EECE 5645 Project Proposal: Federated CNNs for Diabetic Retinopathy Classification on Edge Devices

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Diabetic Retinopathy is primarily caused by elevated levels of blood sugar over consistent, prolonged periods of time. Notably, elevated blood sugar levels increase the probability that the vasculature of the eye swells and/or leaks, leading to vision impairment [1]. When the vasculature of the retina swells or leaks, blood flow to distally positioned sections of the retina decreases, leading to long term retina damage and possibly the growth of new vascular networks. Both changes to the vasculature of the eye can severely impair normal vision, though the symptoms of Diabetic Retinopathy can be treated through a combination of early detection of the disease, lifestyle changes and medication. The most common and accurate method of diagnosing Diabetic Retinopathy is to image the retina using an optical coherence tomography (OCT) based system, though a more commonly used imaging modality is a Fundus based imaging system [1].

The dataset we will use is the Diabetic Retinopathy Detection Dataset provided by Kaggle [2]. The data contains over 35,000 high resolution retina images from both eyes, captured under various imaging conditions using different camera models. All images are labeled by a medical professional with a retinopathy progression score on a 0 to 4 scale: 0 (No DR), 1 (Mild), 2 (Moderate), 3 (Severe), and 4 (Proliferative DR). The dataset comes structured in training, testing, and sample files, with a separate file delineating the training labels. Given the different imaging types, visual noise, and image artifacts, a significant challenge lies in developing algorithms robust against these variations, which our federated learning model aims to solve.

Given the dataset and background, the application of parallelism in this project is to use many machines to perform federated CNN learning on distributed versions of the dataset, where the output model's goal is to accurately predict Diabetic Retinopathy based images. Federated learning is a distributed machine learning paradigm that enables the training of algorithms across decentralized edge devices without the need to transmit or store local data at a centralized location [3]. This feature is particularly important in healthcare applications, where it ensures that sensitive personal data remains securely on the device [4]. Federated learning not only enhances data privacy by keeping personal data on the user's device but also bolsters security against centralized data breaches [5]. Furthermore, it can potentially distribute computational loads more evenly across devices, unlike centralized machine learning methods, which often rely on powerful central servers [6]. Federated learning involves distributing the entire model training process to edge devices [7]. Each device independently trains the model on its local data and sends only the updated model parameters, such as weights or gradients, which reflect their individual learnings, back to the aggregator. The aggregator then typically uses techniques such as Federated Averaging to update the global model [8]. Consequently, Federated Learning not only mitigates privacy concerns inherent in traditional machine learning methods but also promotes greater scalability and more efficient utilization of distributed data sources [9].

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