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PFA2 Report
Diabetic Retinopathy detection

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PFA 2
Diabetic Retinopathy detection

Résumé

Ce rapport décrit minutieusement la méthodologie utilisée dans le développement d'un système de classification multiclasse adapté à la détection de la rétinopathie diabétique à partir des images de la rétine. En intégrant des techniques de traitement d'images de pointe et en exploitant les capacités des réseaux de neurones convolutifs (CNN), le projet cherche à comparer l'approche d'apprentissage distribuée et l'approche traditionnelle centralisée de détection de la rétinopathie diabétique. Grâce à l'analyse systématique des images de la rétine, le système améliore la précision et l'efficacité de la détection des maladies, permettant une intervention rapide et une gestion proactive de tout risque pour la santé.

Mots clés : Classification multiclasse; Vision par ordinateur; L'apprentissage profond; Réseaux de neurones convolutifs; Apprentissage fédéré; apprentissage distribué; Détection de la rétinopathie diabétique.

Abstract

This report meticulously outlines the methodology employed in the development of a multi-class classification system tailored for detecting diabetic retinopathy from retina images. By integrating state-of-the-art image processing techniques and harnessing the capabilities of convolutional neural networks (CNNs), the project seeks to compare the distributed learning approach and traditional approach to diabetic retinopathy detection. Through systematic analysis of retina images, the system enhances the accuracy and efficacy of disease detection, enabling timely intervention and proactive management of any health risk.

Keywords: Multi-class classification; Computer vision; Deep Learning; Convolutional Neural Networks; Federated learning; distributed learning; Diabetic retinopathy detection.

Academic year: 2023 - 2024

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General Introduction

Machine learning has become commonly used in the field of data analysis. Essentially, it involves creating algorithms that are capable of learning from data and using that information to make predictions or decisions without the need for explicit programming. This falls under the umbrella of artificial intelligence, which aims to imitate human cognition and decision-making in machines.

Distributed data in different locations justifies the need for a distributed machine learning to explore distributed data while preserving it in its location. This is very important in the medical field where medical data are dispersed in different healthcare institutions. In this context, we conduct our project to explore distributed medical data related to diabetic retinopathy detection. We propose a federated learning approach based on federated medical data among different ophthalmology centers.

This report is organized into three chapters as follows. the first chapter explores distributed and centralized learning which are some of the most exciting and rapidly growing fields in computer science and artificial intelligence today. These technologies are transforming how we interact with machines and learn and process information. Meanwhile, distributed learning is revolutionizing the way we communicate with machines, allowing us to interact with computers more safely.

The second chapter focuses on Diabetic Retinopathy, which represents a threat to our vision that can cause blindness. The third chapter details the proposed distributed learning approach for the effective detection of the disease based on distributed medical data. The proposed approach also determines the stage of the disease in order to react faster and avoid any danger.

Chapter 1

Distributed Learning

1.1 Introduction

With the evolution of machine learning, there's an increasing demand for scalable and powerful models that motivate researchers to find innovative approaches such as distributed machine learning. When it comes to big data and complex computations, traditional machine learning faces limitations prompting the need for distributed learning. The rise of distributed learning is transforming the landscape of big data computing and data processing capabilities contributing to economic and societal impact. In this chapter, we present the centralized learning approach and its differences with the distributed approach.

1.2 Centralized learning

As a classic approach, we will introduce in this section the centralized learning concept.

Centralized learning within the field of machine learning is characterized by a conventional approach where the training of the model is performed on a singular, centralized server or any other computing system. This approach involves the concentration of all pertinent data and computational resources at a single location, with the model being trained on the whole dataset available on a specific central server.

As shown in Figure 1.1, centralized learning does not involve the decentralization of data or computations across multiple machines or nodes. While serving as a traditional method, it may encounter challenges, particularly in handling extensive datasets or in scenarios where scalability and processing speed assume paramount significance. Despite some limitations, centralized learning is a foundational paradigm in machine learning methodologies.

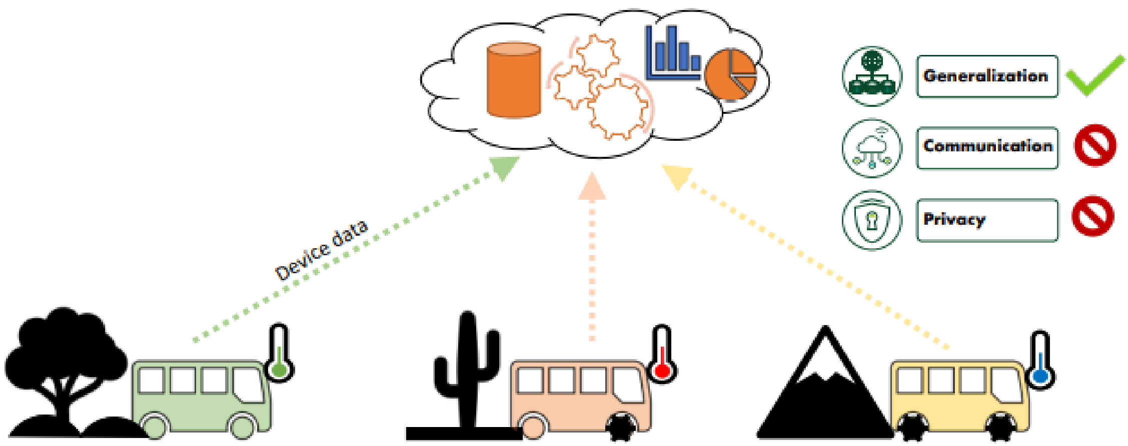

Figure 1.1: Centralized machine learning[22]

1.2.1 Application fields

Centralized learning, with its strong approach, has multiple application fields due to its efficiency. There are some fields where centralized learning could shine:

- Manufacturing and industry: Centralized learning is used to optimize solutions and predict potential equipment failures. It's also used to control quality and improve efficiency.
- Telecommunications: In telecommunication, centralized machine learning can help predict infrastructure maintenance, improve customer service experience, and optimize networks.
- Finance: In the financial sector, centralized machine learning is used for fraud detection, risk management, algorithmic trading, and customer relationship management. It helps institutions make data-driven decisions and mitigate financial risks.
- Smart Cities: Centralized learning contributes to the development of smart cities by optimizing traffic management, predicting environmental changes, and improving overall our quality of life.

1.2.2 Advantages

In machine learning, centralized learning represents the traditional and pivotal approach when tackling real-life problems. Centralized learning has several advantages and a variety of use cases that make it used in many industrial and economic contexts. Here, we will discuss the advantages of centralized learning.

- Simplicity and Ease of Management: In centralized machine learning, there's more control over hardware, resources, and data management. The entire learning process, including storing the data, and training the model, occurs in a centralized location.
- Unified Data Source: In machine learning, data is primordial in the learning process and the quality of the output. So, centralized learning helps cleaning, storing and preprocessing data.
- Simplified Monitoring and Debugging: Monitoring the performance of a centralized model and debugging any issues can be easier since all the relevant information is unified.
- Faster Decision-Making: If we have a real-time decision-making problem, a centralized system usually responds fast since all the data processing and decision-making is performed in one location.

1.2.3 Limitations

Centralized learning is an important and effective approach to machine learning. However, it has several limitations[1].

- Vast dataset: As datasets grow over time, the central storage may face problems in handling this voluminous information, especially in applications where bigger data is necessary for accurate model training.
- Computational power: When training a model on a large dataset on a single machine, this operation will be resource-intensive. The computation power and memory usage can be a real challenge for centralized learning.
- Processing time: As the model becomes more complex, the time required to process and analyze information may extend and become a time-consuming task that will have economic issues. Prolonged processing time can negatively affect real-time decision-making and responsiveness, especially in applications with high demand.
- Privacy concerns: In most of the cases, users' data is sensitive and should remain on-site. Balancing between effective model training and

protecting data privacy(such as in medical and industrial situations) remains a challenge in centralized learning[22].

1.3 Distributed Learning

In this section, we will define a new approach which is distributed learning. Distributed learning refers to the process of training machine learning models using multiple computing resources that are interconnected. Rather than relying on a single machine, distributed learning harnesses the collective computational power of a network of machines or nodes. By dividing the workload and data across multiple nodes, distributed learning enables parallel processing, leading to faster and more efficient training of machine learning models. In distributed learning as shown in Figure 1.2, data is partitioned into subsets that are distributed on separate machines that conduct computation on its subset. This new approach helps for faster convergence and enhances efficiency[1].

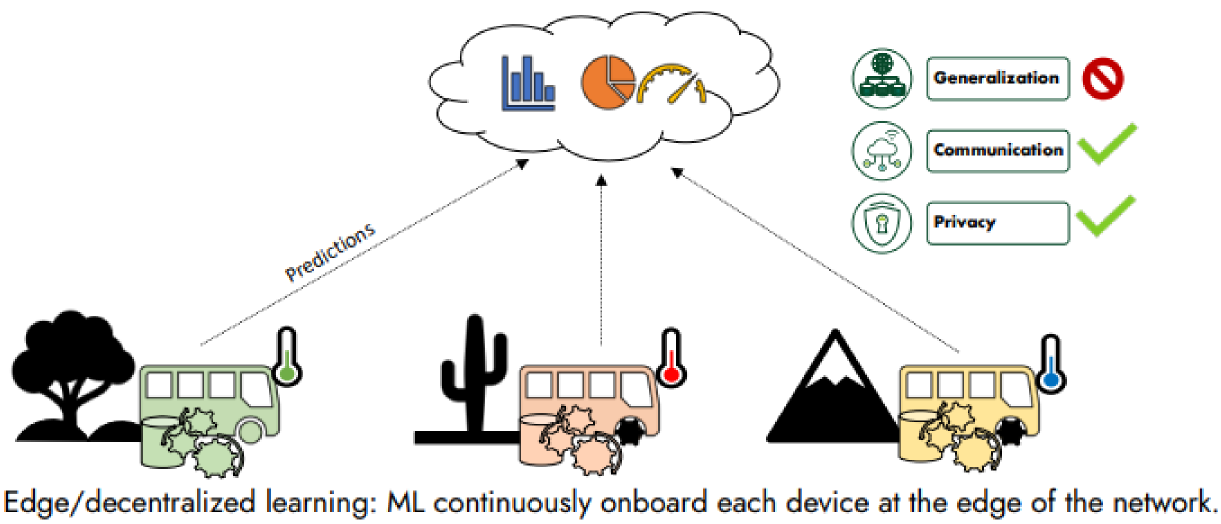

Figure 1.2: Distributed machine learning[22]

1.3.1 Application fields

Distributed learning has proven many successful implementations in different fields. In this part, we will discuss some of these use cases[1].

- Healthcare: One of the major use cases of distributed learning is healthcare. It helps ensure data privacy and avoid leakage of sensitive information. This approach improves diagnostic accuracy and collaborative research.

- Financial services: Distributed learning frameworks have been used to create efficient fraud detection systems by combining insights from various financial institutions and keeping the data private.
- Self-driven cars: In recent years, self-driven cars collaboratively work to train one global model using distributed learning to ensure a better driving experience.

1.3.2 Advantages

Distributed learning uses distributed devices to train a model. This recent approach has many advantages[1].

- Reducing training time: By balancing the workload across multiple devices, the overall training time decreases significantly. This allows for faster convergence time and avoids time-consuming processes.
- Scalability: Distributed learning is a strong approach that can scale rapidly and easily due to the fact that it uses multiple devices and this helps perform more complex algorithms and work on larger datasets.
- Fault tolerance: Since distributed learning is distributed architecture. If one device fails or encounters any interruption, the rest of the devices continue their tasks independently and give the same results. This fault tolerance makes this system more robust and reliable.
- Computational efficiency: The computational resources of multiple machines can be exploited at the same time, which results in improved computational efficiency. This use of resources enables the training of models that may be expensive to train on a single machine because of resource limitations.

1.3.3 Limitations

Distributed learning has a strong and useful architecture. Hence, it has some limitations that must be taken into consideration. Here, we address some of these challenges[1].

- Resource management: it's one of the biggest challenges of the distributed learning approach because it requires careful selection and balancing between devices and sophisticated protocols to make sure that the tasks are performed efficiently.

- Synchronization issues: Due to the large number of devices training simultaneously, synchronizing becomes an important task because it may become costly if there's no consistent communication between the devices and the central server.
- Security concerns: The data distribution across many devices would make privacy a challenging task. Also, multiple techniques such as secure aggregation must be implemented to ensure data privacy and avoid leakage of any sensitive information.

1.4 Federated Learning

In this section, we will dive deeper into the concept of federated learning and its characteristics.
Federated learning (FL) represents a distributed machine learning approach where multiple clients (IoT, mobile devices, organizations, etc.) collaboratively train a model orchestrated by a central server while keeping the training data decentralized. FL embodies the principles of focused data collection and minimization and can mitigate many of the systemic privacy risks and costs resulting from traditional, centralized machine learning and data science approaches[3].
FL as shown in Figure 1.3 is one instance of the more general approach of "bringing the code to the data, instead of the data to the code" and addresses the fundamental problems of privacy, ownership, and locality of data.

1.4.1 Federated learning protocol

In federated learning protocol, devices collaborate to achieve a common task. This protocol includes three main phases to update the global model as shown in Figure 1.4[3].

Selection phase : In the first phase, the devices meeting eligibility criteria check in with the FL server. After that, The server selects a subset of devices based on specific criteria such as connectivity and the optimal number of devices.

Configuration Phase : In the second phase, the server is configured based on the aggregation mechanism chosen and then he sends the configuration and the model to each selected device.

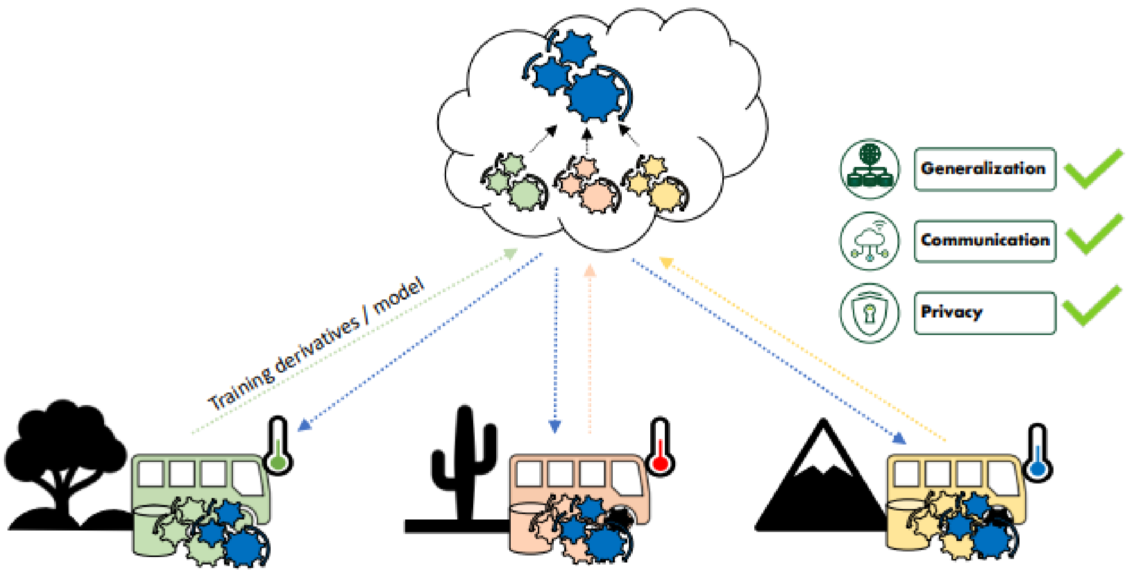

Figure 1.3: Federated machine learning[22]

Reporting Phase : In this phase, the server tends to receive all the updates to confirm a successful round and aggregate the models to update the global model.

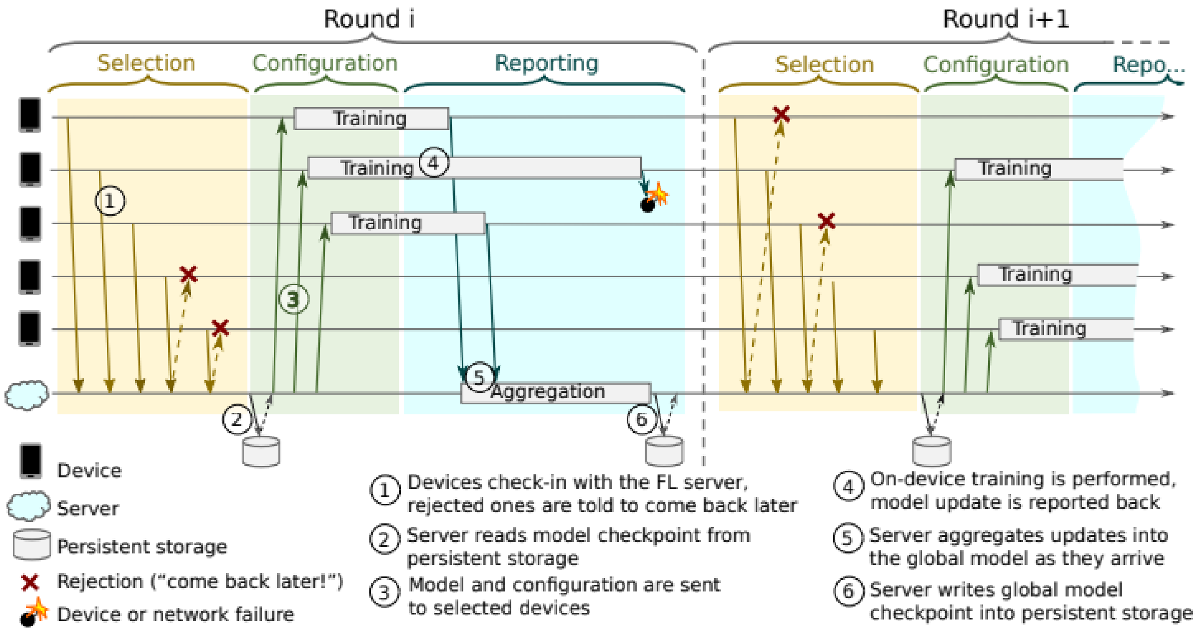

Figure 1.4: FL Protocol[3]

1.4.2 Types of federated learning

Federated learning can be classified into various types which depend on the use case. We mainly mention horizontal, vertical, and transfer learning as follows[7]:

- Horizontal FL: In datasets with a horizontal orientation, data is organized into rows with the same features, which is more efficient with supervised tasks. Each row is linked to a specific context. In our illustration, the context is a person. In essence, Google GBoard is employing Model-Centric, Cross-Device, Horizontal Federated Learning. In Figure 1.4, we illustrate an example of horizontal learning.

- Vertical FL: In vertical FL, the features are different for each device. This approach is useful when each device contains complementary information, and its goal is to create a model that can handle all the features. In Figure 1.5, we illustrate an example of vertical data.

- Transfer learning: In some federated learning cases, the transfer learning principle is applied. It includes adapting existing knowledge to a specific task at each device to improve a global model on that task.

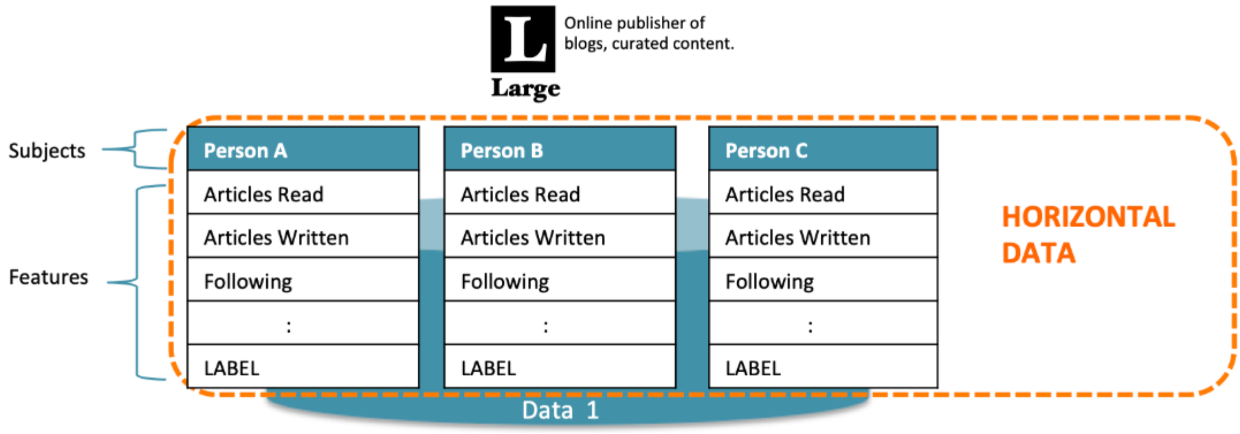

Figure 1.5: Example of horizontal data(same features)[7]

In addition, we have many other types of FL. We also find data-centric and model-centric as follows[7]:

- Data-centric: The data-centric approach is mostly used in scenarios where an individual or organization owns the data they are protecting. In this model, instead of hosting the entire model, the focus is on hosting the data itself. This setup enables a data scientist, who probably isn't the data owner, to submit requests for training using that specific dataset.
- Model-centric: In this approach, the data is distributed in the users' devices, and remote data is used to improve the global model using different types of averaging. The model parameters are managed on a central server. In this framework, the central server is extremely important in managing the learning process.

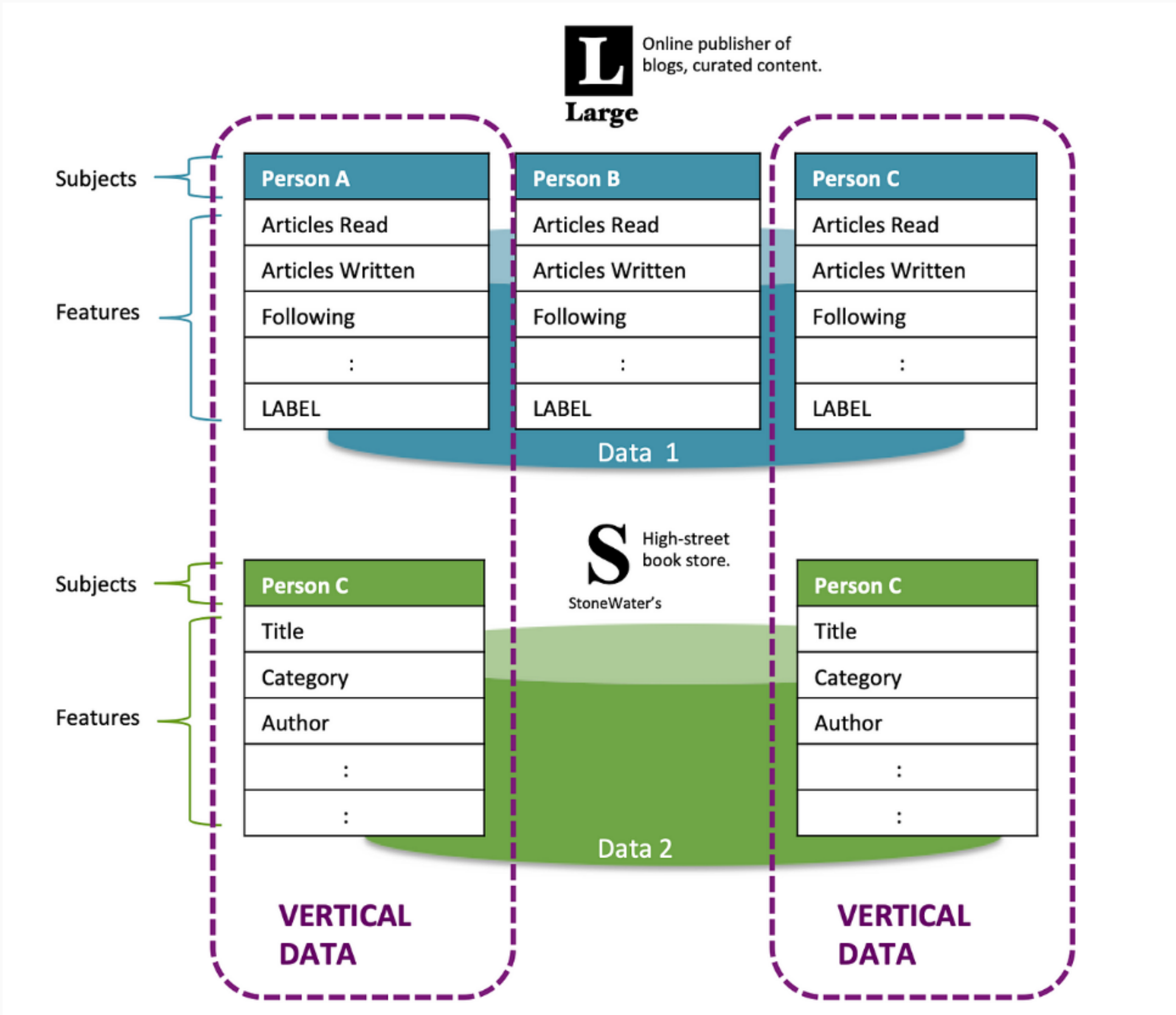

Figure 1.6: Vertical data with different features[7]

1.4.3 Federated learning workflow

Federated Learning workflow defining tasks in Python, testing them using provided TensorFlow functions, and deploying them to a group of mobile devices using the FL server. The process includes modeling and simulation, plan generation, versioning, testing, and deployment. FL tasks are validated against test data and must meet specific conditions before deployment, to ensure compatibility with the clients. The workflow enables engineers to focus on model development while leveraging FL system tools. The Figure 1.7 illustrates the FL workflow[3].

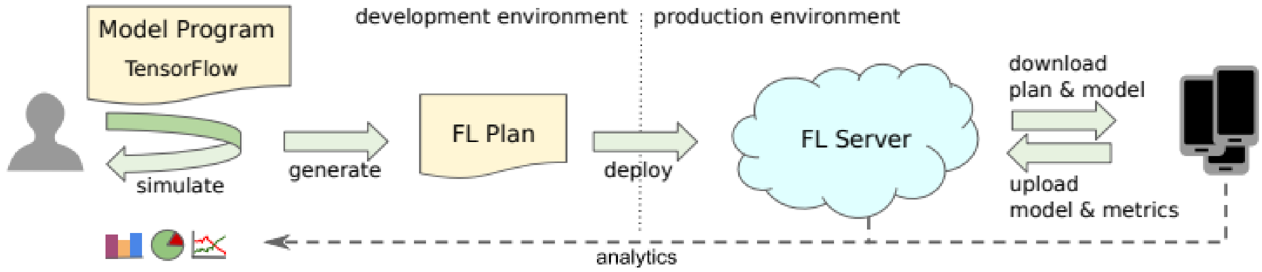

Figure 4: Model Engineer Workflow

Figure 1.7: FL workflow[3]

1.4.4 Application fields

Federated learning has become widely used in numerous fields due to its efficiency and easy exploitation. When the generated data on devices is more important than those on the central server, it's more convenient to use federated learning (such as when devices are the primary data sources), where privacy is a critical concern, or when transmitting the data to servers is undesirable or impractical. Presently, Federated Learning is mostly applied to supervised learning tasks such as typing words or clicking on links[22].

- Mobile devices: when individuals think of Federated Learning, their thoughts often go toward the various applications on smartphones. There are countless devices, numbering in the millions if not billions, each housing highly sensitive data. These devices exhibit variations in both hardware and data output. Moreover, due to battery constraints, they are only accessible for FL processes during the charging phase. An illustrative real-world instance in this domain is Google's predictive text feature in Gmail.

  Naturally, the information shared in emails is exceptionally sensitive. However, it is possible to facilitate cross-device learning while preserving privacy. This can be achieved by processing data on the mobile device and transmitting an encrypted partial training derivative.

- Organizations: Certain entities, such as hospitals and airports, might find the necessity to share data but are constrained by regulatory limitations. In such cases, the challenge is seldom related to issues like bandwidth, power, or the number of devices; rather, it revolves around concerns of privacy and the heterogeneity of systems.

- Internet of Things: Connecting billions of devices poses challenges, and it is impractical to transmit all the generated data to the cloud, considering both bandwidth limitations and privacy concerns. Furthermore, typical IoT devices often feature limited hardware, necessitating more efficient solutions.
  Despite these challenges, the industrial IoT sector holds significant promise. This is due to the relatively smaller number of devices involved, usually fewer than 10^5, consistent power supply, and the potential to leverage persistent models. Consequently, many applications in industrial IoT align well with silo-based Federated Learning.

- Next word prediction: The utilization of our FL platform by Gboard extends to training a recurrent neural network (RNN) for next-word prediction. This RNN model, boasting approximately 1.4 million parameters, achieves convergence in 3000 FL rounds after processing 6×10^8 sentences from 1.5×10^6 users during a 5-day training period (with each round taking approximately 2–3 minutes). The model exhibits notable improvements, enhancing top-1 recall from 13.0% to 16.4% compared to a baseline n-gram model. Furthermore, it matches the performance of a server-trained RNN that necessitated 1.2e8 SGD steps. In live A/B experiments, the FL model surpasses both the n-gram and server-trained RNN models[3]. In Figure 1.7, we illustrate an example of this application.

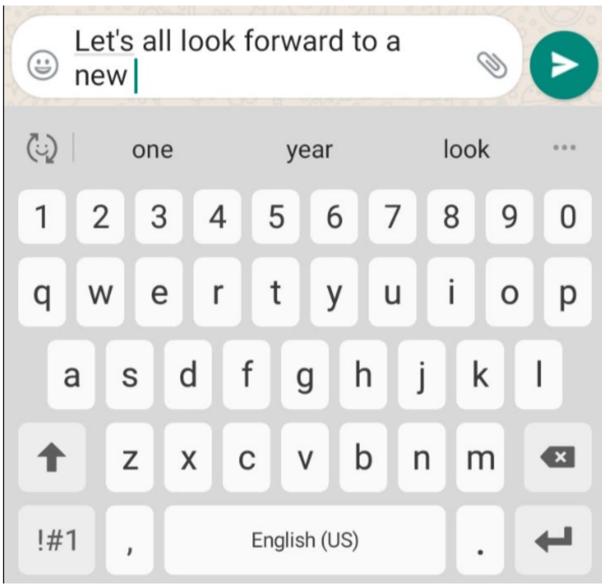

Figure 1.8: Predicting the next word in chats[5].

1.4.5 Advantages

The main advantages of federated learning are:

- Privacy Preservation: in FL, models are being trained without sending data to the central server. The training is performed locally on devices, and only the model is updated, not raw data are transmitted to a central server. This helps protect user privacy, especially when dealing with sensitive information.

- Edge Computing: FL is well-suited for edge devices (e.g., smartphones, IoT devices) where computational resources are limited. Training models locally allow these devices to contribute to the learning process without relying heavily on central servers.

- Adaptability to Heterogeneous Data: FL is well-suited for situations where data is diverse and heterogeneous across devices. Each device can contribute its unique data, and the model is trained to generalize across these diverse datasets.

- Collaborative Learning: FL allows for collaborative model training across devices without directly sharing data. This fosters cooperation among different entities, such as organizations or users, while respecting data privacy.

1.4.6 Limitations

In the last few years, FL has succeeded in being reliable and adaptable to multiple situations. However, limitations and imperfections make these approaches give unsatisfying results and even create issues. For that, it is crucial to be aware of these limitations, enabling us to recognize them in practical situations and prevent unnecessary exploitation of resources and time.
Here, we will discuss the challenges that should be considered to have a successful implementation[6].

- Expensive communication: Effective communication is extremely important in federated networks. This challenge, exacerbated by privacy concerns related to transmitting raw data, underscores the importance of keeping data generated on individual devices localized. Federated networks, potentially involving millions of devices such as smartphones, face slow communication within the network compared to local computation, owing to constrained resources like bandwidth, energy, and power. To handle this problem, it is necessary to reduce the number of messages sent over the network and the size of each message, all while sending only the model updates instead of the user's data.

- Systems heterogeneity: Due to the large diversity of the devices used for training, which includes many parameters such as network connectivity, hardware characteristics, battery level, etc. This can create a problem in getting satisfying results. Additionally, certain devices may face problems during training which can affect the quality of the model. That's why this problem must be taken into consideration.

- Privacy concerns: While federated learning is working on securing clients' data, privacy remains a major problem as the process can face leaking some private data. While recent approaches are trying to improve the privacy of federated learning through tools like secure multiparty computation (SMC) or differential privacy, these methods frequently come with a trade-off, compromising model performance or overall system efficiency . Navigating and striking a balance between these trade-offs, both in theory and in practice, presents a significant challenge in the development of effective private federated learning systems.

Conclusion

To conclude, in a world where data become more and more crucial and is impacting the way we live, distributed learning comes as an innovative approach that uses collaboration across multiple devices to achieve bigger results. In this chapter, we discussed the difference between centralized, distributed, and federated learning and their use cases. We also presented the major challenges for each type to choose the best alternative depending on the task. In the next chapter, we will explore our application field which consists of detecting and categorizing the retinopathy anomaly.

Chapter 2

Retinopathy Detection

Introduction

The growth of medical data in recent years has created a need for strong machine-learning algorithms and techniques to make sense of it.
Machine learning and deep learning have revolutionized many aspects of healthcare diagnosis and treatment.
In this chapter, we will explore diabetic retinopathy disease, which is one of the main causes of vision loss for people with diabetes. We will focus on the risk factors, symptoms, diagnosis, and how to treat this disease. We will also provide an overview of the importance of early proactive management strategies to avoid any risk. By the end of this chapter, we will have a deep understanding of diabetic retinopathy and how to avoid it.

2.1 Definition

Diabetic retinopathy is an eye condition disease related to diabetes that causes damage to the blood vessels in the retina, the light-sensitive tissue at the back of the eye. The retina, located at the back of the eye, functions much like the film in a camera, which transmits signals to our brain. It has an important role in converting light rays into electrical impulses and facilitates communication with the brain[9].
This disease happens when high blood sugar levels cause damage to blood vessels in the retina. These blood vessels can swell and leak. Or they can close, stopping blood from passing through. Sometimes abnormal, new blood vessels grow on the retina. All of these changes can steal your vision. It is a leading cause of vision loss and blindness among individuals with diabetes[8].

2.2 Causes

Diabetic retinopathy has a main cause which can be highly dangerous if not treated.
In the long term, elevated blood sugar levels can cause blockages in the small blood vessels that supply nutrients to the retina. So, new blood vessels are formed in the eye. However, these newly formed vessels usually develop abnormally and cause leakage. The Figure 2.1 illustrates the leakage of blood into the retina and how it can affect vision[10].

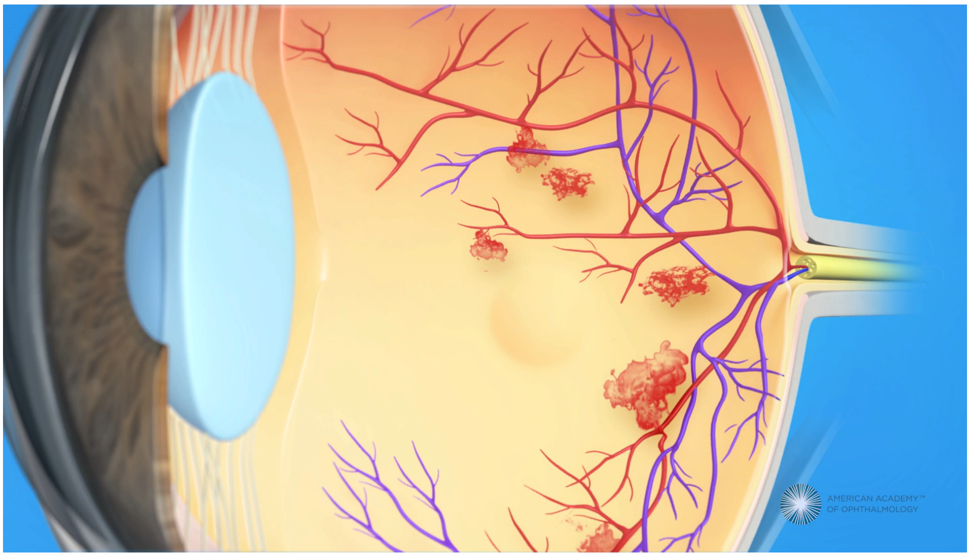

Figure 2.1: Blood leakage into the retina[8]

These compromised vessels can result in reduced blood circulation (ischemia), inflammation, and eventually legal blindness if left untreated[9].

2.3 Diagnosis

DR is a critical issue to the eye so it needs to be identified as soon as possible to prevent any risks. To do that, doctors use some diagnosis. The ophthalmologist will put Drops in your eye to widen the pupil and this will help him to look through a special lens and see the inside of your eye.

An option is that the doctor can take optical coherence tomography (OCT) to conduct a thorough examination of the retina. During OCT, a dedicated machine scans the retina to provide high-resolution images that allow for precise measurement of macular thickness. So, it's easier to detect and evaluate macular swelling.

Another option is fluorescein angiography or OCT angiography and it's used to assess the condition of the blood vessels within the retina. Fluorescein angiography is the injection of a yellow dye called fluorescein into a vein, typically in the arm. Then the dye circulates through the bloodstream, and a specialized camera takes images of the retina, tracking the dye's movement through the retinal blood vessels. This will help identify blockages or leakage of fluid from the blood vessels, as well as the detection of abnormal blood vessel growth[8].
In the next section, we will use images of the fluorescein angiography test to identify the types of DR.

2.4 Types

Before discussing each type individually, it's helpful to know that there are two main types of diabetic retinopathy: non-proliferative diabetic retinopathy, which is the early stage of this disease, and proliferative diabetic retinopathy, which represents the advanced stage of DR. In this section, we will describe each type and compare them to illustrate the difference.
No Diabetic Retinopathy: In Figure 2.2, we present a normal eye image of a normal person who has no diabetic retinopathy. We can notice that there's no blood leakage or abnormal vessels.

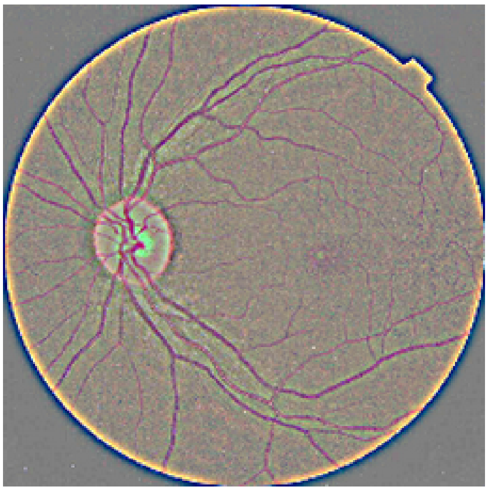

Figure 2.2: Retina scan image of a No DR individual[12]

Non-proliferative diabetic retinopathy: This is the initial phase of diabetic retinopathy for several individuals with diabetes. In Non-Proliferative Diabetic Retinopathy (NPDR), small blood vessels cause leakage that would make the retina swell. When this swelling affects the macula, it results in macular edema, which is the principal cause of vision impairment for people with diabetes .

Furthermore, NPDR can also involve the closure of retinal blood vessels, a condition known as macular ischemia. As a result, the macula is incapable of receiving blood, potentially resulting in the formation of exudates within the retina and this can impact vision.

NPDR individuals usually have blurry vision[8].
In Figure 2.3, we present an NPDR eye image of a diabetic person. We can notice the difference compared to a healthy retina.

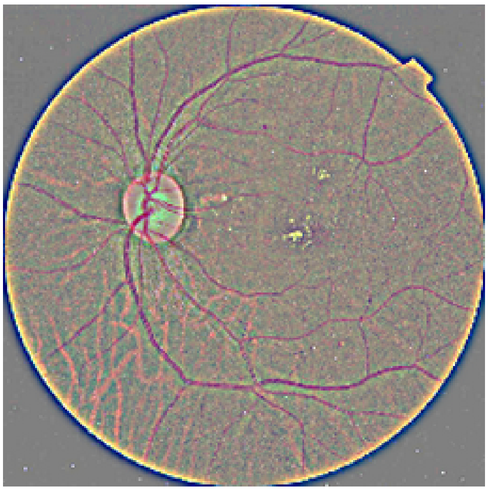

Figure 2.3: Retina scan image of a NPDR individual[12]

Proliferative diabetic retinopathy: Proliferative Diabetic Retinopathy (PDR) is the most dangerous phase of this eye disease. When we have neovascularization, which is defined as the growth of new blood vessels, these new vessels can bleed into the vitreous of the eye. A small bleeding may result in the appearance of dark floaters, while extensive bleeding can potentially affect the entire field of vision.

In addition, the newly formed blood vessels can result in development of scar tissue. This scar tissue formation can lead to complications that affect the macula or even result in retinal detachment.

PDR is a real threat to vision, as it can impact both central and peripheral vision considerably[8]. In Figure 2.4, we present a PDR eye image of a diabetic person. We can notice the advanced stage where bleeding is more important compared to an NPDR.

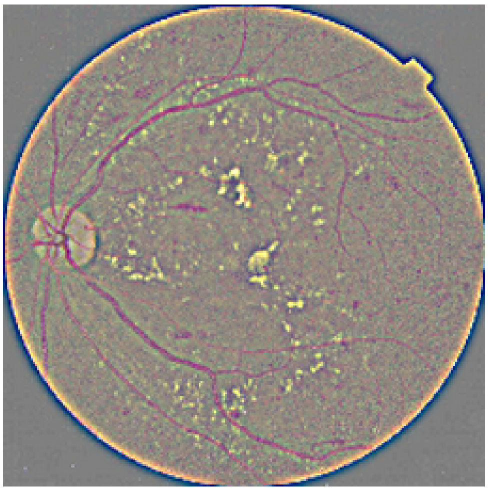

Figure 2.4: Retina scan image of a PDR individual[12]

2.5 Symptoms and risk factors

2.5.1 Symptoms

Usually, for a diabetic individual, there are no symptoms for this eye disease so the concerned person will not notice any problems or any vision issues. It starts to show symptoms when it is at an advanced stage.
In this case, there are some symptoms which include[13]:

- **gradually worsening vision**
- **sudden vision loss**
- **shapes floating in your field of vision (floaters)**
- **blurred or patchy vision**
- **eye pain or redness**
- **difficulty seeing in the dark**

Sometimes, some symptoms disappear on their own, but it's important to be treated instantly else it can cause scars on the back of the eye. Blood vessels may also start to bleed again and so the bleeding may get worse[14]. This is not a direct sign that the disease is diabetic retinopathy, but it is important to check with a doctor to avoid any advances or major risks. It is crucial not to wait until the next screening appointment[13].

2.5.2 Risk factors

The development of diabetic retinopathy can be influenced by multiple risk factors. Some signs and factors can increase the chances of getting diabetic retinopathy so it's important to know them and avoid any future complications that could happen. Anyone with diabetes can get a DR including type 1, type 2, and gestational diabetes (which is a diabetes that can develop during pregnancy).

Also, individuals who have been living with diabetes for a long period are at a big risk of developing this disease. In addition, individuals who don't control their blood sugar levels over time can exacerbate the risk. Another factor is that High blood pressure and high cholesterol levels further contribute to the likelihood of DR. Pregnancy can also increase the susceptibility to this eye complication, particularly in diabetic individuals.

It's important to understand that Tobacco use is another significant risk factor even some people may ignore their negative impact. Furthermore, according to Mayo Clinic, certain racial and ethnic backgrounds, such as being Black, Hispanic, or Native American, are associated with increased chances of getting this anomaly. To conclude, a diabetic person must be aware of these risk factors to prioritize proactive measurements and regular screenings to mitigate the risk of diabetic retinopathy and preserve their eye health[10].

2.6 Treatment

Diabetic retinopathy is a serious complication that should be treated rapidly and effectively to preserve vision and prevent further deterioration. For now, multiple treatment approaches exist, each addressing different stages and manifestations of the condition. The ophthalmologist is responsible for the type of treatment depending on what he sees. During the initial phase of the disease, when the vision is unaffected, doctors often adopt a wait-and-see strategy. So, the person just needs to do his regular examination and keep track of his eye condition, ranging from every two to four months, especially if his vision remains stable. The goal is to determine the necessity for further treatment.

If the DR is in an advanced stage, three treatments are used which are: Injections, Laser treatment, and Eye surgery[13].

- **Injections:** The ophthalmologist will perform direct injections of

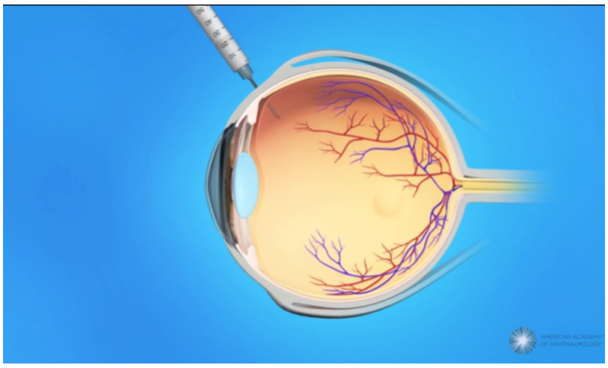

Figure 2.5: Injections of substances to treat DR[8]

anti-VEGF medication into the eyes that prevent blood vessels from growing at the back of the eyes. Medications used for this purpose are ranibizumab (Lucentis) and aflibercept (Eylea). These injections stop the progression of eye-related issues and can lead to improved vision.

During the procedure, the doctor cleans the covers the eye, while small clips are used to make sure the eyes are open. Local anesthetic drops are applied to numb the eyes, after which a fine needle is guided into the eyeball for the injection. Initially, injections are typically given every month, depending on the vision stabilization and improvement.

- **Laser treatment:** Laser treatment is used to address new blood vessels forming at the back of the eyes when in the advanced stages of DR. The doctor should do the intervention because these newly formed vessels are fragile and can cause bleeding within the eye. While the primary goal of treatment is to stabilize diabetes-induced changes in the eyes and prevent further deterioration of vision, this operation doesn't improve vision.
  The procedure includes directing a laser into the eyes after performing local anesthetic drops for numbing. Eye drops dilate the pupils, and specialized contact lenses are employed to keep the eyelids open and focus the laser on the retina. This operation lasts between 20 to 40 minutes, and laser treatment is usually conducted on an outpatient basis, without the need for overnight hospital stays. This type of treatment could be done multiple times to complete the treatment procedure. Although it's not painful, individuals undergoing the procedure may experience a sharp pricking sensation in certain areas of the treated eye.

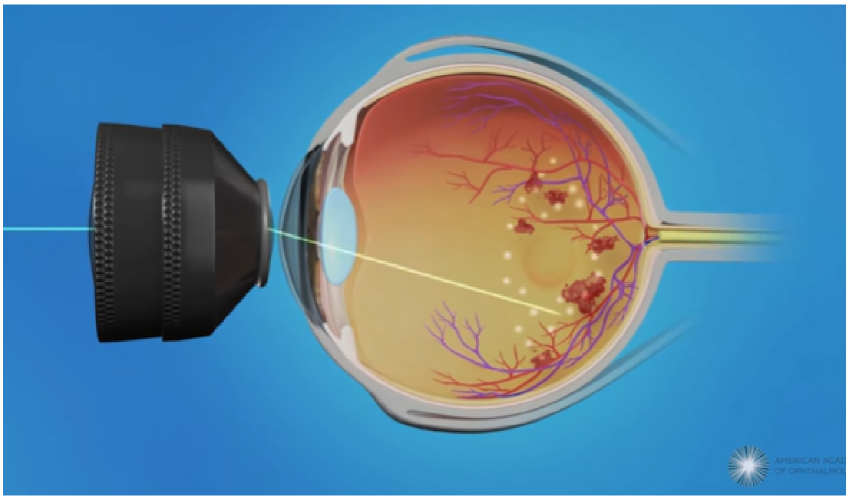

Figure 2.6: Laser treatment to treat DR[8]

- **Eye surgery:** Vitreoretinal surgery, treatment consists of removing a part of the vitreous humor from the eye, and this may be necessary in some cases. For Instance, where a significant blood accumulation occurs within the eye or when extensive scar tissue is creating a problem or has already led to retinal detachment, may oblige this intervention. During the operation, the surgeon makes a small incision in the eye to extract a portion of the vitreous humor. This technique eliminates any scar tissue and employs laser techniques to prevent further problems of vision. Typically done under local anesthesia, this ensures that individuals undergoing the procedure remain pain-free and unaware of the surgery being performed.

To conclude, the doctor may also consider other factors in choosing the adequate treatment such as age and medical history, extent of retinal damage, Visual acuity, and HgbA1c(which is a test for average blood sugar for the last two months).

2.7 Prevention and the importance of early detection

The best action that a diabetic individual can take is to prevent himself from any dangerous complications before it is too late to be treated. Several ways are proposed by specialists to reduce the risk of getting diabetic retinopathy[13].
First, it's important to talk regularly to the doctor to keep blood sugar and cholesterol levels at normal rates and control it however it will damage the blood vessels.
Second, controlling blood pressure is another factor that should be taken into consideration. The concerned person should take regular blood pres-

sure tests.
In addition, it's highly recommended to adopt a healthy lifestyle by eating healthy food, practicing sports regularly to remain in a strong condition, and avoiding bad habits such as smoking or alcohol which present a high risk to our health.
Finally, it's important to attend eye screening regularly even if there are no noticeable signs. This helps to detect if there's any DR development, at an early stage so the treatment will be easier and more effective.

To conclude, while managing diabetic retinopathy is essential, prioritizing preventive measures remains more important in reducing the risk of progression of this condition. By incorporating these preventive strategies into daily life, diabetic individuals can take proactive steps toward preserving their vision and minimizing the impact of diabetic retinopathy.

Conclusion

To conclude, in this chapter, we covered the diabetic retinopathy problem which concerns diabetic individuals. we defined the disease and presented the major symptoms and risk factors that are responsible for making this anomaly more dangerous and can cause partial or total vision loss due to abnormal growth of blood vessels. Then, I covered the types and stages of DR and what are the tests done to identify each type.

Finally, we illustrate the different treatments available and in which stage every treatment is used. Then we focused on the importance of early detection and preventing this anomaly to avoid these problems before they happen or get more complicated. In the next chapter, we will develop the proposed approach used to help doctors detect the DR stage using fluorescein angiography test images.

Chapter 3

Proposed Approach for Diabetic Retinopathy Detection

3.1 Introduction

In this chapter, we are going to present the proposed approach to detect diabetic retinopathy(DR). First, we explored the dataset and performed preprocessing techniques to enhance the data quality. Second, we selected multiple pretrained models to compare their performance and find the most suitable model for our multi-class classification task. In addition, we tried to apply federated learning to distribute the training process across multiple clients, and then evaluate its performance in improving model performance. So, we will explain these steps in detail.

3.2 Runtime Environment

In this section, we introduce the selected environment for the development process, Kaggle Notebook.

Kaggle Notebook is a cloud-based platform based on Jupyter Notebooks, it supports Python and R. This environment offers a free GPU processor, 29GB of RAM, and over 73.1GB of storage[12].

For the development language, we have chosen **Python**, a high-level programming language. It is also a more common and popular language for machine learning and artificial intelligence due to its flexibility and the large number of available open-source software libraries.

The TensorFlow[18] and **Keras** [19]frameworks were chosen for the implementation of the proposed deep learning methods. TensorFlow is an open-source deep learning library developed by Google, used for performing complex numerical operations and various other tasks to model deep learning architectures.

3.3 Data Exploration and Preprocessing

In this section, we present the considered dataset in our study. Then, we describe the steps of processing the dataset and building the model.

3.3.1 Presenting the dataset

This dataset is a publicly available dataset on Kaggle[12]. It consists of a collection of retina images taken using fundus photography, which corresponds to different imaging conditions. These images have been labeled by doctors who has assigned a severity range of diabetic retinopathy. These results are based on various indicators such as the presence of microaneurysms, hemorrhages, exudates, and neovascularization, among others. This dataset is divided into five classes according to the disease stage which are: No diabetic retinopathy, mild, moderate, proliferative, and severe. Advanced stages are proliferative and severe and may have significant retinal damage and risk of vision loss. In Figure 3.1, we represent the content of this dataset.

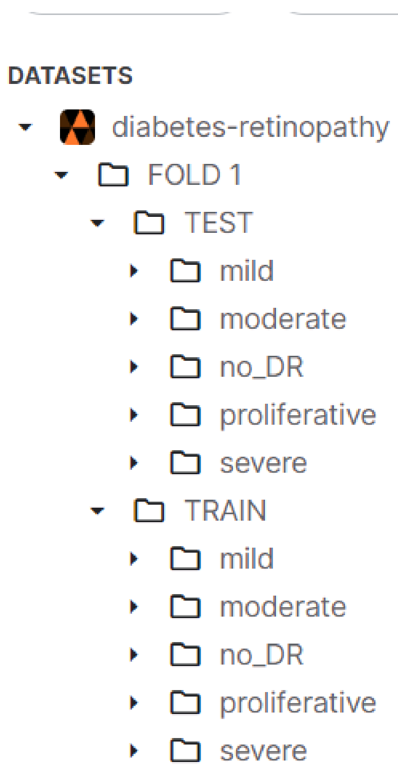

Figure 3.1: Presenting all files in the dataset

3.3.2 Exploratory Data Analysis

First, we started our analysis by exploring the dataset to gain insights into its features and its structure. In this part, we examined the distribution of classes, checking for class imbalances, and understanding the overall size of the dataset.

3.3.3 Visualizations

To better understand the dataset, visualizations were an important step to understanding the characteristics of the data. we have used many plots such as histograms, pie charts, and bar plots to visualize class distributions and image dimensions. In Figure 3.2, we illustrate the plots used to explore the dataset.

As shown in Figure 3.2, the dataset is highly imbalanced. The no DR class which corresponds to normal people is dominant with 73.5 % of the dataset for both train and test sets. This distribution may lead to inaccurate results and the model will be biased to the majority class. So, this will significantly impact the model performance and increase the false negatives.

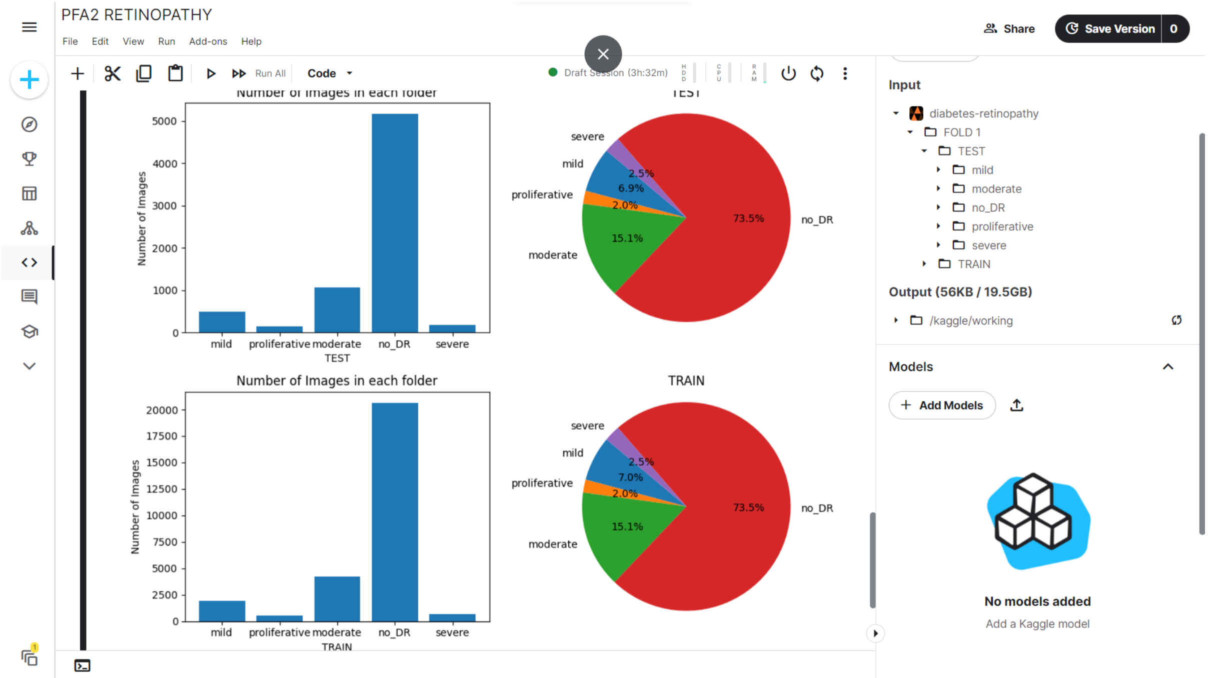

Figure 3.2: Plots used to visualize the DR dataset

3.3.4 Data augmentation

As explained in the previous subsection, imbalanced data is a big challenging issue in our study. So, as a solution, we are going to perform data augmentation to make the results more accurate. Data augmentation is a strong and efficient technique to augment the dataset's variability and its balance. By synthetically creating more samples from the dataset using various transformations such as rotations, cropping, flips, and zooms.

In practice, we implemented data augmentation as a preprocessing step during the training phase. We used libraries like TensorFlow and Keras, in order to integrate data augmentation techniques into the model pipeline. The classes mild(7%), moderate(15%), severe(2.5%), and proliferative(2%) have a very low pourcentage. In figure 3.3, we illustrate the results of applying data augmentation to these classes.

After performing data augmentation, we can confirm that the dataset is now more balanced.

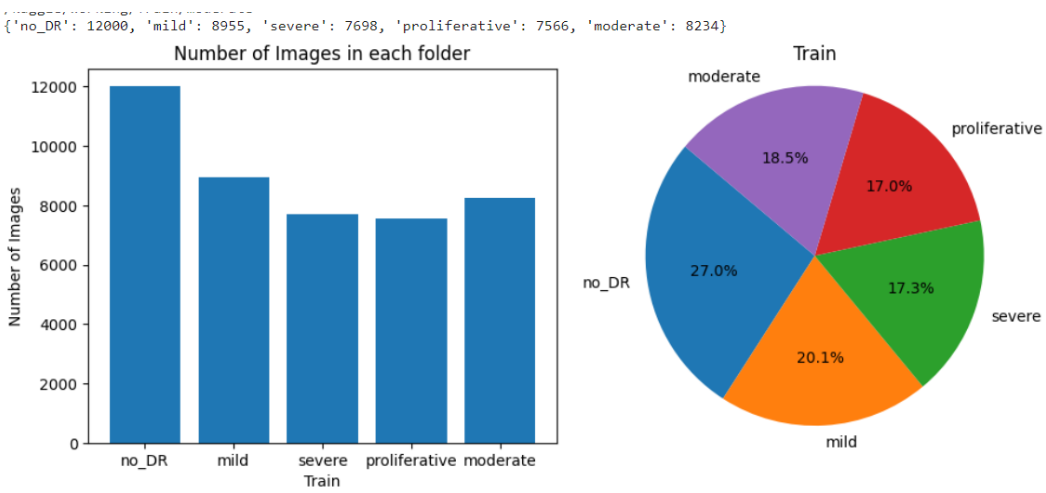

Figure 3.3: Dataset after performing data augmentation

3.3.5 Preprocessing techniques

Before embedding the data in the model, the raw data needs to be preprocessed using different techniques and functions. These functions help significantly remove the noise in the images, extracting the features or make them more clear to make the learning process faster and more accurate. For our task of image classification in diabetic retinopathy detection, preprocessing plays an important role as our dataset doesn't show effectively the necessary features. In the following, we will present the used techniques to preprocess our data.

- **Crop image from gray function** The main goal of this first function is to crop out uninformative areas in the images. It analyses their grayscale representation.

  It verifies the color scale of the image (grayscale or RGB). If it's grayscale, it creates a binary mask where pixel values greater than a specified tolerance are considered informative. If the image is RGB, it converts it to grayscale and then redo the same process. This binary mask is then applied to each color channel of the RGB image to maintain only the necessary parts. Finally, it stacks the filtered color channels to reconstruct the cropped RGB image.

- **load Ben's color function**

  This function uses a technique called Ben Graham's method, which reduces lighting variations and enhancing image contrast. This function was proposed by the winner of a Kaggle competition of diabetic retinopathy detection[23]. It first calls the cropped image from the gray function to crop uninformative areas. Next, we applied a Gaussian blur. This technique makes the images smoother and helps reduce noise while keeping details. Finally, the original image is combined with a blurred one which results in enhances the contrast and reduces lighting variations.

In conclusion, these techniques helped to extract features, reduce noise, and improve the overall image quality by enhancing contrast and luminosity . In Figures 3.4 and 3.5, we show the difference between the original and the preprocessed image.

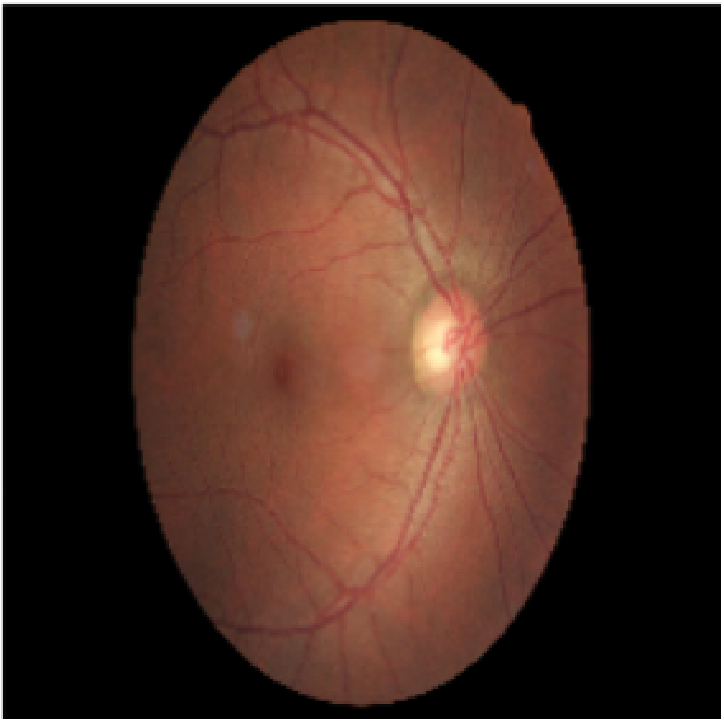

Figure 3.4: The original image

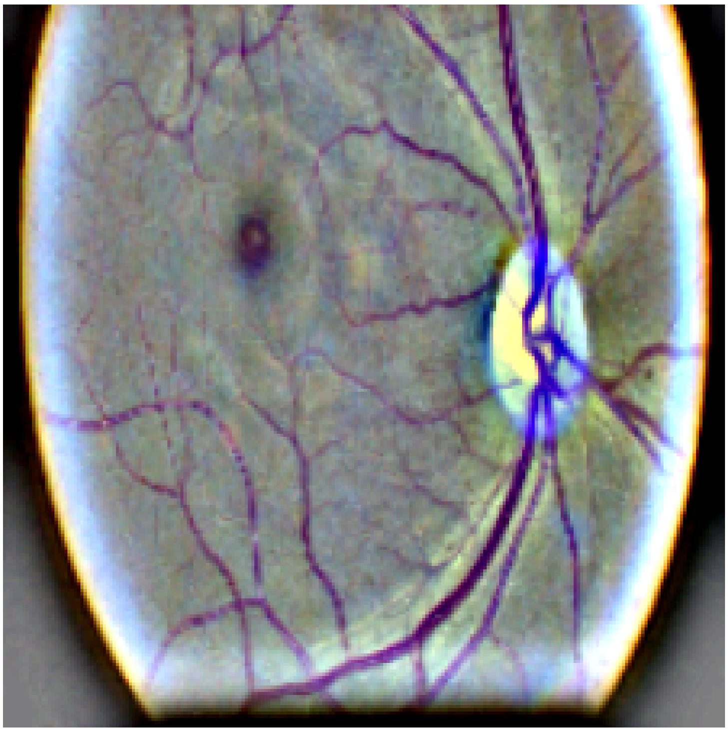

Figure 3.5: The preprocessed image

3.4 Model Selection and Comparison

In the last section, we prepared our data for training. Now, we will create our model to classify the images into 5 classes. Our approach was to try different models, either pretrained or manually defined and perform a comparative study for each model's performance to choose the most efficient model. Model selection is a crucial step that determines the overall performance. Many factors require careful consideration such as the model's complexity and interpretability.

3.4.1 Custom model

As a first model, we have chosen a custom model with a simple structure and low complexity to test the necessary work. This model is composed of the following layers: 2 max pooling and 2 convolutional layers with 2 dense layers. After preparing and splitting the train and test sets, the model seems not to give the best results as shown in Figure 3.6.

To assess our model, we have used the accuracy metric and the Stochastic Gradient descent. The model accuracy has gone to 0.68 for the train set and 0.59 for the validation set. This underfitting issue can be explained by the low complexity of our model which prevents it from learning the complexity of data.

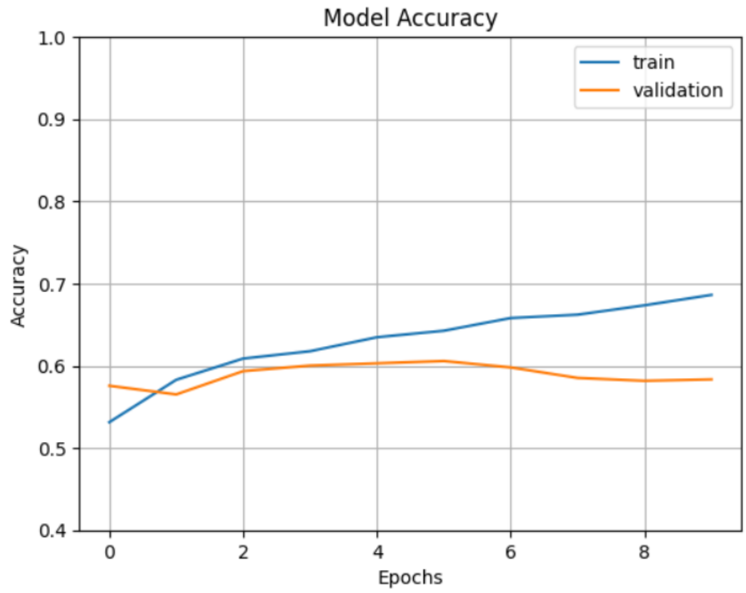

Figure 3.6: Custom model accuracy

3.4.2 Pretrained models

As shown in the previous part, the results of our model are poor and this creates the need for more sophisticated models. As a result, we will use pretrained models to take advantage of their complexity and efficiency. Pretrained models are deep neural networks that have been pre-trained on large datasets, for image classification tasks in this case. These models are very complex and they are trained on diverse datasets, such as ImageNet[21], which contains millions of labeled images spanning thousands of categories and they usually focus on different tasks.
For this task, we have chosen three pretrained models which are VGG16[19], VGG19[19], and RESNET-50[20].

VGG19

The VGG-19 model is a convolutional neural network architecture that was first adopted at the University of Oxford. It is composed of 19 layers, with 16 convolutional layers and 3 fully connected layers as shown in Figure 3.7. VGG19 achieves competitive performance on image classification tasks, especially when pretrained on large datasets like ImageNet[19].

VGG16

It is a powerful model known for its depth, composed of 16 layers, with 13 convolutional layers and 3 fully connected layers as shown in Figure 3.8.

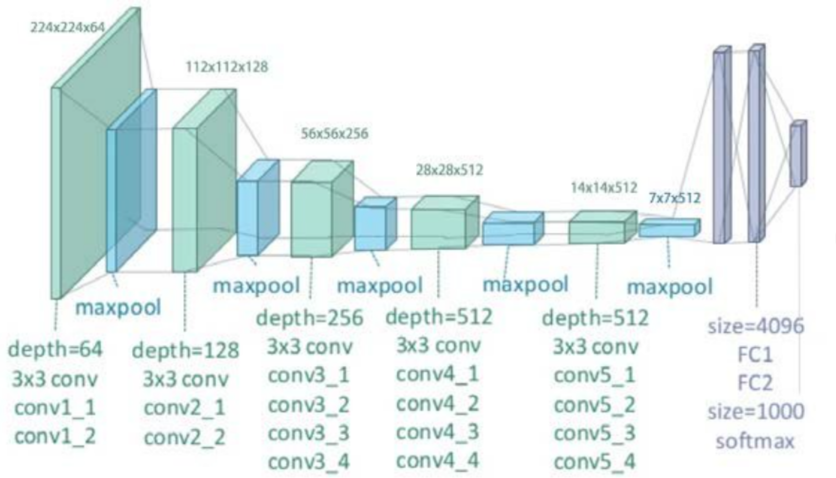

Figure 3.7: VGG 19 architecture[15]

VGG-16 is a simple yet effective model. It can give a strong performance on image classification and object recognition tasks[16].

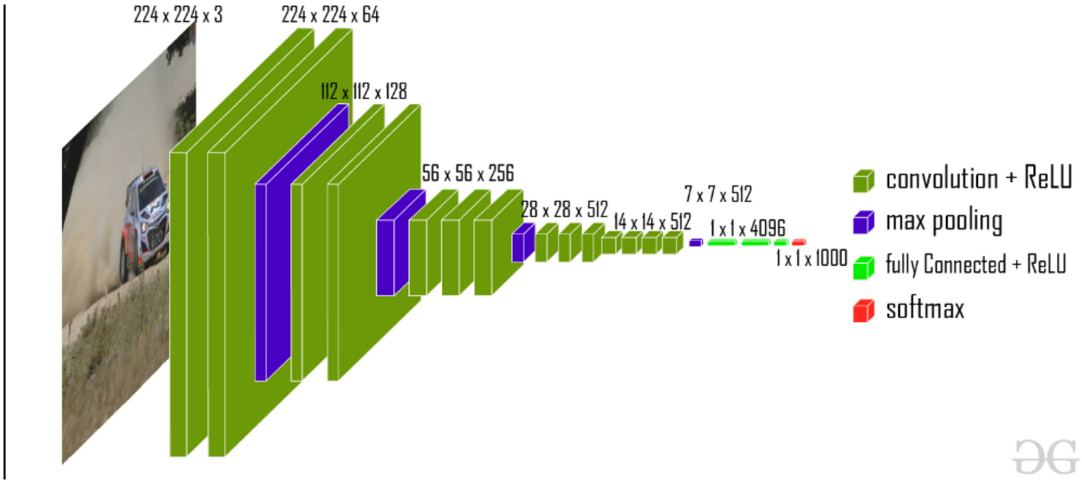

Figure 3.8: VGG16 architecture[16]

RESNET50

ResNet50 is a deep residual neural network architecture proposed by Microsoft Research. It consists of 50 layers, including convolutional layers, pooling layers, and identity blocks with skip connections. ResNet50 introduced the concept of residual learning, where each layer learns residual functions concerning the input, making it easier to train very deep networks. The pretrained ResNet50 model is also used in different computer vision tasks, including image classification, object detection, and semantic segmentation, due to its excellent performance and robustness[20].

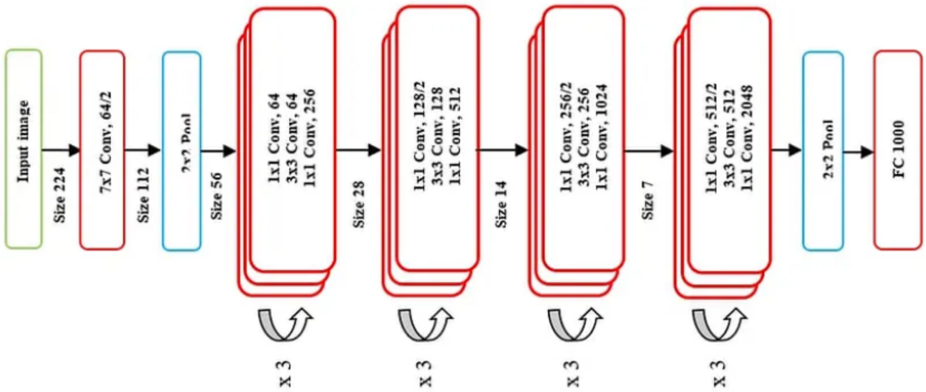

Figure 3.9: ResNet 50 architecture[17]

3.4.3 Comparative study of pretrained models

We Trained the three models on the training dataset and then evaluated them on the test set which gave us various results.

As shown in Figure 3.10, the VGG19 is not giving good results and it has an underfitting problem achieving only 0.53 with the accuracy metric.

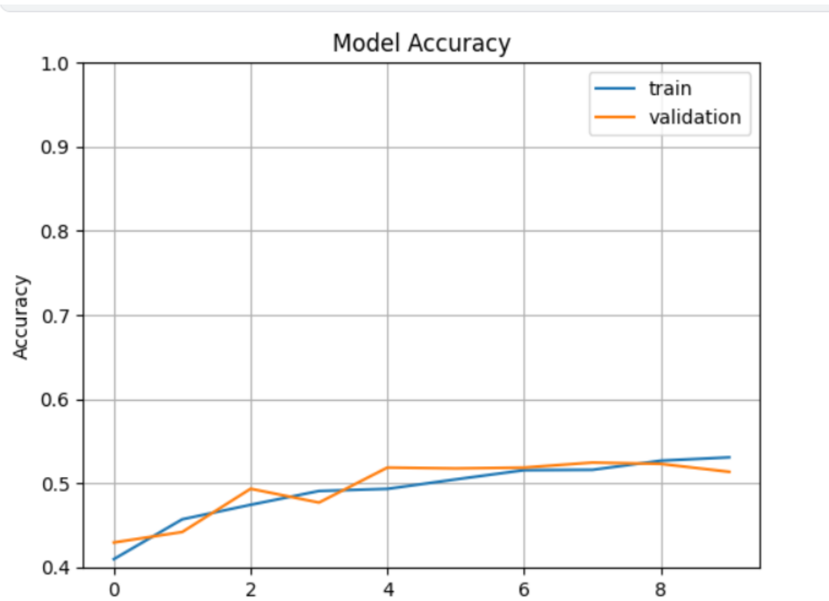

Figure 3.10: VGG19 accuracy

As shown in Figure 3.11, the VGG16 also has an underfitting problem achieving only 0.55.

The ResNet 50 has given the best performance among the three other models.

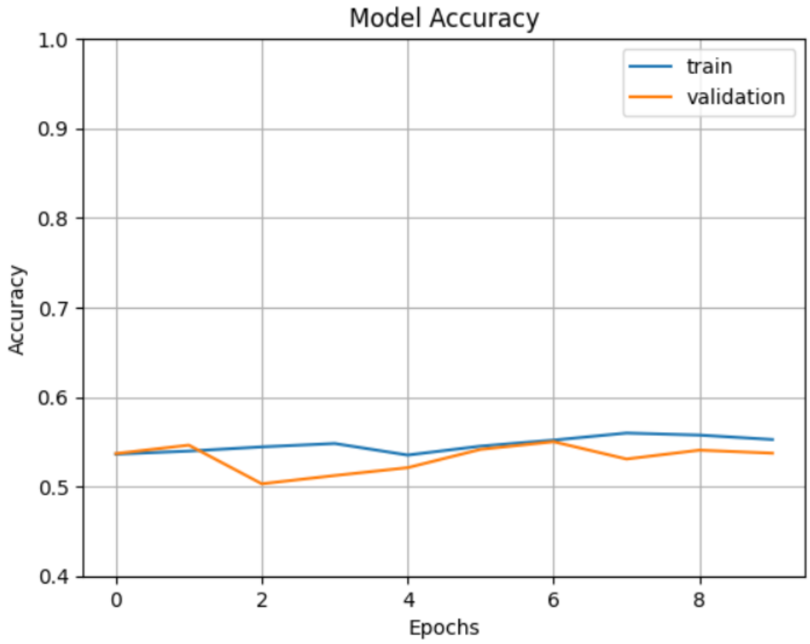

Figure 3.11: VGG16 accuracy

As shown in Figure 3.12, the results of the ResNet-50 are better than the custom model, VGG19 and VGG16 also achieving an accuracy of 0.77 on the train set and 0.73 on the validation set.

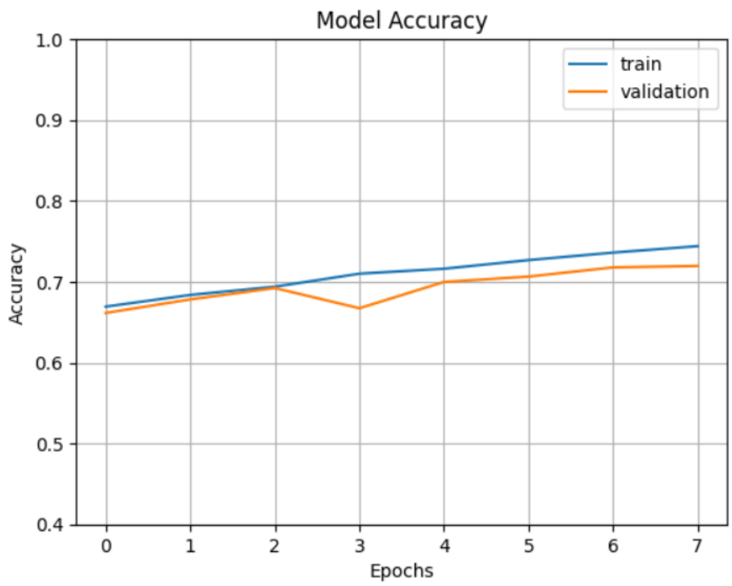

Figure 3.12: ResNet 50 accuracy

3.5 Federated Learning Approach

In this section, we will focus on our federated learning approach for the multi-classification task. We assume that our dataset is distributed among different healthcare institutions. Then, distributed and collaborative learning is performed to improve the accuracy of the multi-classification task. In this section, we describe the different steps of our approach. The Figure 3.13 shows the architecture of our approach, which is defined by a single server connected to different healthcare institutions holding different patient records.

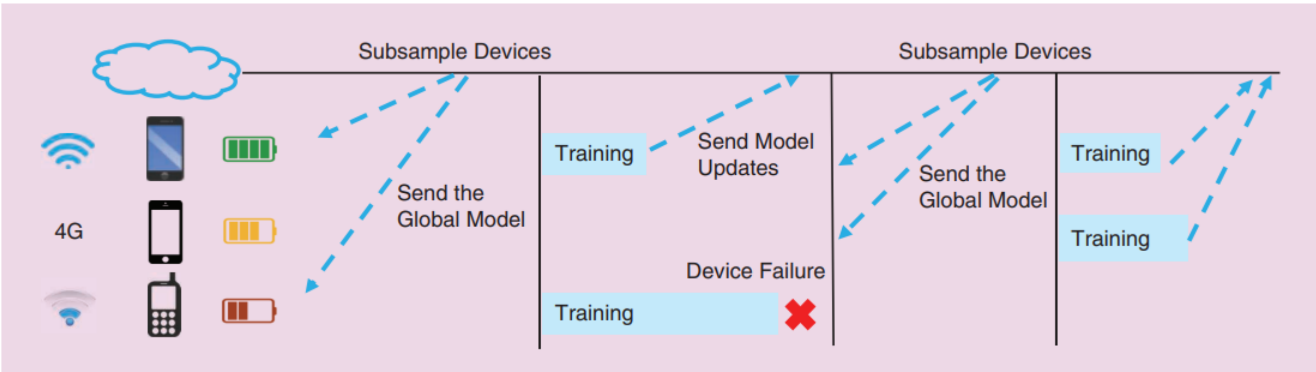

Figure 3.13: FL approach architecture[6]

3.5.1 Preparing the federated datasets

In this step, we divided the original dataset into different subsets, each one assigned to a distinct center. These federated datasets were obtained through a random selection process to reflect the actual diversity and distribution of data across healthcare centers. We assume 10 centers with 10 distinct datasets, where data are private and confidential.

3.5.2 Integration of Pretrained Model

Since we selected ResNet-50 as the best-performing model, we integrated it into our federated approach. We adapted the model to the federated process, including modifications to enable communication between the central server and clients. Additionally, the pretrained model's architecture contributes to adjusting the flow to suit the federated learning setup. This integration ensures that the model can effectively leverage distributed data sources for collaborative training.

3.5.3 Process of federated learning

The federated learning approach is performed on multiple rounds where each round has 4 steps:

- Model diffusion: The model and its configuration are sent to each center.
- Local learning: Each center then trains locally the model on its available private dataset.
- Sending updates and aggregation: the server receives the results of each training process and performs weighted aggregation to update the global model.
- New round with new model update: The global model is sent back to each device to start a new round.

3.5.4 Evaluation and challenges of Federated Learning

In this section, we present the obtained results from federated learning experiments and compare them with centralized training results. Furthermore, we noticed that the training process using the federated process is much slower than the centralized approach and it needs more rounds to achieve convergence although it results in the same results. In Figure 3.14, we focus on the results of the training process given with the federated approach.

```
Round 16: OrderedDict([('distributor', ()), ('client_work', OrderedDict([('train', OrderedDict([('sparse_categorical_accurac
y', 0.5062987), ('loss', 1.207005), ('num_examples', 80016), ('num_batches', 2502)]))])), ('aggregator', OrderedDict([('mean_v
alue', ()), ('mean_weight', ())])), ('finalizer', OrderedDict([('update_non_finite', 0)]))])
Found 44453 files belonging to 5 classes.
Using 26672 files for training.
Found 44453 files belonging to 5 classes.
Using 26672 files for training.
Found 44453 files belonging to 5 classes.
Using 26672 files for training.
Round 17: OrderedDict([('distributor', ()), ('client_work', OrderedDict([('train', OrderedDict([('sparse_categorical_accurac
y', 0.51583433), ('loss', 1.1880139), ('num_examples', 80016), ('num_batches', 2502)]))])), ('aggregator', OrderedDict([('mean
_value', ()), ('mean_weight', ())])), ('finalizer', OrderedDict([('update_non_finite', 0)]))])
Found 44453 files belonging to 5 classes.
Using 26672 files for training.
Found 44453 files belonging to 5 classes.
Using 26672 files for training.
Found 44453 files belonging to 5 classes.
Using 26672 files for training.
Round 18: OrderedDict([('distributor', ()), ('client_work', OrderedDict([('train', OrderedDict([('sparse_categorical_accurac
y', 0.5284818), ('loss', 1.1603318), ('num_examples', 80016), ('num_batches', 2502)]))])), ('aggregator', OrderedDict([('mean_
value', ()), ('mean_weight', ())])), ('finalizer', OrderedDict([('update_non_finite', 0)]))])
Found 44453 files belonging to 5 classes.
Using 26672 files for training.
Found 44453 files belonging to 5 classes.
Using 26672 files for training.
Found 44453 files belonging to 5 classes.
Using 26672 files for training.
```

Figure 3.14: Federated learning training results

Finally, we discussed the rounds' number chosen for the training. We have chosen to perform 20 rounds for the beginning. It would be more efficient to add many other rounds for the model to converge and give better accuracy scores. The necessary rounds for the federated training process is between 200 and 300 rounds.

3.6 Conclusion

To conclude, in this chapter we covered the proposed approach to detect diabetic retinopathy using convolutional neural networks and the tensorflow federated framework. We have explored the dataset, tried different image preprocessing techniques, and utilized pretrained models like VGG19, VGG16, and ResNet50 to get accurate results. Then, we Integrating the most-performing model into a federated learning process, we conducted collaborative training across multiple clients. Finally, our study has focused on the potential of federated learning in healthcare, offering improved model performance while keeping the data private.

General Conclusion

In conclusion, in this study, we provided a comprehensive overview of centralized, decentralized, and federated learning. Specifically, we focused on the application of these techniques to detect diabetic retinopathy. Also, we have explored various machine learning algorithms that can be used to analyze huge datasets and extract useful information.

The FL approach is important in the healthcare field to ensure data confidentiality and preservation without sharing, particularly in tasks such as diabetic retinopathy detection. Training a machine learning model for such tasks requires diverse datasets to achieve high precision. However, aggregating medical data in a single center is not possible due to privacy concerns.

In our work, we proposed a distributed learning approach across multiple healthcare centers to address this challenge. We simulated this distribution by splitting a dataset among 10 centers and studied the model's performance through multiple rounds of training. The simulation results are promising, ensuring the privacy of sensitive data. However, we suggest further investigation into the influence of the number of centers on accuracy, as well as the optimal number of training rounds required for excellent precision, among other factors.

Finally, we would like to emphasize that this study is just a starting point for anyone looking to explore the vast and exciting world of machine learning and its applications in the medical field.

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