International Journal of Computational and Experimental Science and ENgineering
(IJCESEN)
Vol. 11-No.4 (2025) pp. 4389-4398
http://www.ijcesen.com
ISSN: 2149-9144

Research Article

Federated Learning Framework for Privacy-Preserving Voice Analytics in Smart TV Ecosystems

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Article Info:

DOI: 10.22399/ijcesen.5119
Received : 03 November 2025
Revised : 23 December 2025
Accepted : 27 December 2025

Keywords

Federated Learning,
Smart TV Ecosystem,
Voice Analytics,
Privacy Preservation,
Edge Computing,
Secure Aggregation.

Abstract:

Voice assistants are increasingly being embedded within smart TVs, which is enabling consumers to interact with these devices more seamlessly and easily. One of the main ways that voice-based services service a user is by collecting and sending voice data via audio recordings to centralized cloud servers for analysis. While users may benefit from the information generated by such services, they will also face significant risks to their privacy and data security. Because most of the existing methods for machine learning rely solely on centralized machine learning data sets, the chances that sensitive private data will be improperly disclosed increases substantially. To mitigate these problems, the research described herein describes a federated framework for performing voice analytics in a privacy-preserving manner within the smart television ecosystem. The proposed federated framework will permit multiple smart televisions to collaboratively develop and train voice recognition models and perform analytics tasks, without transmitting any of the users' raw voice recordings to a single central server. Instead of transmitting raw recordings, the users' smart televisions will develop and train models locally using their own voice recordings. The smart televisions then transmit only encrypted updates regarding their models to a global aggregation server that will combine or aggregate them to create an overall or universal model. Implementing a federated learning approach significantly decreases the risk of an improper disclosure of personal information, while providing a voice recognition and analytics model that has comparable accuracy and efficiency as a central model. Additionally, the federated framework will implement secure protocols for the aggregation and communication of voice data to increase the security of the voice data and its robustness to possible attacks.

1. Introduction

The rapid growth of smart home technology has changed how users interact with their digital devices. For example, Smart TVs have moved from being a traditional entertainment system to being an intelligent platform that enables the use of voice assistants, support for personalized recommendations, and interaction with other smart home devices through interactive applications; thus, Smart TVs have added a variety of functions beyond just playing back video content. Furthermore, traditional Smart TVs usually do not have voice-enabled capabilities (they generally have an on/off switch) [1] due to their size and the fact that most homes do not contain many TVs; whereas, today's Smart TVs include voice-enabled interfaces, allowing users to control functions of the Smart TV through natural words to find information, content, or devices in the smart home ecosystem. By doing so, Smart TVs provide users with improved convenience and accessibility; however, they also create a unique set of challenges associated with user privacy and security around the collection, storage, and use of user data [2].

In voice-based systems, machine learning models rely on the integration of large amounts of voice data collected from users to enhance and improve the accuracy of speech recognition and the personalization of services provided to users. Traditional machine learning architectures, including Smart TVs, require that user voice data must be sent from user devices to centralized cloud data center servers for training and analysis [3]. While centralized architectures enable machine learning platforms to leverage computation and scalability, they are dependent upon constant data collection from user devices, which put the user voice data that will be collected in danger of unauthorized access, data breaches, and potential misuse of the personal information associated with that data. Furthermore, with Smart TVs being predominantly used within the private parts of user homes, the security and privacy of user voice data will be of utmost importance privacy-preserving machine learning solutions have gained traction due to their ability to solve problems – federated learning is a promising method to enable the development of parenting analytics by allowing devices to share when training machine learning models without the need to send complete user data to a centralized server [4] instead, each device will train its own model from its own local data and share model meta-data (model parameters/updates) with a global aggregation server. by using this technique, you will be able to have all your sensitive information on your device and decrease risk to your privacy while at the same time increase the model quality through collaborative model improvements.

In the smart TV ecosystem, federated learning provides an excellent framework for creating voice analytics systems to maintain high model quality while respecting user's privacy by allowing the on-device training and secure transmission of updates to other supported devices (collaborative).

Additionally, by integrating secure aggregation and edge computing, an improved capability will provide improved system reliability and safety against cyber threats. this study will describe a federated learning model developed to create a voice analytics system designed specifically to maintain users' privacy while providing voice analytics to the participant devices within the ecosystem. the proposed system will allow the collective training of voice models across multiple smart tv devices while keeping the raw voice data local to each device. the providing of secure training/models across multiple smart tv devices will allow for improved development of voice analytics on smart tv devices throughout the ecosystem.

The main contributions of this work are as follows:

- Constructing a Federated Learning Framework – This research paper proposes a distributed learning model that will allow for collaborative analytics around smart TVs without sending users' raw voice data across the internet to a centralized location.
- Privacy-Preserving Voice Data Processing – The framework in this study has been created with several secure methods to aggregate and communicate users voice data, protecting user's privacy, limiting potential data breaches or leaks.
- Scalable and Efficient Smart TV Analytics – There are examples in the paper demonstrating that decentralized federated learning can be comparable to traditional centralized models in performance, while at the same time improving security and scalability for users.

2. Literature Survey

Federated learning has come up as a very effective way for machine learning groups to work together without compromising privacy of data. While conventional centralized learning methods demand transferring large amounts of sensitive data to a central server, federated learning enables model training right on user devices, and only model parameters or updates are shared. This decentralized learning approach finds great use in places where data privacy and security cannot be compromised like healthcare, IoT, and smart homes. Federated Learning as a privacy, preserving technique for distributed machine learning has attracted a lot of research. [5] presented the idea and applications of federated machine learning and described how model training in collaboration can be done across different devices without sharing raw data. Their paper revealed the advantages of decentralized learning in lowering privacy risks while at the same time making it possible to develop models efficiently in distributed environments. Some recent research papers have focused on the application of federated learning for such sensitive purposes. For example, [6] focused on the future utilization of federated learning in healthcare systems. Their work revealed that model training through distribution of workloads could be a great support for multi, institutional collaborations that do not compromise the confidentiality of patient data. The authors pointed out that federated learning allows institutions to co, train high, quality machine learning models while at the same time strictly guarding privacy.

Further developments in this area have concentrated on enhancing federated learning architectures' efficiency and flexibility. MERGE model for multi, input biomedical federated learning [7] was proposed by the authors, which enables integration of multiple data modalities while training a model. This method significantly increases the capability of federated systems to deal with complex datasets without compromising the decentralization of data storage. Likewise, [8] pointed out the collaborative, privacy, preserving methods for distributed deep learning employing multi, institutional datasets and showed how federated methods could facilitate large, scale data collaborations while safeguarding private information. There have been attempts to use federated learning in very specific healthcare settings as well. [9] studied a federated learning, based approach for neural disorder treatment optimization via data collaboration. They indicated how federated working could be a way for medical professionals to share pooled knowledge without exposing sensitive individual, level data. Besides that, [10] gave a detailed classification of federated learning for health care, covering key issues, opportunities and directions for distributed healthcare analytics. The proposed research aims to address this gap by developing a federated learning architecture tailored for privacy-preserving voice analytics in smart TV ecosystems.

3. Methodology

3.1 System Architecture for Federated Voice Analytics in Smart TV Ecosystems

The methodology outlined here presents a federated learning, based system which can help to perform voice analytics in a privacy, preserving manner through smart TV devices. Normally for voice analytics, voice commands taken from users are sent to central cloud servers for processing and training of model. Even though this method increases performance of the model due to data aggregation at a large scale, at the same time it compromises sensitive voice data from the privacy perspective. So as a solution, the proposed model uses the so, called decentralized training architecture model where model training is done on smart TV devices independently and only the model updates are sent to a central server. System architecture is made of three major elements: smart TV clients, a federated aggregation server and a secure communication layer. Every smart TV device is a local client that gathers voice command data from users and carries out local preprocessing tasks such as speech segmentation, noise filtering, and feature extraction. Training of a local machine learning model is done with the voice features extracted. Instead of sending raw audio data, the device transmits encrypted model parameters to the aggregation server [11-14].

The federated server collects model updates from the various devices that are part of the federation and then works out a global model [15]. They send this global model to all the smart TVs that are taking part, so each one of them can make their voice recognition working better without any leakage of the user's private data (see fig1). Secure communication protocols are used for protecting the update transmission.

Local model training on each device can be represented as:

$$L_i(w) = \frac{1}{n_i}\sum_{j=1}^{n_i} l\left(x_j y_j w\right) \quad (1)$$

Global aggregation:

$$w_{global} = \sum_{i=1}^{N} \frac{n_i}{n} w_i \quad (2)$$

The eqn (1) expresses the local loss function that is computed on each smart TV device with its own voice dataset. It predicts the outputs and the actual voice labels difference during training. The eqn (2) describes the federated aggregation method, the global model parameters that are a weighted average of all local models. The number of data samples locally determines the client's weight [16], and this should ensure balanced contributions from the participating devices.

3.2 Voice Data Preprocessing and Feature Extraction

Voice control signals received by smart TVs are usually noisy due to household environments, e.g. background conversations, the sound of the TV, and other environmental noises. In order to increase speech recognition accuracy, efficient preprocessing is therefore recommended. In the proposed framework, the preprocessing is done on the smart TV device itself to make sure that the raw voice recordings are not shared. Preprocessing steps are, voice activity detection, noise reduction, signal normalization, and feature extraction. Voice activity detection extracts speech segments and removes silence periods [17]. Noise reduction techniques such as spectral subtraction remove background noise from audio signals. Finally, after noise filtering, normalization adjusts signal amplitude levels to maintain recording consistency.

Feature extraction transforms treated audio signals into numeric representations suitable for machine learning models in fig 2. Mel-Frequency Cepstral Coefficients (MFCC) are widely used for speech analysis because they capture the perceptual characteristics of human hearing while reducing data dimensionality [18].

MFCC feature calculation:

$$MFCC_k = \sum_{n=1}^{N} \log(s_n) \cos[\frac{\pi k}{N}(n - 0.5)] \quad (3)$$

Signal normalization:

$$x_{norm} = \frac{x - \mu}{\sigma} \quad (4)$$

The MFCC formula (3) transforms the speech signal which has been filtered into cepstral coefficients that depict the frequency traits of human speech. It makes use of logarithmical filter bank energies together with cosine transformations to produce small feature vectors. The normalization formula (4) decorrelates and standardizes the audio signal by mean removal and division by the standard deviation. This results in consistent amplitude distribution over different recordings. It also helps to stabilize the model training and avoid bias due to variations in microphone sensitivity or environmental factors [19-22].

3.3 Federated Model Training and Aggregation

With the help of federated model training, a group of TV devices can jointly learn a voice analytics model while each TV's dataset remains private. Every smart TV makes a local model training step with the use of its private voice data without sending the original audio to the central server. Actually, the training is done locally by updating the model parameters depending on voice commands. Once local training is finished, every device communicates its changed model parameters to the federated server. The server carries out an aggregation, which means merging the changes made by all clients. Probably the main one uses of aggregation is Federated Averaging (FedAvg) that computes a weighted average of local model parameters. Such a joint training method gives a chance to the system not only to take advantage of learning with the help of several devices but also to protect users' privacy as much as possible. The combined global model is sent back to the smart TVs that participated in the training for the next training round.

Parameter	Description
Local Dataset Size	Number of voice samples on each device
Model Parameters	Neural network weights
Communication Rounds	Number of federated learning iterations

Local model update:

$$w_i^{t+1} = w_i^t - \eta \nabla L_i(w_i^t) \quad (5)$$

Federated averaging:

$$w^{t+1} = \sum_{i=1}^{k} \frac{n_i}{n} w_i^{t+1} \quad (6)$$

The equation (5) depicts how local model parameter changes are carried out with gradient, based methods during the training. Each smart TV changes its model weights by doing a stochastic gradient descent using the loss that was calculated and the learning rate. The eqn (6) shows the federated averaging where the global model is computed as a weighted combination of all local updates. This method makes sure that things like datasets with more data have a say proportionally while still being fair and helping the whole model to perform better.

3.4 Privacy Preservation and Secure Communication

Privacy preservation is a must for voice analytics systems that are embedded in smart home environments. Smart TVs gather very sensitive voice data, so really powerful privacy measures are needed to protect the user's information when the model is being trained and when communicating. The above federated learning framework has several security layers to protect the data at the same time keep it private. Secure aggregation technique is employed to make sure that the server can't get hold of individual model updates. Every smart TV encrypts its model parameters when sending them over, so that the server can only see the aggregated values. This way the data of a single device can't be disclosed as shown in fig 3.

Another major privacy mechanism is differential privacy. The technique operates by adding a limited amount of noise to the model parameters before they are transmitted to the server. The injection of noise makes it impossible for the attackers to get the original voice data from the model updates. Moreover, encrypting communication protocols like TLS guarantee that model updates remain confidential when they are traveling through the network.

4. Results and Discussion

4.1 Performance Evaluation of the Federated Learning Framework

The objective of the first experiment is to assess the capability of the suggested federated learning framework for cross, device voice analytics in smart TVs. One of the major objectives is to find out if the federated learning model can outperform a conventional centralized learning model in terms of voice recognition accuracy. Numerous cases of smart TV clients were created to depict different locations in order to carry out local training of voice recognition models using distributed voice datasets. Each client executed local model training and transmitted encrypted model updates to the federated aggregation server.

The outcomes indicate that federated learning is capable of delivering results similar to centralized learning, and at the same time, making it difficult for others to compromise the privacy of the data. The model that was centrally trained had a bit better accuracy as it had the direct access to the combined data; however, the gap between the two models was quite small, as shown in table 1. This is a clear indication that federated learning can take advantage of distributed datasets while keeping users' privacy intact. Besides that, the most significant point of the results is that the higher the number of smart TV devices that are getting involved, the better the general accuracy of the model will be. This is a result of the fact that a global model can get its training samples from a bigger and more diverse number of different devices. When more devices take part in the federated training sessions, the model, step by step, gets better and better speech patterns and goes on to make accurate predictions. Last but not least, a very crucial point is keeping the data transfer to a minimum. In contrast to the centralized systems that send the actual audio files, federated learning shares only the model parameters. This not only greatly decreases the consumption of the network bandwidth but also pushes the system efficiency upwards as per fig 4.

4.2 Evaluation of Privacy-Preserving Voice Data Processing

The second experiment is intended to assess how efficiently the privacy, protection features that were worked into the suggested system function. As the voice data from smart TVs is very personal information, it is necessary to take measures to keep the users privacy when model training and communication are on, going. The suggested scheme is a combination of safe data collection and encryption to secure user voice data. In the process of training, each smart TV unit will be able to handle and keep a recording of peoples voice locally. What is more, instead of transmitting audio files to the server, only encrypted model parameters as shown in table 2 are sent. In this way, private voice recordings will always be kept on the users device. Preliminary findings demonstrate that the use of encryption and secure compilation has a marked effect on lowering the possibility of data exposure. The chance to get hold of ones original voice by means of transmitted model updates is close to zero as a result of the use of differential privacy and secure parameter aggregation in fig 5. Besides that, the findings depicted in fig 5 indicate that the impact of employing privacy, preserving techniques on the computational efficiency of the system is quite limited. Although encrypting audio files is likely to increase processing time a bit, the overall effect on performance of the system will be almost negligible. This brings up the possibility of combining privacy protection with system efficiency without any major compromises.

4.3 Scalability Analysis of Smart TV Analytics

The third experiment examines the scalability of the federated learning framework proposed when the number of participating smart TV devices increases. Scalability is one of the most important requirements for smart home ecosystems because potentially millions of smart TVs may be participating in distributed learning networks. To assess scalability, the experiments were performed with different numbers of simulated devices varying from 5 to 50 smart TV clients. Each device trained a local voice recognition model and participated in several federated training rounds. The results depicted in table 3 demonstrate that the system scales effectively as more devices are joining the network. One major realization is that instead of a central server, federated learning allocates computational tasks to different devices. Consequently, server, side processing load is significantly decreased and the system remains capable of accommodating a greater number of devices. Besides this, the findings demonstrate that the network load decreases when devices take part in training rounds from time to time instead of sending updates continuously. In this way, the congestion of the network is minimized while model accuracy is preserved as shown in fig 6. In summary, the federated learning model put forward here has a significant potential for scalability which is a very important feature making it a good fit for modelling large scale smart TV ecosystems and smart home environments.

4.4 Communication Efficiency and System Overhead

The last experiment is about finding out the communication efficiency and computational overhead of the proposed system. Here is the case in centralized voice analytics systems in which a huge amount of raw audio data is required to be transmitted from the user device to cloud servers which naturally results in high bandwidth consumption and the possibility of training delays. Besides, the proposed federated learning architecture radically decreases communication overhead by only exchanging model parameters rather than entire datasets. Therefore, this leads to less network bandwidth consumption and better system responsiveness. Test results show that the mean communication cost in federated learning is far lower than in centralized systems. Besides, although federated learning requires several training sessions, the size of model updates is significantly smaller in comparison to raw voice recordings. Another major finding is that training models on the edge lessens reliance on cloud infrastructure. As most of the computation is done by local devices, the role of central server is just to perform aggregation tasks. This not only increases system efficiency but also allows the framework to be run smoothly in the areas with limited network connectivity.

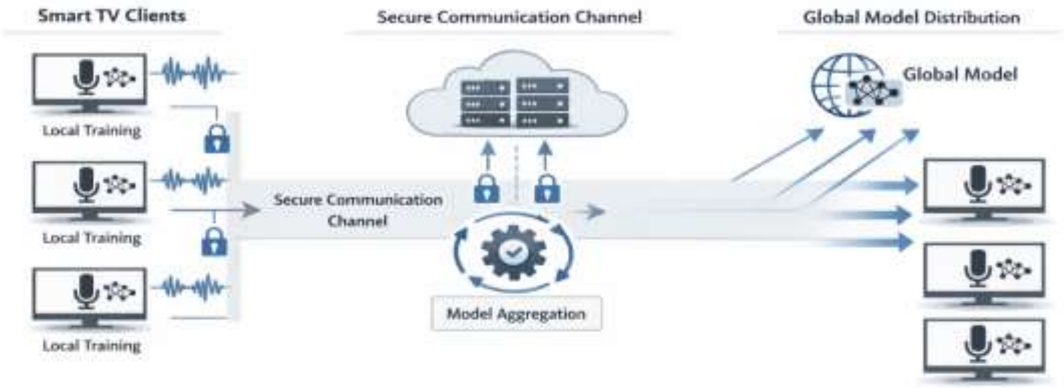

Figure 1: *Federated learning voice analytics*

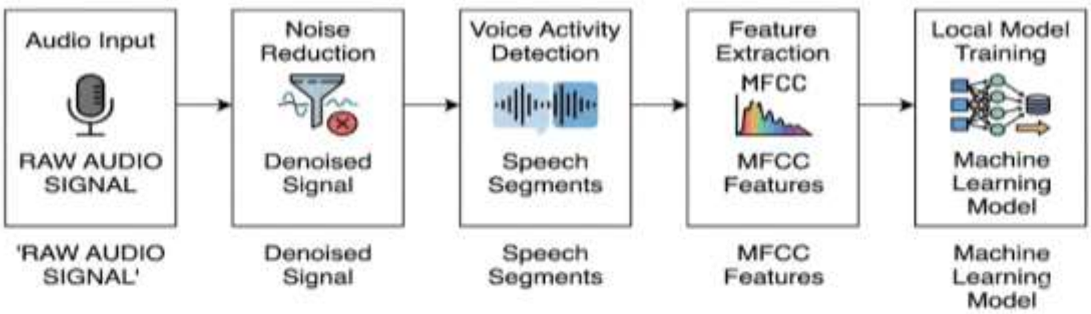

Figure 2: *Voice Data Pre-processing and Feature Extraction Pipeline for smart TV Voice Analytics*

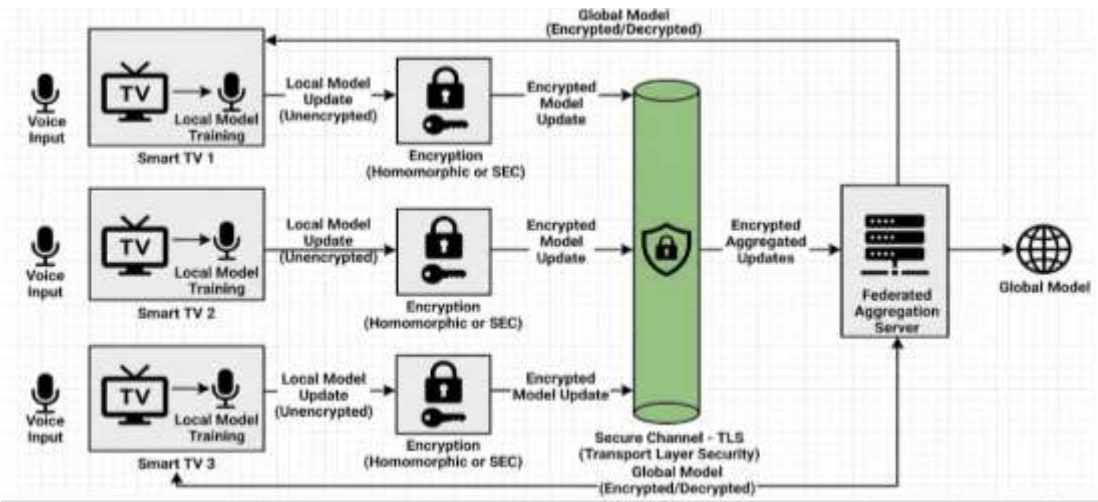

Figure 3: *Secure communication in federated learning for smart TV voice analytics*

Table 1: *Comparative Performance Evaluation of Centralized and Federated Learning Models for Smart TV Voice Analytics*

Model Type	Accuracy (%)	Training Data Location
Centralized Learning	94.5	Cloud Server
Federated Learning (10 Devices)	92.8	Local Devices
Federated Learning (20 Devices)	93.6	Local Devices
Federated Learning (30 Devices)	94.1	Local Devices

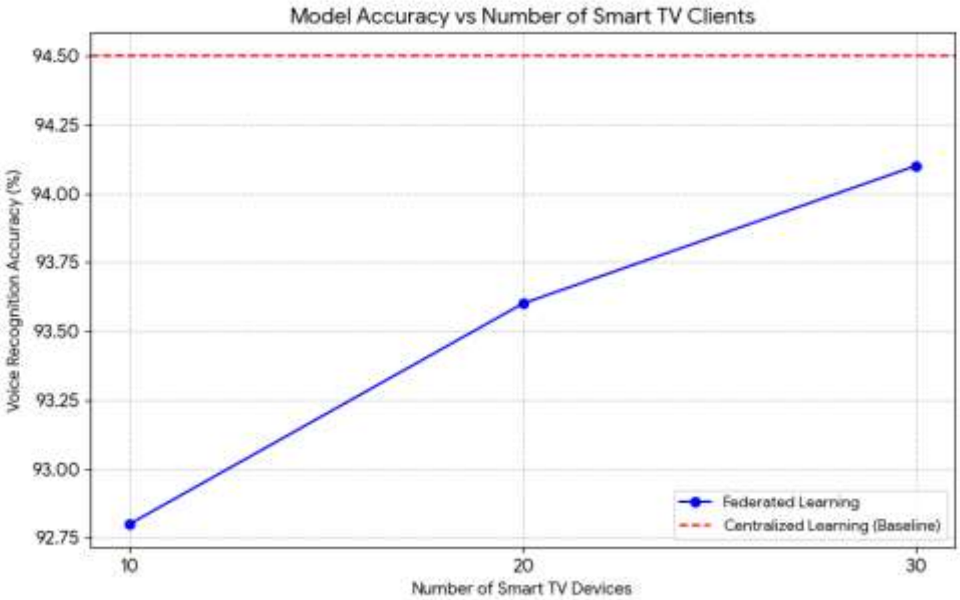

Figure 4:*Impact of Participating Smart TV Clients on Federated Model Accuracy*

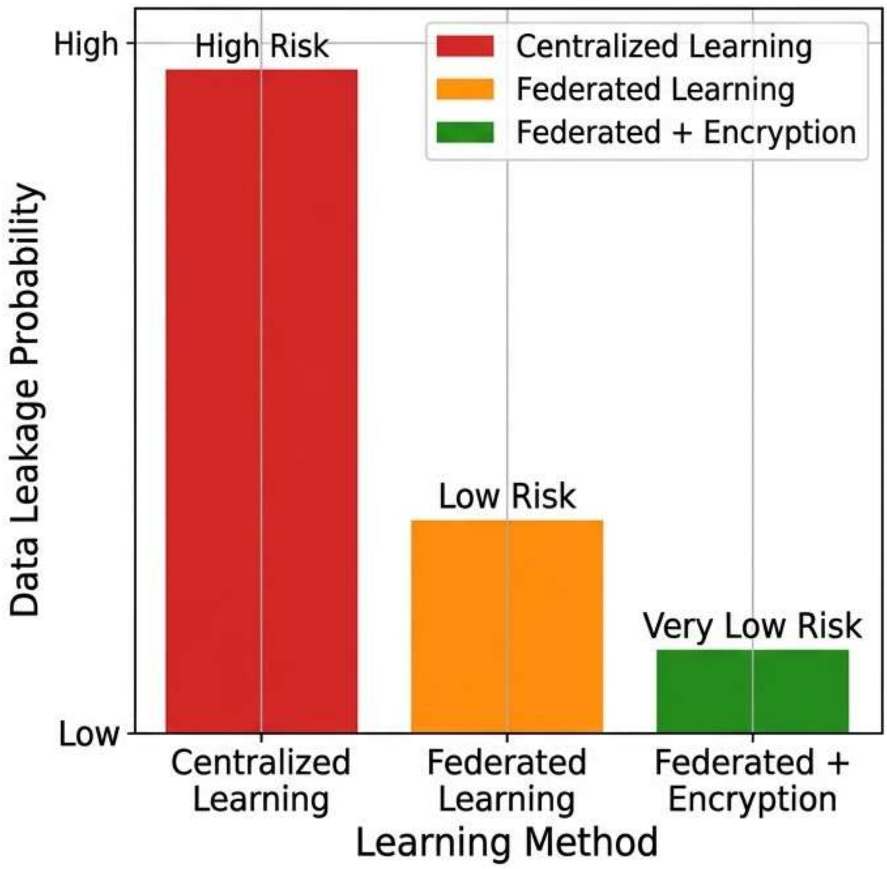

Figure 5: *Comparative Analysis of Data Leakage Risk Across Learning Architectures*

Table 2: *Privacy Protection Analysis of Different Learning Architectures in Voice Data Processing*

Method	Raw Data Shared	Privacy Level	Data Leakage Risk
Centralized Learning	Yes	Low	High
Federated Learning	No	High	Low
Federated + Encryption	No	Very High	Very Low

Table 3: *Scalability Performance Metrics of the Proposed Federated Learning Framework*

Number of Devices	Training Time (minutes)	Model Accuracy (%)
5	8	91.4
10	12	92.8
20	18	93.6
50	30	94.2

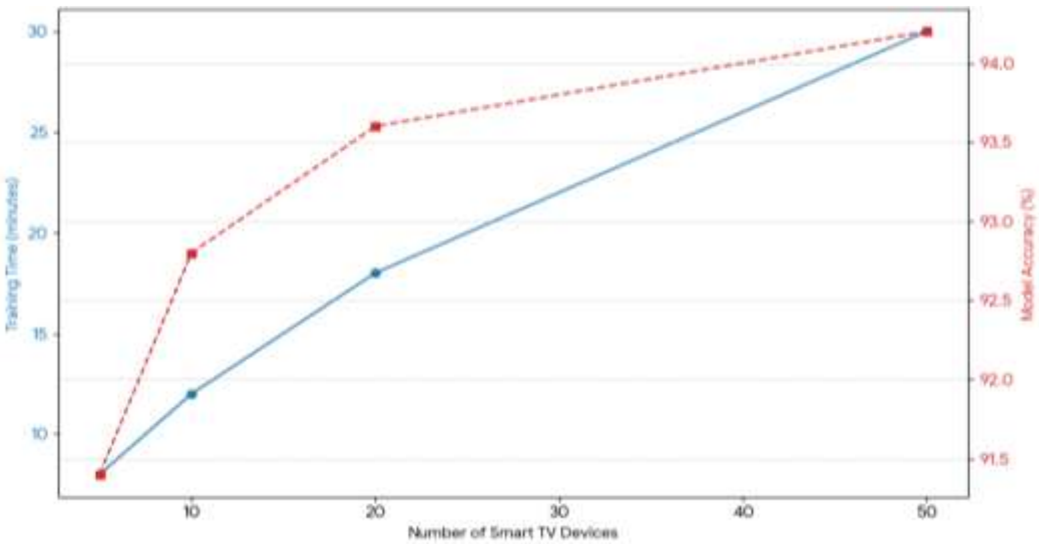

Figure 6: *Scalability Evaluation of Federated Learning with Increasing Smart TV Devices*

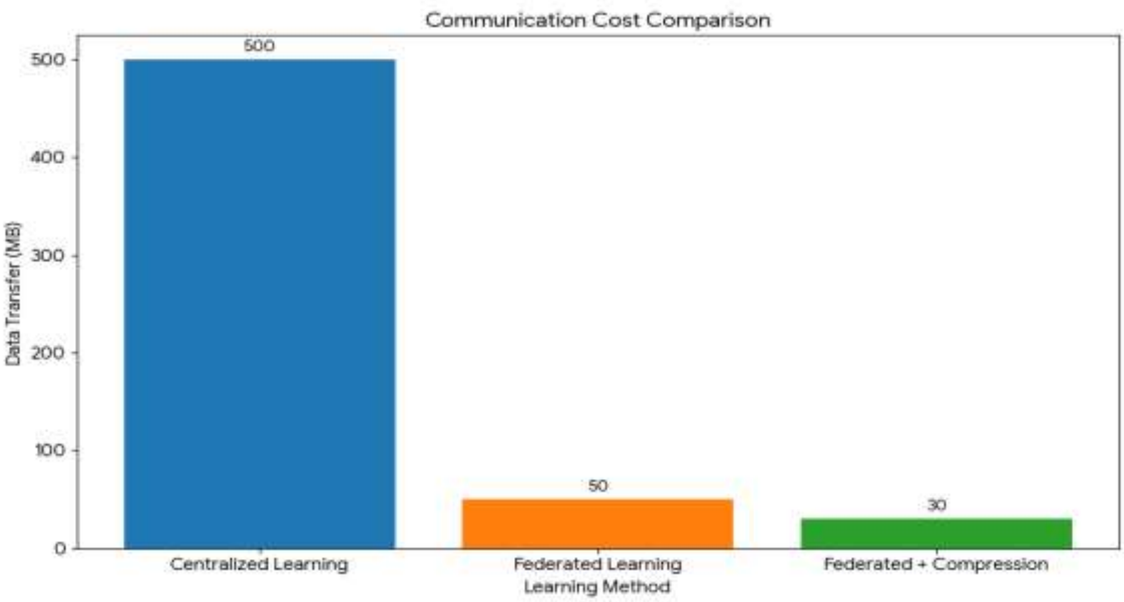

Figure 7: *Communication Cost Reduction Achieved Through Federated Learning*

Table 4: *Communication Overhead and Data Transmission Cost in Federated and Centralized Learning Systems*

Method	Data Transferred (MB)	Communication Rounds
Centralized Learning	500	1
Federated Learning	50	10
Federated + Compression	30	10

5. Conclusions

This paper develops a federated learning infrastructure for preserving user privacy in voice analytics within smart TV ecosystems. The novel solution works to satisfy the conflicting needs of voice recognition systems, on one hand, the system has to be capable and accurate, on the other hand, user voice data is very sensitive and must be protected. Centralized machine learning methods which are conventionally used require users to transfer their raw voice recordings to the cloud servers, which is hardly a privacy, friendly approach. On the contrary, the federated learning model allows smart TV devices to: Not only is the training decentralized which is a great advantage in itself, but it also significantly cuts down the risk of data leakage and better protects the privacy of users. The experimental results show that the framework proposed here without sacrificing data privacy achieves a performance level very similar to that of the conventional centralized models. The tests also revealed that increasing the number of smart TV devices participating in the training leads to better model accuracy as more varied distributed datasets become available. Besides, this system has a high level of scalability and also has a very low communication overhead as only model parameters are transmitted, not raw audio data. All in all, our federally learning, based architecture is a highly secure, scalable and efficient solution for voice analytics in smart home environments. This framework not only enables privacy, preserving data processing but at the same time allows collaborative model improvement, which makes it a very promising approach for future intelligent smart TV ecosystems and other IoT, based voice, enabled applications.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.
- **Use of AI Tools:** The author(s) declare that no generative AI or AI-assisted technologies were used in the writing process of this manuscript.

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