ITM Web of Conferences **79**, 01040 (2025) https://doi.org/10.1051/itmconf/20257901040
KEIS-2025

Knowledge-Constrained Federated Learning for Medical Image Classification with SE-ResNeXt-50

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Abstract. Recently, the classification of medical images plays an important role in healthcare, especially in diagnosing diseases and planning treatments. Advancements in intelligent systems operate in external or centralized environments concerning patient confidentiality, which is progressively essential. Traditional Machine Learning (ML) methods depend on data collection, which represents sensitive medical information and reduces the performance. To address this issue, Federated Learning (FL) is a suitable method that allows multiple institutions to collaboratively train models by incorporating knowledge constraints using their current data, without sharing confidential records. FL not only preserves privacy, but also supports robust and safe model development across various data sources. The proposed FL includes SE-ResNeXt-50, which combines the multibranch ResNeXt-50 design with a squeeze-and-excitation (SE) attention mechanism, allowing more discriminative feature extraction and adaptive channel weighting. The SE-ResNeXt-50 improves the models ability to handle heterogeneous and non-ID (non-identically distributed) medical imaging data across institutions. The proposed FL model integrating SE-ResNeXt-50 is evaluated using two different medical imaging datasets, BR35H (Brain Tumor Detection 2020) based on MRI images and SARS-CoV-2 CT on COVID-19, a lung CT scan image. The proposed FL model integrating SE-ResNeXt-50 achieves an accuracy of 98.8% for MRI images and 99.3% for CT scans, which is superior to the existing convolutional neural network (CNN) with the Gray-Level Co-occurrence Matrix (GLCM) model.

1 Introduction

Federated learning (FL) is a recent technique that allows model training on distributed datasets without sharing sensitive data, and is useful in medical image classification, where privacy regulations prevent centralized data collection [1]. Intelligent and digital healthcare devices have become dominant and continuous in producing large volumes of sensitive patient data [2]. Hospitals are increasingly replacing traditional paper records with Electronic Health Records that digitally capture a patient's diagnosis, treatment details, and other medical data for ongoing and future care [3]. The dominant healthcare model imposes significant financial strain on society, largely because it prioritizes treatment over prevention [4]. Artificial Intelligence (AI) and Machine Learning (ML) technologies continue to evolve by improving medical diagnostics, particularly FL, which offers a secure way to collaborate across institutions without compromising sensitive data [5]. Despite the capacity of Deep Learning (DL), challenges such as limited annotated datasets and strict privacy regulations continue to delay collaborative model development in healthcare [6]. A shortage of labeled medical data significantly degrades the effectiveness of ML models, which is a key challenge for building intelligent diagnostic systems [7]. The complexity and variability of patient cases in advanced methods enable hospitals to connect and share data efficiently. To meet this need, more hospitals are adopting secure data-sharing practices to enhance early detection and diagnosis of new diseases [8]. DL models, particularly Convolutional Neural Networks (CNNs), are suitable for extracting hierarchical features from medical images and allowing automated classification by learning complex patterns directly from raw data [9]. The integration of domain-specific limits into FL not only enhances model accuracy but also encourages interpretability and assurance in clinical decision-making [10].

The contributions of the proposed FL with SE (Squeeze and Excitation) integrating the ResNeXt-50 method are as follows.

- This paper introduces a unique integration of SE-ResNeXt-50 with FL, which provides superior accuracy for medical image

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classification while preserving patient privacy across decentralized healthcare institutions.

- By incorporating attention mechanisms and federated training, the improvement in the ResNeXt-50 model results in interpretability and supports real-time diagnostic decision making, which is suitable for deployment in clinical environments.
- The federated setup allows collaborative learning without sharing raw data, confirming agreement with privacy regulations, while allowing scalable training across multiple institutions with heterogeneous data sources.

In this paper, Section 2 provides information about the literature survey of five contributors in medical image classification. Section 3 describes the problem statement, which is solved in Section 4 of the proposed method. Section 5 and 6 discuss the experimental results and conclusions of this study.

2 Related Works

Imran Arshad Choudhry et al. [11] introduced FedXNet, which is a decentralized framework for thoracic disease diagnosis using chest X-rays. The introduced framework deployed xNet, a SWIN-inspired model enhanced with multiheaded self-attention and depth-wise separable convolutions. Edge devices are trained models locally, and a central server aggregate features using a performance-weighted fusion. The introduced framework preserves data privacy while improving the diagnostic accuracy across diverse institutions. Custom loss function perceptual, contrastive, edge, and zoomed error-based functions were used for feature learning. However, the dynamic feature selection mechanism excluded low-performing contributors, limiting exposure to rare disease patterns and reducing simplification.

Parvathaneni Naga Srinivasu et al. [12] employed the FL method to enhance medical image classification by integrating pretrained models with local feature engineering. The employed method consists of EfficientNet with CNN architectures developed using a Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP). Local models trained on decentralized data transmit feature weights to a central server, where aggregation forms a global model. The employed method preserved data privacy while improving the diagnostic precision of MRI and CT scans. EfficientNet's complex scaling and transfer learning results in quicker convergence and improved generalization. However, the employed method lacks an evaluation of feature selection robustness and model interpretability by limiting transparency and clinical trust in decision-making processes.

Amer Kareem et al. [13] developed FL-ResNet-50 for pneumonia image classification using chest X-rays. The developed model consisted of the ResNet-50 model for four virtual clients; each trained locally on partitioned data. The central server aggregates model updates without sharing raw data, ensuring privacy compliance under the General Data Protection Regulation (GDPR) and Data Protection Act (DPA). The training process involves iterative model refinement through secure aggregation, enabling collaborative learning in institutions. ResNet-50's skip connections and deep architecture enhanced the feature extraction and classification accuracy. However, the developed model exhibited inferior performance when the client data quality changed significantly, leading to performance reduction in devices and limiting robustness in heterogeneous clinical environments.

Nasser Alalwan et al. [6] introduced the FED-CNN-GAN method to enhance brain tumor identification using MRI images. The proposed method integrates synthetic image generation using Generative Adversarial Networks (GAN) with federated convolutional neural networks (CNN) to address data scarcity and privacy concerns. GANs generated accurate MRI samples to augment training diversity, whereas DenseNet121 extracted discriminative features locally across institutions. To safeguard sensitive information, only model updates were shared and combined using secure methods, whereas the original data remained within each institution. However, the introduced method lacks clinical decision-making, and model transparency remains limited, posing challenges for trust and regulatory adoption in the healthcare setting.

Nazia Shehnaz Joynab et al. [14] employed CNN-FL (Convolutional Neural Network with Federated Learning) method for classifying cervical cancer using PAP-smear images. The employed model combined locally trained CNN models from multiple clients into a global model, enabling collaborative training without centralizing sensitive data. Each client trained its model independently, and updates were combined to enhance the classification accuracy while preserving privacy. CNN-FL showed a strong performance in both IID and non-IID settings, allowing institutions with limited data to contribute effectively. However, the employed method faced challenges in handling nonuniform data distributions across clients, which affected model generalization and consistency in prediction across heterogeneous sources.

3 Problem Statement

Developing a consistent model for medical image classification is challenging because of the strict privacy requirements and the essential unpredictability of imaging data collected from different hospitals and geographic regions. Centralized training methods, which require pooling of sensitive information in one location, raise serious ethical and legal concerns. Simultaneously, differences in imaging protocols, equipment, and patient populations lead to non-identical data distributions, making it difficult for conventional models to perform consistently across diverse clinical settings.

4 Proposed Method

The proposed method includes FL framework for preserving patient privacy and allows multiple institutions to collaboratively train models without sharing confidential data. The SE-ResNeXt-50 model is integrated with FL to enhance feature extraction and improve the model's ability to handle heterogeneous data, as shown in the architecture diagram in Figure 1. During training, each client updated the SE-ResNeXt-50 model using its local data, and only the model parameters, not the raw images, were shared with a central aggregator. The aggregator combines these updates, typically using algorithms such as FedAvg, and reorganizes the improved model back to clients. The iterative process continues until convergence, resulting in a robust and generalizable model that performs better for different datasets. The SE blocks enhance accessibility by highlighting diagnostically relevant features, whereas the federated setup confirms the agreement with data protection regulations. Together, FL with the SE-ResNeXt-50 model develops a scalable, ethical, and high-performance model for real-world deployment in medical diagnostics.

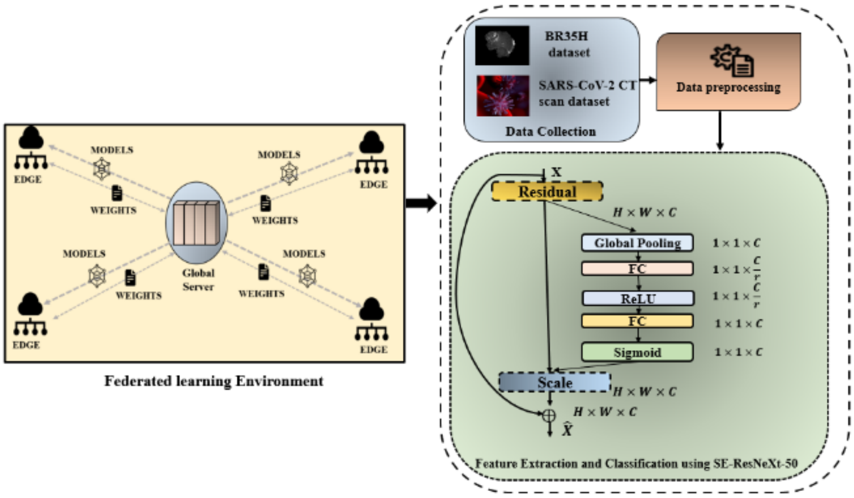

Fig. 1. The overall architecture of FL with SE-ResNeXt-50 model.

4.1 Data preprocessing

All the input images are resized to a uniform resolution to maintain consistency across the training and evaluation phases. Samples that fall below the minimum size threshold are excluded to prevent distortion and ensure a reliable analysis. No external augmentation, denoising, or padding techniques were applied to preserve the original structure or quality of the images. An efficient preprocessing method confirmed that the input data remained consistent, clean, and suitable for FL environments.

4.2 Federated Learning for secure and collaborative learning

In traditional ML methods, data are typically collected and stored on a central server, where the models are trained directly using aggregated information. This centralized method allows models to learn patterns and make predictions; however, it raises serious concerns about data privacy, especially in sensitive domains such as healthcare, where FL offers a more privacy-conscious alternative. Instead of transferring raw data to a central location, each participating device or institution trains a local version of the model by using its own data. What is shared with the central server is not the models themselves, but selected model parameters, such as weights. This advanced but important distinction helps to reduce the risk of exposure to sensitive information. The term model exchange is often used in federated learning and does not fully capture the complexity of communication between clients and the central server. In practice, it is the exchange of model parameters, and not all models enable collaborative learning. FL algorithms are designed to learn from data that remains distributed across multiple client devices. A central server typically coordinates the process by aggregating the updates from each client to build a shared global model. FL systems face critical issues, including safeguarding sensitive data, ensuring its accuracy and protection, managing user permissions, and accepting diverse formats and distributions of data in all institutions. Each institution trains a local copy of the shared model using its own data, transmitting only model updates to a central server and ensuring full compliance with privacy regulations by keeping patient information confined to its original source. The function FL is computed as in Equation (1), where $f(\omega)$ is the complete function of the weight applied for dataset trials (a, b) related to client x. The term $f_x(\omega)$ refers to the feature-specific weight function derived from the local data of client; x. Variable m indicates the total number of participating clients in the federated learning setup. The notation U_x corresponds to the local model maintained by client x and V_y denotes the size of the dataset exchanged during training. The function $f(\omega_z, a_{xy} b_{xy})$ evaluates the model's performance on the z th data sample belonging to client x, where ω_z represents the model parameters used during the evaluation, and $(a_{xy,} b_{xy})$ defines the input–output pair for the z th sample from client y. This formulation supports decentralized learning by enabling model updates based on locally computed gradients, without transferring raw data to a central server. In federated learning, the loss function is projected by adjusting the global model learning rate based on the updates received from the local models. The optimization process is guided by the gradient of the local loss function, denoted as $\nabla F_i(l(t-1))$, which reflects how the model should change at each iteration. The learning rate, represented by γ, determines the extent of this adjustment, ensuring that the global model evolves effectively by incorporating insights from decentralized training. This relationship is mathematically expressed in Equation (2) and defines how node i updates its local model l(t) based on the previous iteration's value l(t-1), with the learning rate γ leading to the extent of adjustment during iteration t.

$$\underset{\omega\in K}{Updated} f(\omega,a,b) = \frac{1}{m}\sum_{x=1}^{m}\frac{1}{A_x S_z}\sum_{y=1}^{U_x V_z} f(\omega_z, a_{xy,} b_{xy}) \quad (1)$$

$$Z_l^i = l(t-1) - \gamma.\nabla S_i(l(t-1))\ where\ \forall\ i \in W_{i,q} \quad (2)$$

FL avoids transmitting raw data over the Internet by updating and sharing feature weights. Each client device trains its local model independently, and the server receives these updated weights to refine the global model. During each training, the model loss was evaluated, and the weights were adjusted to improve performance. To illustrate this process, two distinct local models operating within a federated setup were considered. Each client, denoted as $A_x\ and\ A_y$ contributes feature weights from their respective models:$\omega_{S_a}^{A_x}$ and $\omega_{S_b}^{A_y}$. These weights correspond to the $S_a$and S_b, both designed for tumor classification. The combination of these weights is crucial in constructing a robust and accurate global model, as shown in Equation (3).

$$\omega_{S_a}^{A_x} = \omega_{11} \quad \dots\dots\dots \quad \omega_{1coly} \quad (3)$$

$$\omega_{row_x 1} \quad \dots\dots \quad \omega_{row_x 1coly_{x\times y}}$$

4.3 SE-ResNeXt-50 for feature extraction and classification

SE-ResNeXt is suitable for FL in medical fault diagnosis owing to its integrated architecture and built-in attention mechanism. In a federated environment, each client, such as a hospital or an embedded device, locally trains a copy of the SE-ResNeXt model using its own sensor or imaging data. The ResNeXt backbone enables efficient feature extraction through grouped convolutions, while squeeze-and-excitation (SE) blocks apply channel-wise attention to emphasize the most informative features, such as subtle fault patterns in gyroscope signals or anomalies in medical images. After local training, clients share only model updates or compressed feature weights with a central server, thereby preserving data privacy. These updates are aggregated using algorithms, such as FedAvg, to refine a global model, which is then redistributed to all clients. This decentralized approach allows SE-ResNeXt to learn from diverse non-ID datasets without compromising sensitive patient or device data. Its ability to focus on salient features improves interpretability and diagnostic precision, making it particularly valuable in healthcare applications where privacy, robustness, and real-time fault detection are critical. The Squeeze-and-Excitation (SE) module enhances the ability of neural networks to focus on the most relevant features by adaptively recalibrating the strength of each channel. It works by analyzing the interdependencies between channels and assigning varying levels of importance, allowing the model to emphasize informative features while suppressing less useful ones. ResNeXt integrates the strengths of VGG and ResNet by employing a split-transform-merge strategy within its block-based architecture. Building on this foundation, SE-ResNeXt preserves the multi-branch structure of ResNeXt while enhancing model performance through the addition of SE attention modules. The most significant enhancement in SE-ResNeXt is its use of cardinality and the number of parallel paths within each block, which enables richer feature interactions across branches. By introducing covariant connections between these branches, the model captures more diverse and complex patterns, leading to improved representational power without substantially increasing computational cost. Additionally, to ensure that the model maintains a parameter count similar to that of a standard ResNet, the values of the parameters C (cardinality) and d (depth per group) within the ResNeXt block are carefully selected based on Equation (4).

$$C = (256\ \times d + 3\ \times\ 3\ \times d\ \times\ d + d\ \times 256) \quad (4)$$

The first step in the SE module is the squeeze operation, which uses global average pooling to reduce the spatial dimensions of each input feature map from a height × width to a single scalar value. The important features are directly used by the networks of fully connected layers to classify medical conditions, such as brain tumors or COVID-19 appearances. The dual functionality updates the SE-ResNeXt model to reduce the difficulty and ensure a high diagnostic accuracy within the FL setup. The process effectively compresses each two-dimensional feature channel into a single number that captures the overall spatial information. The resulting values represent global context of each channel and the number of outputs corresponds directly to the number of input channels. This transformation allows the model to assess the relative importance of each channel across the entire feature map, as shown in Equation (5).

$$m_c = F_{rs}(g_{c)=} \frac{1}{H\times W}\sum_{a=1}^{H}\sum_{b=1}^{W} g_c(a,b) \quad (5)$$

5 Experimental Results

5.1 Datasets and splitting

The effectiveness of the proposed model is measured using two separate medical imaging datasets: one including brain MRI scans and the other consisting of liver CT images. Both datasets are structured as binary classification tasks to enable a clearer and more focused valuation of model performance within an FL framework.

5.1.1 BR35H [15] (Brain Tumor Detection)

The dataset comprises 1,500 brain MRI images, each with a resolution of 192 × 192 pixels, representing two categories: images with and without tumors. For the model development and evaluation, the data is randomly divided into 80% training and 20% testing subsets.

5.1.2 SARS-CoV-2 CT scan [16]

The dataset comprises 2,482 CT scan images sourced from Sao Paulo, Brazil, including 1,252 scans from COVID-19 positive cases and 1,230 from negative cases. The image dimensions varied between 119×104 pixels and 416×512 pixels, reflecting a diverse range of resolutions across the samples. Figure 2 shows graph showing the data splitting of both dataset.

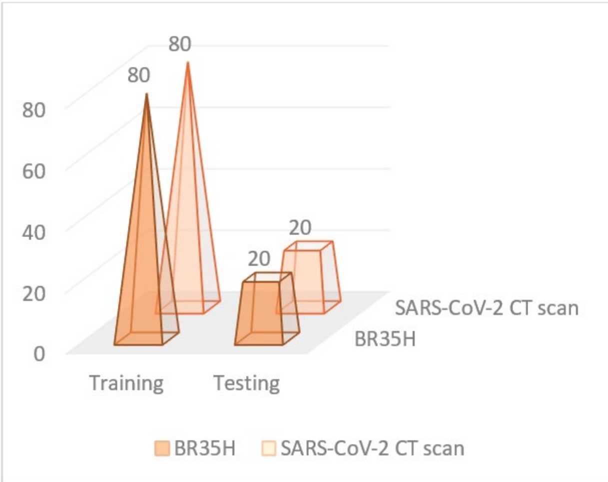

Fig. 2. Graph showing the data splitting of both dataset.

5.2 Software and Hardware Configurations

The proposed FL framework using SE-ResNeXt-50 for medical image classification is tested using client devices equipped with NVIDIA GPUs (e.g., RTX 3060 or Tesla V100), at least 16 GB RAM, multi-core CPUs for efficient local training, and a central server with high-throughput networking and GPU support for handling aggregation. The software configuration included Python with TensorFlow or PyTorch for model implementation, with libraries such as NumPy, OpenCV, and scikit-learn for data handling and evaluation. Secure communication through gRPC or REST APIs with SSL/TLS encryption ensures privacy and containerization tools such as Docker and Kubernetes support scalable deployment across institutions.

5.3 Evaluation Metrics

The FL is applied to medical image classification, where evaluation metrics are important in measuring the performance and reliability of the proposed SE-ResNeXt-50 for the two datasets. Accuracy is the overall accuracy of the model predictions, indicating how often the model correctly identifies both diseased and healthy cases. However, in medical environments, where false positives and false negatives carry different risks, precision and recall provide more accurate results. Precision measures the proportion of correctly identified positive cases among all predicted positives, confirming that when the model detects a disease that is likely to be accurate, it reduces unnecessary alarms. Recall, however, captures the model's capability to detect actual positive cases, which is important for avoiding missed diagnoses. The F1 score harmonizes precision and recall into a single metric and is especially useful when the dataset is imbalanced or when both false positives and false negatives must be carefully managed. Equations (6) to (9) show the formula for calculating the metrics, where TP is true positive, TN is true negative, FP is false positive, and FN is false negative.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

$$Precision = \frac{TP}{TP+FP} \tag{7}$$

$$Recall = \frac{TP}{TP+FN} \tag{8}$$

$$F1 - Score = 2 \times \frac{Precision+Recall}{Precision \times Recall} \tag{9}$$

5.4 Quantitative Comparison with state-of-art methods

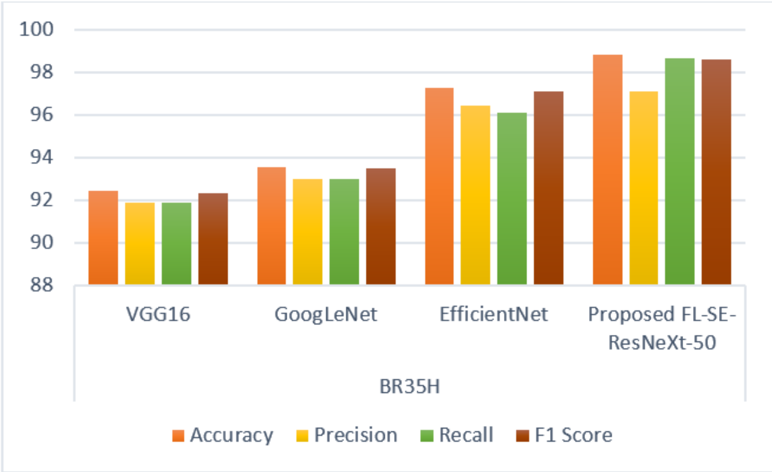

Fig. 3. Graph presenting performance evaluation by using BR35H dataset.

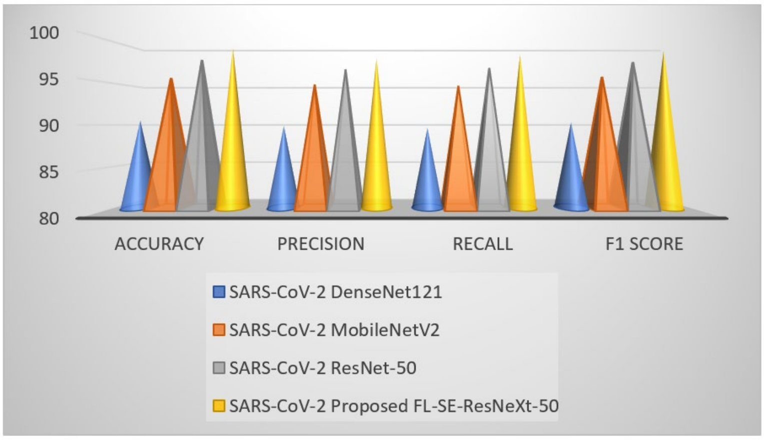

Fig. 4. Graph presenting performance evaluation by using SARS-CoV-2 dataset.

To objectively assess the performance of the proposed FL-SE-ResNeXt-50 model, Figures 3 and 4 present a quantitative comparison with several state-of-the-art DL architectures including VGG16, GoogLeNet, EfficientNet, DenseNet121, MobileNetV2, and ResNet-50. This evaluation included two benchmark datasets, BR35H and SARS-CoV-2 CT, using key metrics such as accuracy, precision, recall, and F1-score to reflect diagnostic reliability. The results demonstrate that FL with SE-ResNeXt-50 consistently performs better because of the FL framework and attention-enhanced feature extraction, which together enable a robust overview in decentralized, privacy-sensitive medical data.

5.5 Time Complexity and Statistical Analysis

The proposed FL with the SE-ResNeXt-50 method shows computational efficiency and statistical robustness for various medical image classifications. From a time-complexity perspective, the model controls grouped convolutions and attention-enhanced SE blocks, resulting in a per-client training cost of $O(C.d^2.H.W + C^2)$,where C denotes cardinality, d is the depth per group, and H×W is the spatial dimension. Federated aggregation introduces an additional overhead of $O(m.P)$ per round, with m clients and P model parameters. The overall training complexity scales as $O(R.m.N.(C.d^2.H.W + C^2))$,where R is the number of global rounds and N is the number of local iterations, but remains manageable because of the parallelized client-side training and lightweight SE modules. A paired t-test on F1-scores confirm the significance of these improvements (p-value 0.0032), validating the reliability and robustness of the models across non-ID medical datasets.

5.6 Ablation Study

Tables 1 and 2 present the ablation study to understand how each component of the proposed FL with the SE-ResNeXt-50 model contributes to its overall performance. By testing different combinations of ResNeXt-50 alone, Federated Learning (FL) alone, and FL with ResNeXt-50, the analysis shows how all metrics change for all systems. The results help explain the value of integrating squeeze-and-excitation blocks with federated learning. The classification highlights that the overall FL-SE-ResNeXt-50 model performs better than its individual parts, proving that combining attention mechanisms with privacy-preserving training leads to a robust and more reliable medical image classification.

Table 1. Component wise analysis of proposed method for BR35H dataset.

Dataset	Components	Accuracy	Precision	Recall	F1 Score
BR35H	ResNeXt-50	92.04	91.18	91.37	92.01
	FL	95.57	94.56	94.48	95.31
	FL+ResNeXt-50	93.48	92.85	91.07	93.64
	Proposed FL-SE-ResNeXt-50	98.8	97.07	98.67	98.57

Table 2. Component wise analysis of proposed method for SARS-CoV-2 dataset.

Dataset	Components	Accuracy	Precision	Recall	F1 Score
SARS-CoV-2	ResNeXt-50	95.78	94.56	94.71	95.81
	FL	90.57	90.04	90.97	90.99
	FL+ResNeXt-50	93.78	93.57	93.07	93.68
	Proposed FL-SE-ResNeXt-50	99.3	98.07	98.54	99.02

5.7 Comparison Study

Table 3 compares the proposed FL-SE-ResNeXt-50 model with other existing methods used for medical-image classification. The comparison included models such as FedXNet, CNN combined with GLCM and LBP, FL-ResNet-50, and CNN-FedAvg. The evaluation is performed using two datasets, BR35H and SARS-CoV-2 CT scans, and focuses on key metrics such as accuracy, precision, recall, and F1-score. The results show that FL-SE-ResNeXt-50 performs better than the other models on both datasets. The results prove that combining FL with SE-ResNeXt-50 improves classification accuracy while keeping patient data private.

Table 3. Comparing the proposed method with Existing methods for both dataset.

Dataset	Models	Accuracy	Precision	Recall	F1 Score
BR35H	FedXNet [11]	98.12	97.91	97.84	97.87
	CNN+GLCM+ LBP + EfficientNet [12]	96.45	95.88	95.72	95.80
	Proposed FL-SE-ResNeXt-50	98.8	97.07	98.67	98.57
SARS-CoV-2	FL-ResNet-50 [13]	94.36	NA	NA	NA
	CNN-FedAvg [14]	94.36	NA	NA	NA
	Proposed FL-SE-ResNeXt-50	99.3	98.07	98.54	99.02

5.8 Discussion

The proposed FL with the SE-ResNeXt-50 model demonstrated superior performance for both the MRI and CT scan datasets, achieving 98.8% and 99.3% accuracy, respectively. The improvement against baseline models, such as EfficientNet and DenseNet121, shows the strength of integrating FL with attention-enhanced architectures. The SE blocks contributed to better feature discrimination, whereas federated training preserved data privacy without compromising the diagnostic precision. Compared with traditional centralized methods, the model preserved robustness across heterogeneous data sources, ensuring consistent classification even in non-ID settings. The ablation study further confirmed that combining FL with SE-ResNeXt-50 yielded higher F1 scores than using either component alone. The results suggest that the proposed FL with the SE-ResNeXt-50 model is suitable for real-world clinical deployment, offering both scalability and interpretability in privately sensitive environments.

6 Conclusion

The propose model addresses significant challenges in medical image classification, such as patient privacy concerns and the heterogeneity of data across different institutions. Traditional centralized methods are not suitable for this domain because of ethical and legal issues. To overcome these problems, this study introduces an FL framework integrated with a SE-ResNeXt-50 architecture. The effectiveness of the proposed model was demonstrated through its superior performance on two distinct medical imaging datasets. The superior performance of this model is based on a unique combination of FL for privacy preservation and the SE-ResNeXt-50 architecture for robust feature extraction. The SE attention mechanism allows the model to adaptively recalibrate channel importance, which is crucial for handling non-ID medical imaging data. An ablation study showed that the combination of FL and SE-ResNeXt-50 yielded better values than using either component alone. Further, can be extended by using improved DL architectures, which helps to improve the security and efficiency of the models for handling real-world clinical challenges, such as communication overhead and data heterogeneity.

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