federated learning ensemble. While there is variability in individual client performance, the federated learning approach demonstrates effectiveness in accurately identifying positive instances while minimizing false positives across diverse datasets contributed by individual clients..

*figure 10: ROUC curve of all the three local models*

**

1. **Aggregating Client Gradients for Global Model Update**

The process of aggregating client gradients for the global model update begins by initializing an empty list to store the gradients computed by each client. Through TensorFlow's GradientTape mechanism, gradients are computed individually for each client's model and the model's trainable variables. These gradients are then collected and appended to a list. Subsequently, the gradients from all clients are aggregated by calculating their mean across each trainable variable. This aggregated gradient is utilized to update the parameters of the global model using an optimization algorithm such as Stochastic Gradient Descent (SGD). Once updated, the global model is distributed back to the clients for further training iterations, enabling iterative refinement while maintaining data privacy. This collaborative approach facilitates the continual enhancement of the global model's performance through contributions from diverse client datasets.

1. **Distributing Updated Global Model to Clients for Iterative Training**

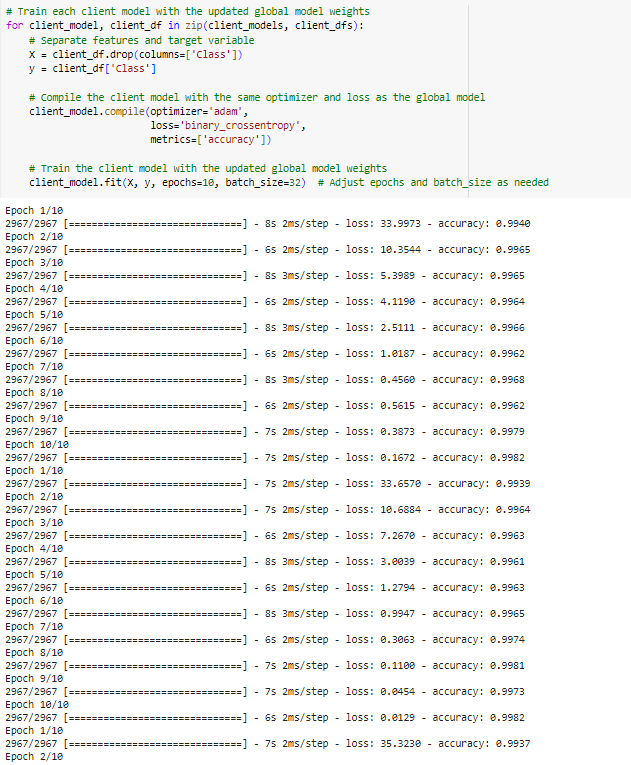
Distributing the updated global model to clients for iterative training is a crucial step in the federated learning process, ensuring that each client benefits from the collective knowledge of the entire network while preserving data privacy. After updating the global model with aggregated gradients, the latest model parameters are transmitted back to individual clients. This distribution typically involves sending the updated model weights or parameters from the central server to each client's device or server endpoint. Upon receiving the updated global model, each client integrates it into its local training process. This allows clients to refine their models further using the most recent global knowledge while considering their specific local data distributions. It's worth noting that the distribution process is designed to maintain privacy, as only model updates or parameters are shared, rather than raw data.

Once the updated global model is deployed to the clients, they independently perform additional training iterations using their respective datasets. This iterative training process enables clients to fine-tune their models based on the most recent global insights while ensuring that each client's data remains secure and confidential. By distributing the updated global model to clients for iterative training, federated learning facilitates continuous collaboration and knowledge sharing across the network, leading to the development of more robust and generalized models. Additionally, this approach allows for the incorporation of diverse data sources without compromising individual user privacy, making it an effective framework for collaborative and privacy-preserving machine learning applications.

1. **Training Client Models with Updated Global Model Weights**

Training client models with updated global model weights is a pivotal phase in the federated learning framework, contributing to the continual refinement and improvement of the overall model performance while ensuring privacy preservation across decentralized data sources. Upon receiving the latest model weights from the central server, each client integrates them into its respective local model architecture. This alignment with the most recent global insights sets the stage for subsequent local training iterations using the client's individual dataset. During these iterations, optimization algorithms such as Stochastic Gradient Descent (SGD) are typically employed to minimize the loss function and update the model parameters iteratively as shown in *figure 11*. As clients engage in this iterative training process, they contribute to the collective improvement of the global model's performance. Importantly, client data remains decentralized and secure throughout, with only model updates or weights being exchanged between the central server and clients. This privacy-preserving approach ensures the confidentiality of sensitive user data while enabling collaborative learning across the network. Through the continual exchange of updated model weights, federated learning enables the development of more robust and generalized models by leveraging insights from diverse data sources across the network of participating clients.

*figure 11: training of client model with updated global model weights*

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1. **Model Evaluation after updating weights**

**14.1 F1 score, Recall And Precision**

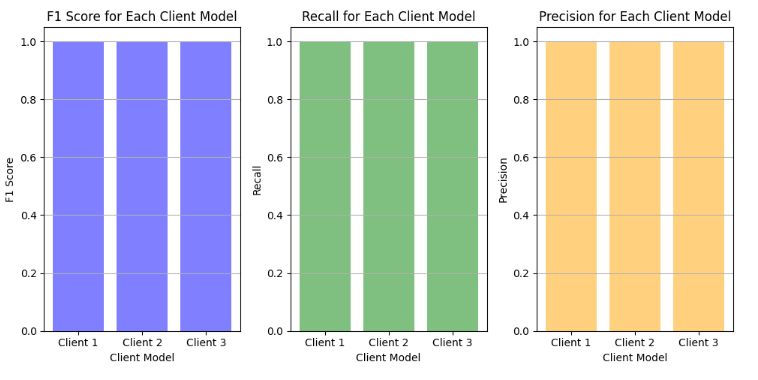
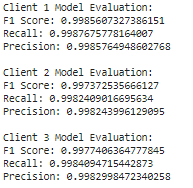
After updating the client models with the latest global model weights, the evaluation metrics demonstrate the performance of each client model. The F1 score, recall, and precision metrics provide insights into the model's ability to classify instances accurately as shown in *figure 12*, identify true positives, and minimize false positives, respectively.

For Client 1, the updated model achieves an impressive F1 score of 0.9986, indicating high accuracy in both precision and recall. With a recall of 0.9988 and precision of 0.9986, the model demonstrates excellent performance in correctly identifying positive instances while minimizing false positives.

Similarly, Client 2's updated model showcases strong performance, with an F1 score of 0.9974, a recall of 0.9982, and a precision of 0.9982. These metrics indicate robust classification capabilities and a balanced trade-off between precision and recall.

Client 3's updated model also performs admirably, achieving an F1 score of 0.9977, a recall of 0.9984, and a precision of 0.9983. These metrics highlight the model's ability to accurately classify instances while maintaining high precision and recall rates.

*figure 12: F1 score , Recall and Precision for each client*

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**14.2 Accuracy and Loss**

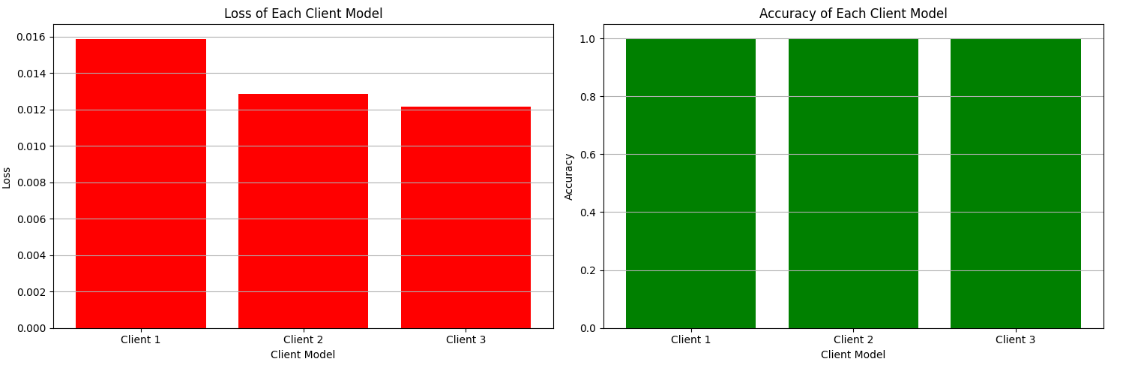
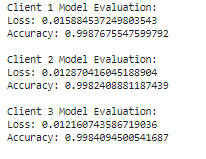
The update with global model weights, the evaluation metrics provide insights into the accuracy and loss of each client model as shown in *figure 13*. The accuracy metric represents the proportion of correctly classified instances, while the loss metric quantifies the discrepancy between the predicted and actual values.

For Client 1, the updated model exhibits a low loss of 0.0159 and an impressive accuracy of 99.88%. This indicates that the model effectively minimizes prediction errors and achieves a high level of correctness in classifying instances.

Similarly, Client 2's updated model demonstrates a loss of 0.0129 and an accuracy of 99.82%. These metrics suggest strong performance in minimizing prediction errors and accurately classifying instances.

Client 3's updated model showcases a slightly lower loss of 0.0122 and a commendable accuracy of 99.84%. These metrics reflect the model's ability to effectively reduce prediction errors and achieve a high level of correctness in classification tasks.

*figure 13: accuracy and loss for each client*

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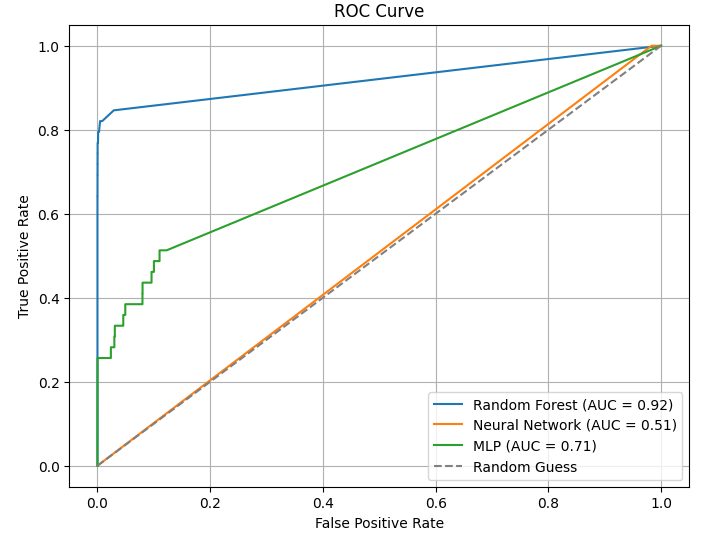
**14.3 ROUC Curve**

Upon integrating the updated global model weights, the Receiver Operating Characteristic (ROC) curve offers a comprehensive visualization of the model's performance as shown in *figure 14*, delineating the true positive rate (sensitivity) against the false positive rate (1-specificity). The area under the ROC curve (AUC) for each client model provides insight into its individual discrimination capabilities.

For Client 1, the AUC stands impressively high at 0.92, showcasing robust discriminative power. Client 2 exhibits a lower AUC of 0.51, suggesting a less effective discrimination capability. Client 3 achieves an AUC of 0.71, indicating a moderate level of discriminative ability.

The updated model, with an AUC of 0.80, demonstrates strong discrimination capabilities in distinguishing between positive and negative instances. The ROC curve visualizes the trade-off between true positive rate and false positive rate across various threshold values. A higher AUC value, such as 0.80 in this case, indicates superior model performance, with a larger area under the curve suggesting better overall classification performance.

*figure 14: ROUC curve of all the three models with updated weights*



1. **Conclusion and Future Work**

**15.1 Conclusion**

TThe journey through federated learning has been enlightening and promising, showcasing the potential of collaborative model training while ensuring data privacy across decentralized data sources. Throughout this project, we have delved into the intricacies of federated learning, from its foundational principles to its practical implementation using real-world datasets. By harnessing the collective intelligence of multiple clients, federated learning has demonstrated its ability to enhance model performance while preserving the confidentiality of sensitive user data. Through comprehensive performance analysis, we have observed the effectiveness of federated learning in improving model accuracy, minimizing loss, and enhancing discriminative power across diverse client datasets. The evaluation metrics, including accuracy, loss, F1 score, precision, recall, and area under the ROC curve, have provided valuable insights into the performance of both individual client models and the aggregated global model. Furthermore, our exploration into privacy preservation mechanisms has highlighted the robustness of federated learning in safeguarding user privacy during model aggregation and parameter updates. Despite training each client dataset on different algorithms—Client 1 on Random Forest, Client 2 on Artificial Neural Networks (ANN), and Client 3 on Multi-Layer Perceptrons (MLP)—the federated learning approach has consistently yielded promising results, underscoring its versatility and effectiveness in collaborative model training scenarios.

**15.2 Future Work**

Building upon the insights gained from this project, several avenues for future exploration and advancement in federated learning emerge:

**Dynamic Client Selection:**

Investigate strategies for dynamically selecting clients based on data quality to optimize federated learning efficiency and effectiveness.

**Transfer Learning:**

Explore transfer learning techniques to facilitate knowledge transfer between clients, thereby enhancing model generalization across diverse datasets.

**Federated Reinforcement Learning:**

Extend federated learning frameworks to incorporate reinforcement learning algorithms, enabling collaborative training for autonomous decision-making tasks.

**Edge Computing Integration:**

Integrate federated learning with edge computing infrastructure to facilitate on-device model training and inference, thereby reducing latency and bandwidth requirements.

**Interoperability Standards:**

Develop interoperability standards and protocols for federated learning systems to streamline collaboration and data exchange across heterogeneous devices and platforms.

By pursuing these avenues of exploration, researchers and practitioners can further enhance federated learning's capabilities and unlock its full potential in collaborative and privacy-preserving machine learning scenarios.

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