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Liver Cancer Diagnosis with Lightweight Federated Learning Using Identically Distributed Images

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Abstract—**A major obstacle for cancer research is the prediction of liver cancer progression. This research looked at models that can predict how Hepatocellular carcinoma (HCC) would develop. As medical science has advanced, records of people with liver cancer at different stages have been collected, and the illness remains the top cause of cancer-related mortality. Keeping private information safe, this study presents a streamlined architecture for federated deep learning to categories liver cancer illnesses. This system uses a distributed client-server architecture to safeguard client data and IID for validating federated deep learning models. The framework was tested with a single client and numerous clients in both conventional and federated learning contexts. We compared several pre-trained models and ultimately settled on AlexNet as our standard because of its exceptionally high accuracy of 98.53 percent. Then, federal learning (FL) was used to assess IID datasets. Due to its enhanced capabilities, the framework is the best choice for diagnosing and classifying liver cancer at an early stage.**

Keywords: Liver cancer, Diagnosis, Lightweight Federated Learning, Identically Distributed Images, Federated Learning, Distributed Learning, Deep Learning

I. Introduction

Up to 17 million cases of liver cancer could be reported by 2022[1]. Having access to excellent ways to detect instances might greatly improve medical diagnosis of cancer patients. In order to do this, experts from several fields worked together to develop state-of-the-art computational methods that improve medical diagnosis. A computer method based on gene expression data to differentiate between benign and malignant thyroid nodules was proposed by Stokowy et al. [2] for improved preoperative detection of thyroid nodules. As a benchmark for cancer diagnosis, microarray data sets are used; Zhang et al. [3] introduced an ELM that is compatible with all of these datasets, including lung and lymphoma data. The experimental results showed that ELM performed better than other support vector machines in terms of accuracy. Wang et al.[4] prioritized tumor classification in their machine-learning proposal. The unique method was evaluated against standard methods using microarray data. Recent advances in machine learning have led to improved methods for cancer detection.

Successful applications of deep neural networks (DNNs) include image categorization, NLP, and autonomous cars. The opposite is true for deep neural networks (DNNs): building one with a high-quality architecture often necessitates human experimentation with a large number of hyperparameters, which is a time-consuming procedure that necessitates expertise in both machine learning and the application area. brain architecture search (NAS) is a well-known method that has been around since at least [5] and aims to automatically discover useful brain structures. When building a global model, using a centralised learning strategy raises serious privacy problems because all training data must be transmitted from different devices to a central server or cloud platform for analysis. In order to prevent unauthorised access to sensitive user information, the federated learning [6] solution was presented. Even if NAS is still in its infancy, its usefulness is enhanced when it is integrated into a federated learning ecosystem.

The goal of this study is to improve liver disease detection by using neural architecture and federated learning. We divide federated learning systems into two categories: those that operate offline and those that operate online, with the latter posing more difficulties due to constrained computational resources and increasing demands on network performance during the search phase. In order to highlight the various approaches to

addressing different objectives in federated learning, such as accuracy, memory requirements, model complexity, and communication costs for local devices, we compare and contrast single and multifold objective neural architecture search methods. We discuss the major roadblocks that prohibit neural architectures from using federated search in further detail.

II. Literature Review

A. An Evolution Towards Federated Learning

Federated learning requires public education, which is a revolutionary architecture for privacy security. The following illustrations show how federated learning works in practice. For the sake of argument, let's say that many companies are keen on working together to train an automated model [7]. Users' data from one party cannot be significantly merged with data from the other party without the users' consent, according to the privacy standard [8]. However, a company can use its own data to train a machine-learning model. Training a good machine learning model with the available data will be time-consuming even if everyone agrees on a task model. As a result of these problems, educational authority is shifting to the federal government. The use of federated learning protects the privacy of each business's sensitive information. To avoid breaching privacy regulations, clients and servers exchange encrypted parameters during the setup of a global model.

B. Subtypes of Federated Learning

This section provides a brief overview of the key aspects of federated learning, including the division of data, privacy safeguards, appropriateness, resolution of heterogeneity, machine learning models, and communication structure tactics.

1) Data partition

Vertical, horizontal, and federated transfer learning may be identified by examining distribution patterns in the data sample space and feature space [7].

2) Horizontal federated learning

Horizontal federated learning is a good option when two datasets' user characteristics are very similar but the users themselves are different. To train on data with the same user attributes but different users, horizontal federated learning splits datasets horizontally (along with the user dimension). When more users are represented by horizontal federated learning, there is consistency between rows respecting data properties (user characteristics).

Even if the same service is provided in more than one location, customers will often only come from one of those locations. Because the two companies are so similar, their publications' user interfaces are also very similar. Consequently, horizontal federated learning enables us to train a model with greater precision and a bigger number of training examples. To create a global model, horizontal federated learning participants typically compute and send local gradients to a centralised server. Users' privacy may be at risk during horizontal federated learning due to the transmission and processing of gradients. To ensure the safety of gradient switching in horizontal federated learning, standard methods including differential privacy [9, 10], homomorphic encryption [6], and secure aggregation [11] are used.

When there is a lot of similarity between the features of individuals in two datasets but little similarity between the people themselves, horizontal federated learning can be used. To train on data with identical user features but different users, horizontal federated learning splits datasets horizontally (along with the user dimension). In horizontal federated learning, more users are represented, leading to uniformity in data attributes (user characteristics) across rows.

Even if the same service is provided in more than one location, customers will often only come from one of the locations. The two publications share the same user experience since their parent corporations are so close. Therefore, we may build a model with higher accuracy and more training data thanks to horizontal federated learning. By computing and sending local gradients to a centralised server, participants in horizontal federated learning can collectively create a global model. Users' privacy could be at risk due to the transmission and processing of gradients in horizontal federated learning. Gradient switching in horizontal federated learning is protected using industry-standard methods such differential privacy [9, 10], homomorphic encryption [6], and secure aggregation [11].

3) Vertical federated learning

When there is a lot of overlap between users but not many shared features across databases, vertical federated learning might be useful. Users' attributes are utilised to create vertical partitions in datasets for vertical federated learning. Data from users with identical profiles are removed from the training set. This slicing takes place on the axis of user attributes. Duplicate data points in the dataset may be an indication of user bias. The feature dimensionality in the training data can be expanded by utilising vertical federated learning. It's feasible for a bank and an online retailer to share space. Since most locals will probably fit into their respective target categories, their user bases will likely overlap. While financial institutions record their clients' earnings, outgoings, and creditworthiness, online merchants monitor their shopping habits. Vertical federated learning is a strategy that aggregates these varied attributes securely and can be utilised to increase the performance of the model. Many kinds of machine learning models can be built on top of the basic data structures and algorithms of this federated system.

Various machine learning methods, including statistical analysis [17], classification [18], gradient descent [19], secure linear regression [20], and data mining, can be used for the task of vertical data partitioning. Vertically partitioned data is used in several applications of vertically federated learning. SecureBoost, proposed in [21], is a vertical federated learning system in which all participants exchange user attributes during training using a lossless training method, to improve the dependability of decisions. In [22], the authors present a logical regression model that protects users' privacy by using vertical federated learning. To aid radiology departments in quickly gathering many X-ray scans, the model makes use of pipelined entity analysis and distributed logic regression of Paillier additive homomorphic encryption [23]. By first mastering unrelated tasks, like picture identification, we can then apply those skills toward learning a radiological diagnosis system. By transferring the model of auxiliary tasks to director learning using federated transfer learning, we may improve a classifier's performance while simultaneously solving the challenge of maintaining the privacy of a small dataset.

4) Federated Transfer Learning

We forgo data segmentation and instead depend on transfer learning to fill in the blanks when there is minimal overlap between the users and user attributes of two datasets. The term "federated transfer learning" is used to describe this approach. Online marketplaces in China and social media apps in the US are two such examples. Customers of the two businesses are unlikely to overlap due to physical distance. Little dissimilarity in the underlying datasets. Little dissimilarity in the underlying datasets. short unilateral data size and short label samples are problems that develop during federated learning, and they can only be fixed by incorporating transfer learning into the model. Transfer learning is your best option if you are aiming to enhance your performance on a task but require additional training data. The radiology division of a hospital, for example, has a hard time collecting enough X-rays to put together a solid radiological diagnosis system. Applying transfer learning to similar tasks, like image recognition, can help us obtain a radiological diagnosis system, for instance. Using federated transfer learning, we can safeguard user privacy and solve the problem of insufficient data at the same time [24].

III. Materials and Methods

A. Data Set

In Fig. 1 shows that a dataset typically consists of around 576 liver pictures. All the livers seen here are sick, except some of the leaves. Our data collection, shown in Fig. 1, follows the same patient over time, providing reference photos and diseases as they manifest.
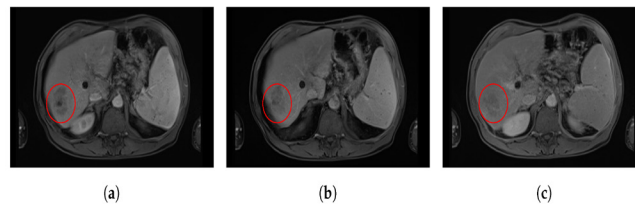

Fig. 1: Liver Images of Same Patient

B. Feature Extraction

Feature extraction is a necessary step before raw data can be used in analyses or machine learning. Feature extraction is a technique used in machine learning, NLP, and signal processing to isolate relevant aspects of data. The analytical and modelling procedures benefit greatly from this approach. The pooling and convolutional layers of deep learning networks can't function without feature extraction. Target detection and location are derived from image data via these layers. Classifier training was improved through the use of deep features extracted from the fully linked layer.

Adding layers, altering the learning rate, or adjusting the number of neurons per layer can increase models for identifying rice leaf illnesses. To hasten things along, use pre-trained models. These models result in substantial savings in both time and resources. This research makes use of seven pre-trained models to find significant differences. The deep neural networks AlexNet, ResNet, and SqueezeNet have been trained on big datasets to extract relevant image properties. Using object identification, segmentation, and classification, the collected features allow for precise detection of rice leaf diseases. If you tweak each segment before extracting characteristics, you can get more accurate results from less data. In order to speed up training and boost accuracy, this strategy uses multi-layer model topologies including reshape, flatten, dense, dropout, and activation functions.

IV. Results and Discussion

Experiment hardware included an Nvidia Quadro 5000 GPU and Ubuntu 16.04.7 LTS running at 2.60 GHz on an Intel Xeon E-2224G processor. Pytorch and Keras, two Python-based library options, were explored for use throughout the trial. Variable optimal parameters such as variable client, epoch, and learning rates were employed in the experiment. Client values of 3.50 and 7.00 were used in the trial. The learning rate is 0.01, and epoch values can range from 10 to 50.

VGG11, AlexNet, SqueezeNet, ShuffleNet, RestNet18, and MobileNet were only some of the pre-trained neural networks used in the study. When AlexNet is trained with the liver disease dataset using the default parameters, it obtains virtually equal accuracy, recall, precision, and F1-Score. In Table I, we see that AlexNet

Table I: Models Performance Comparison

	CLINET = 3				CLIENT=5				CLIENT=7			
	Recall	F1-Score	Accuracy	Precision	Recall	Accuracy	Precision	Recall	F1-Score	Accuracy	Precision	Recall
AlexNet	98.53	98.53	98.53	98.53	98.35	98.34	98.35	98.36	98.31	98.31	99.31	99.31
SqueezeNet	97.38	97.38	97.38	97.38	97.38	97.38	97.38	97.38	97.38	97.38	97.38	97.38
ResNet-18	95.23	95.23	95.23	95.23	95.23	95.23	95.23	95.23	95.23	95.23	95.23	95.23
VGG-11	96.39	96.39	96.39	96.39	96.39	96.39	96.39	96.39	96.39	96.39	96.39	96.39
ShuffleNet	91.75	91.75	91.75	91.75	91.75	91.75	91.75	91.75	91.75	91.75	91.75	91.75
RestNet50	98.29	98.29	98.29	98.29	98.29	98.29	98.29	98.29	98.29	98.29	98.29	98.29

has a 99.59 percent success rate in tests using seven pre-trained networks.
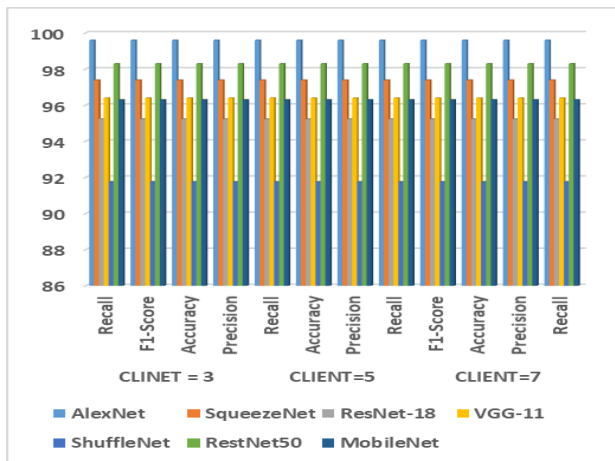

Fig. 2: Performance Evaluation of Models

Evaluation metrics for 3, 5, and 7 clients are compared in Fig. 2. Fig. 2 indicates unambiguously that regardless of the number of clients, the categorization accuracy of machines is consistent across all categories.
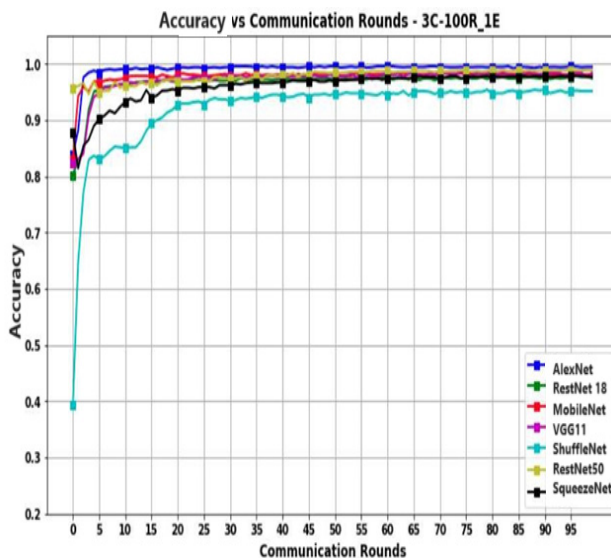

Fig. 3: Comparison Diagram for Accuracy *vs*. Communication Round Among and Server

Accuracy across all 100 transmission cycles is shown in Fig. 3. After 100 rounds of information dissemination, data were dispersed in a standardized, decentralized fashion.

V. Conclusion

Lifesaving treatment decisions and course of action depend on an accurate diagnosis of liver cancer. This research shows that liver cancer can be detected using machine learning methods. Classifying liver cancer disorders while keeping patient privacy in mind has become increasingly important today. In this research, we investigate the feasibility of using lightweight federated deep learning to categorize liver cancer. Initially, MobileNet, SqueezeNet, VGG11, Resnet50, Resnet18, ShuffleNet, and AlexNet were tried and reviewed. We determined that AlexNet has the highest accuracy rating (99.59%) of all the algorithms we tested. Once the best model, AlexNet, has been determined, federated learning can be utilised as a jumping-off point.

Additionally, federated learning using AlexNet was applied to the categorization of liver cancer. The results of federated deep learning ecosystems have exceptional parallel enceintes when compared to those of the machine learning environment. In the context of federated deep learning, the results reveal that the proposed system produces classification results equivalent to those of the baseline system, while surpassing it in terms of resource utilization and data privacy.

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