A Federated Learning Approach to Accurate Ear Disease Diagnosis with Data Privacy

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled "A Federated Learning Approach to Accurate Ear Disease Diagnosis with Data Privacy", submitted by Md Salim Reza Joy to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 15-07-2024.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Dr. Md Zahid Hasan, Associate Professor, Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Ear diseases, particularly those affecting the tympanic membrane, pose a significant global health challenge, often leading to hearing loss. Traditional diagnostic methods struggle to balance accuracy with patient privacy concerns. This study introduces OtoFL, a federated learning framework, and Fenet5, a deep learning model, to revolutionize ear disease diagnosis. By leveraging diverse ear imaging datasets including “Ear Imagery Dataset” and “Eardrum Dataset”, our approach simulates real-world collaboration while ensuring patient privacy through differential privacy techniques. Fenet5, a five-block deep convolutional neural network, excels in feature extraction and classification, achieving a remarkable accuracy of 95.13%, precision of 0.96%, recall of 0.90%, and F1 score of 0.92% in diagnosing various ear diseases, even with imbalanced data in an FL environment. Notably, Fenet5 outperforms other state-of-the-art models like DenseNet201, MobileNetV2, and EfficientNetB0, demonstrating superior precision, recall, and F1 scores across different disease classes. Our federated learning approach, using FedProx and the proposed OtoFL, further enhances accuracy and privacy compared to FedAvg and FedSGD. OtoFL's scalability and adaptability are validated through experiments with varying client numbers and communication rounds, showcasing its potential to transform ear disease diagnosis globally.

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LIST OF ACRONYMS

ML	Machine Learning
FL	Federated Learning
OtoFL	Otology and Federated Learning

CHAPTER 1
INTRODUCTION

1.1 Overview

People of all ages are afflicted by ear disorders, a common health problem that significantly impairs quality of life and causes considerable morbidity. Approximately 700 million people will need rehabilitative services by 2050, according to the World Health Organization (WHO), and 2.5 billion people will have some form of hearing loss as depicted in figure 1.1.1. Component of the ear anatomy that is essential to sound transmission and infection defense is the tympanic membrane, also referred to as the eardrum. Otitis media, tympanic membrane perforations, and earwax accumulation are among the conditions that affect the tympanic membrane and should be taken very seriously because they can lead to hearing loss and difficulties communicating as a result.

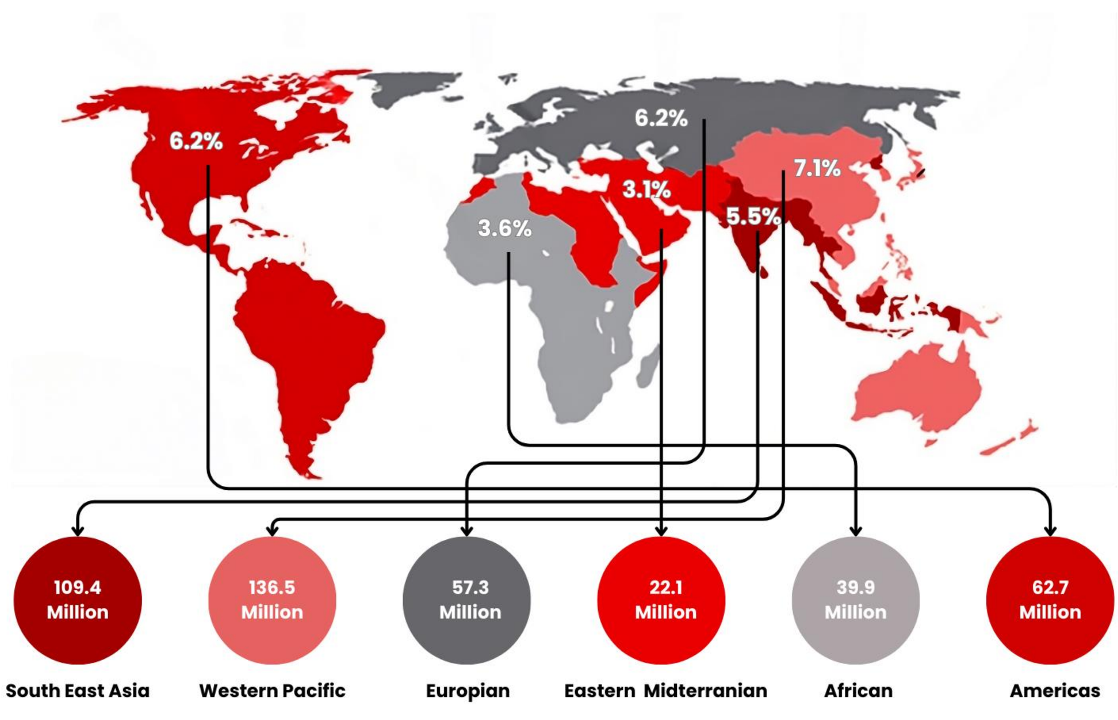

Figure 1.1.1: Global prevalence of ear diseases and projected rehabilitation needs.

The diagnosis of ear problems is usually done by imaging modalities such as tympanometry and otoscopy, as well as clinical tests. These techniques work well, but they have drawbacks as well. For example, they require certain tools and skilled workers, and the accuracy of the diagnosis varies. An further difficulty is the rising demand for healthcare services, which is especially problematic in settings with limited resources and restricted access to specialized treatment.

Prospective answers to these problems can be found in the latest developments in digital health technologies. Artificial intelligence (AI) has transformed many facets of healthcare by being included into medical diagnostics, offering instruments for early detection, precise diagnosis, and customized treatment regimens. AI-powered diagnostic models—especially those that make use of deep learning algorithms—have shown impressive results in the analysis of medical pictures and the accurate diagnosis of pathological disorders.

However, there are many obstacles in the way of developing and using AI models in the healthcare industry, most of which have to do with data security and privacy. Medical data are very sensitive and governed by tight laws, particularly patient health information. It is crucial to investigate alternate strategies that maintain data security while utilizing the advantages of AI, as centralized data collecting for AI model training presents serious privacy concerns.

Federated Learning (FL) is a novel way to deal with these issues. Without transferring data, FL allows machine learning models to be trained on several decentralized devices or servers that store local data samples. By using this method, healthcare facilities can work together to create strong AI models while maintaining patient data on local servers, protecting privacy and adhering to data protection laws.

When it comes to diagnosing ear diseases, FL presents a singular chance to leverage the pooled expertise and information from different medical facilities. FL improves the generalizability and robustness of diagnostic tools by training models on a variety of datasets from various geographic locations. This cooperative strategy promotes thorough research and innovation in the field of otology while simultaneously addressing the problem of data scarcity at individual institutions and increasing diagnostic accuracy.

The necessity to provide an efficient, privacy-preserving ear disease diagnostic tool is the driving force behind this research. Our objective is to develop a system that can offer dependable and precise diagnostics while maintaining patient data confidentiality by utilizing the principles of FL and deep learning capabilities. In this work, we provide OtoFL, a federated learning framework specifically made for diagnosing ear diseases, together with Fenet5, a deep learning model specifically made for this use. By providing a scalable, privacy-preserving solution that healthcare practitioners around the world may use, our research aims to make a significant contribution to the field of digital health.

To summarize, the study's background and purpose stem from the worldwide prevalence of ear disorders, the constraints of conventional diagnostic techniques, and the possibility of federated learning to transform the field of medical diagnosis. This study intends to improve patient outcomes and quality of life by utilizing AI to overcome data privacy challenges and improve accessibility and accuracy in diagnosing ear diseases.

1.2 Background and Present State

To enhance patient outcomes, a number of issues pertaining to the precise and efficient diagnosis of ear illnesses must be resolved. The intricacy of ear illnesses, resource limitations, data privacy, and diagnostic variability can all be used to group these difficulties.

Diagnostic Variability

The disparity in diagnosis methods among medical practitioners is one of the main obstacles to diagnosing ear diseases. Many symptoms are present in ear illnesses, making misdiagnosis of conditions like myringosclerosis, chronic otitis media (COM), and acute otitis media (AOM) easy. For example, AOM is distinguished by sudden onset of ear pain, fever, and sometimes fluid flow shown in table 1.2.2, while COM is characterized by chronic inflammation shown in figure 1.2.1 that may result in tympanic membrane rupture. Accurate diagnosis is challenging in the absence of sophisticated diagnostic techniques due to the overlap of symptoms between various illnesses.

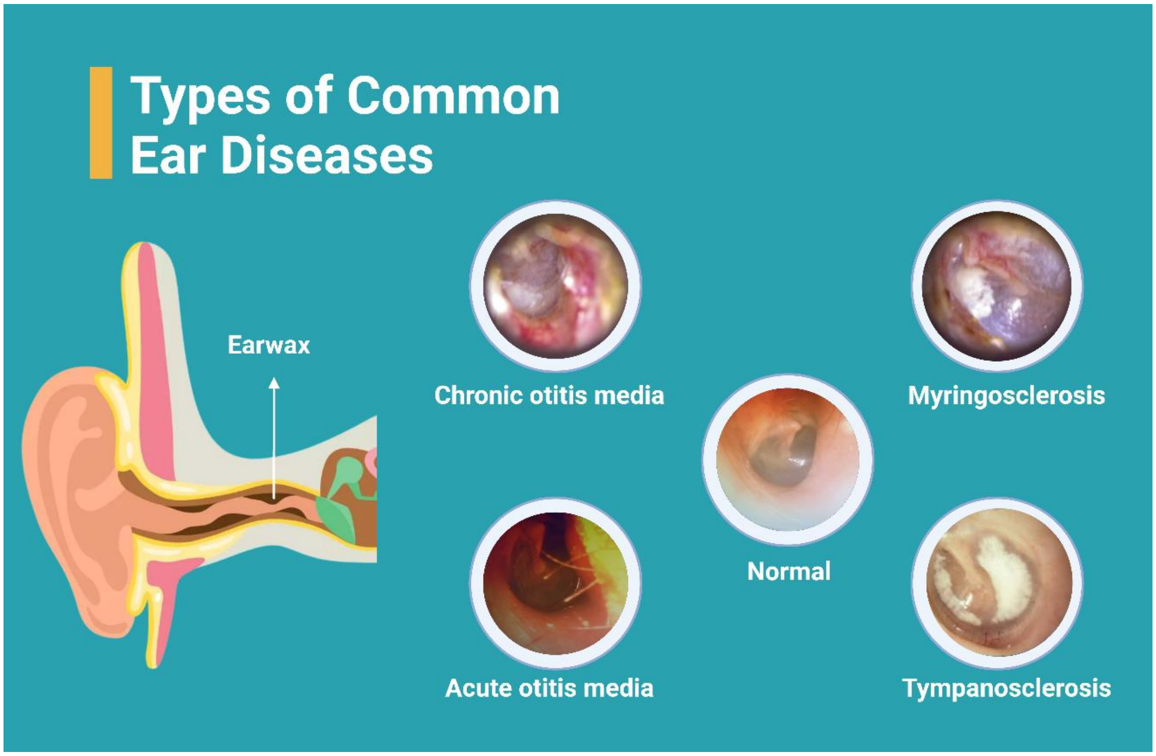

Figure 1.2.1: Different types of ear diseases affecting the tympanic membrane.

Inconsistent diagnoses may result from the subjectivity of clinical evaluations, particularly in the lack of established diagnostic procedures. This discrepancy is even worse in environments with limited resources when access to specialist training and tools is constrained. Therefore, in order to decrease variability and increase diagnosis accuracy, there is an urgent need for diagnostic models that can offer impartial and standardized evaluations.

TABLE 1.2.2: Types of Ear Diseases, Symptoms and Charachteristics

Disease	**Disease Type**	**Symptoms**	**Characteristics**
Acute Otitis Media	Middle Ear Infection	Hearing loss, fluid outflow from the ear, ear discomfort, fever, and agitation	Swift beginning, frequently after erythema, tympanic membrane bulging, middle ear effusion, and upper respiratory infection

Chronic Otitis Media	Persistent Ear Infection	Hearing loss, ear fullness, tinnitus, and occasionally pain persistent ear discharge (otorrhea)	A cholesteatoma, or abnormal skin growth, may be involved in long-lasting inflammation and tympanic membrane perforation.
Earwax	Cerumen Impaction	Tinnitus, vertigo, ear pain, hearing loss, and fullness in the ears	The buildup of cerumen within the ear canal can be either dry and hard or soft and flaky.
Myringosclerosis	Tympanic Membrane Scarring	Loss of hearing, typically without any pain, although occasionally tinnitus	The tympanic membrane may become immobile due to white, calcified areas that are the result of recurrent infections or damage.
Normal Ear	Healthy Ear	No symptoms	Normal middle ear and ear canal, intact tympanic membrane, absence of fluid or inflammation, and normal hearing

Data Privacy Concerns

Serious privacy problems are raised by the gathering and use of medical data to create diagnostic models. In order to abide by laws like the General Data Protection Regulation (GDPR) in Europe and the Health Insurance Portability and Accountability Act (HIPAA) in the United States, sensitive information included in patient health records must be protected [1]. The risk of data breaches and unauthorized access is increased by centralized data gathering approaches, which combine data from several sources to train machine learning models.

These issues are resolved by federated learning (FL), which makes decentralized model training possible. In FL, only model updates are communicated with a central server instead of raw data, which is kept on local devices. Patient information is kept secure and private thanks to this method, which reduces the risks related to data centralization.

Resource Constraints

A major obstacle to accurately diagnosing ear diseases is a lack of resources, especially in low- and middle-income nations. Many times, these areas lack the facilities, tools, and skilled workers needed to carry out exhaustive diagnostic examinations. Because many patients lack early and appropriate diagnosis due to limited access to otolaryngologists and audiologists, diseases may go untreated and complications may arise.

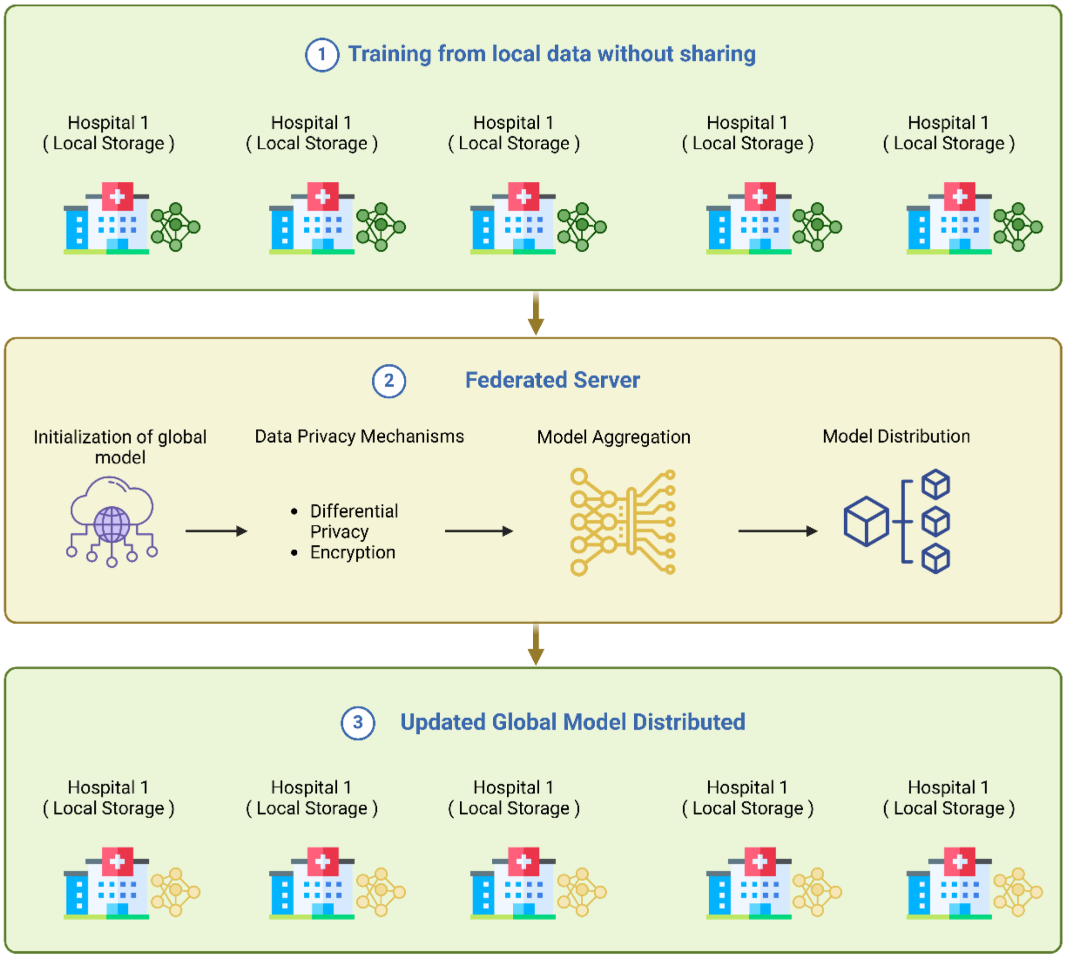

Figure 1.2.3: The OtoFL framework for federated learning in otology.

This gap can be filled by using artificial intelligence (AI) to power advanced diagnostic systems that provide accurate assessments without requiring a lot of resources. Though scalable solutions that can be used in various healthcare settings are necessary, the creation of such tools must take technological accessibility into account.

Complexity of Ear Diseases

Accurate diagnosis is made much more difficult by the complexity of ear disorders. The pathophysiological mechanisms behind conditions like cholesteatoma, otosclerosis, and otitis media are complex and can be challenging to identify. Moreover, patient demographics such as age, genetic predispositions, and environmental factors can greatly influence how ear illnesses appear.

It is necessary to use big, diverse datasets that capture the variety of presentations found in clinical practice in order to develop diagnostic models that can account for this complexity. By allowing cooperative data sharing between institutions while protecting patient privacy, federated learning makes it easier to create these kinds of datasets.

To sum up, the difficulties in diagnosing ear ailments are caused by a variety of factors, including the complexity of ear diseases themselves, data privacy issues, limitation of resources, and diagnostic variability. It will need creative methods to overcome these obstacles, like Federated Learning and sophisticated AI models, to deliver diagnostic solutions that are reliable, consistent, and private-preserving. We can greatly enhance patient care and health outcomes by addressing these challenges and improving the diagnosis and treatment of ear disorders.

1.3 Problem Statement

The fact that many studies rely on comparatively small and homogeneous datasets is one noteworthy finding. This restriction raises questions about how well the created models can be applied to a range of clinical situations and patient populations. Large-scale, diversified datasets are needed in order to train models that can correctly detect ear illnesses in a variety of populations with varying demographics, ethnicities, and disease presentations.

The security and privacy issues around centralized data collection present another difficulty as shown in figure 1.3.1. Although large volumes of data are needed for deep learning models to be trained, gathering private patient information in one place increases the danger of data breaches and illegal access. This makes it necessary to investigate alternate strategies that can harness deep learning's capabilities while protecting patient privacy.

Moreover, the problem of class imbalance—the underrepresentation of specific ear diseases in datasets—remains a difficulty. This disparity may result in skewed models that are not very good at detecting uncommon or uncommon ear conditions. Specialized methods, like weighted loss functions or data augmentation, are needed to address class imbalance and make sure that models benefit from learning from all classes.

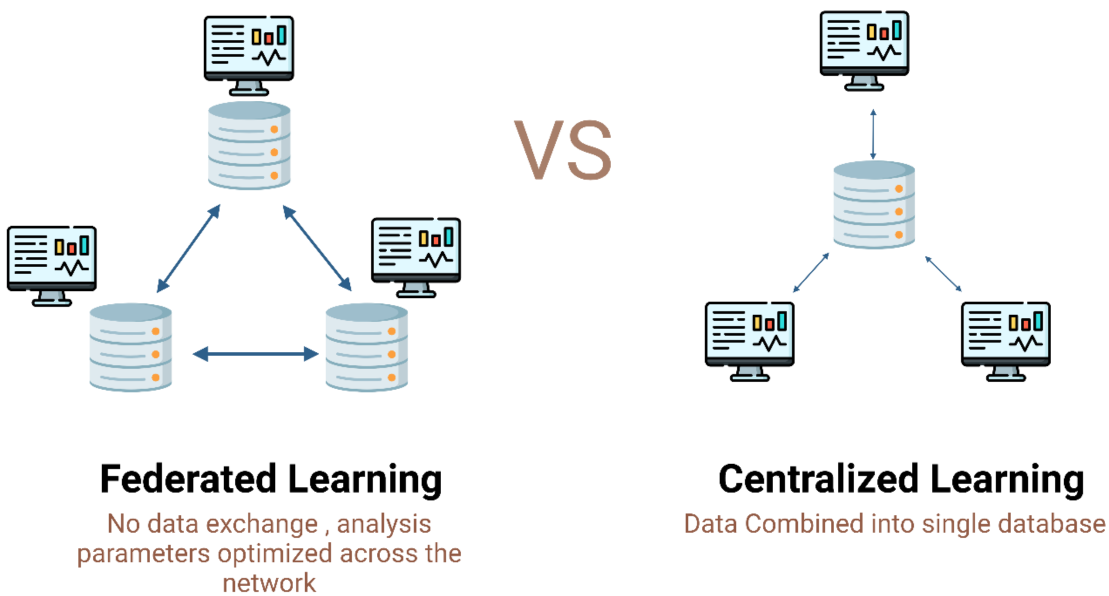

Figure 1.3.1 Federated Learning vs Centralized Learning

An encouraging approach to overcoming these difficulties is the use of federated learning (FL) into the diagnosis of ear diseases. FL addresses privacy concerns and facilitates the use of different datasets by enabling collaborative model training across various institutions without requiring the sharing of raw patient data. FL does, however, come with a unique set of difficulties, including the requirement for strong privacy-preserving measures, communication cost, and heterogeneous data.

1.4 Objectives

This research is driven by the urgent need to treat the worldwide epidemic of ear illnesses, which impede millions of livelihoods by impairing hearing and posing related communication issues. Conventional diagnostic techniques, while somewhat successful, are impeded by variations in clinical evaluations, restricted availability of specialist medical treatment, and noteworthy issues over data privacy. A possible way around these constraints is provided by the development of medical technologies, especially those that combine deep learning and artificial intelligence (AI). But developing strong AI models requires centralized data collecting, which presents serious privacy and security risks and could expose private patient data to breaches. Federated Learning (FL) presents itself as a novel way out of this conundrum, allowing AI models to be developed without centralized data gathering.

FL conforms to strict data protection standards and protects patient privacy by enabling institutions to train models jointly on locally stored data. The potential of FL to create a scalable, privacy-preserving diagnostic tool that utilizes a variety of datasets from many institutions is what drives this research. FL has the potential to change the detection of ear diseases. To provide precise, consistent, and easily available diagnostic evaluations for ear disorders, the development of OtoFL, a federated learning framework, and Fenet5, a customized deep learning model, is underway. This innovation fosters collaborative research among medical professionals and improves diagnostic accuracy while also making resource optimization easier. By solving the present difficulties in ear disease diagnosis with cutting-edge, safe, and effective technology solutions, the ultimate goal is to enhance patient outcomes and quality of life.

The goals of this project are multifaceted: using Federated Learning (FL) to diagnose ear diseases, theoretical advances as well as real-world applications are anticipated summarized in figure 1.4.1. The principal expected results consist of:

- **Development of OtoFL Framework:**

With a focus on ear illness diagnostics, the project attempts to create OtoFL as depicted in figure 1.2.3, a federated learning framework that is both scalable and reliable. This approach will protect patient privacy while enabling the safe, autonomous generation of diagnostic algorithms with data from several institutions.

- **Creation of Fenet5 Diagnostic Model:**

Fenet5, a deep learning framework tailored to diagnose various ear disorders, will be created as a result of the study. Using a variety of datasets, Fenet5 is going to be trained on the OtoFL framework to improve its diagnostic precision and generalizability.

- **Enhanced Diagnostic Accuracy:**

Comparing FL to centralized AI models and conventional approaches, it is anticipated that diagnostic models with greater accuracy and dependability will be produced. For use in various healthcare settings, these models will offer uniform and consistent diagnostic evaluations.

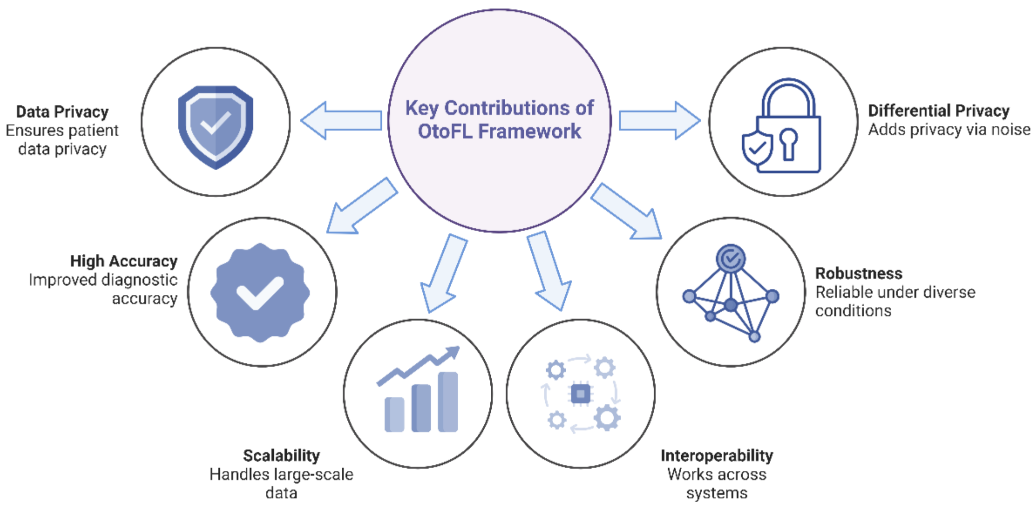

Figure 1.4.1: Summary of key contributions and innovations in the study.

- **Improved Data Privacy and Security:**

One of the main results is the illustration of how using FL might improve data security and privacy. This study aims to demonstrate how FL approaches, such differential privacy and local data processing, allow for collaborative model training while maintaining patient privacy.

- **Resource Optimization Insights:**

Significant insights into the requirements for resources and optimization techniques for applying FL in many healthcare settings will be gained from this research. This involves examining the scalability across various geographies, financial implications, and requirements for computational infrastructure.

- **Framework for Collaborative Research:**

Healthcare institutions will be able to share resources and knowledge while maintaining data privacy thanks to the study's establishment of an structure for collaborative research. Large-scale research and ongoing diagnostic model development will be made easier by this approach.

- **Comparative Performance Analysis:**

There will be a thorough comparison of the effectiveness of centralized AI models, conventional diagnostic techniques, and FL-based models. This analysis aims to illustrate the benefits and possible drawbacks of FL in the diagnosis of ear diseases.

- **Guidelines for FL Implementation:**

The project will result in best practices and useful guidance for using FL in healthcare diagnostics. These recommendations will address technical, moral, and legal issues and offer a path forward for legislators and healthcare professionals.

- **Publication of Findings:**

The study's conclusions will be shared at conferences, workshops, and academic journals. This will guarantee that the research's findings are disseminated to larger scientific and medical communities, encouraging more advancement and innovation.

The necessity to provide an efficient, privacy-preserving ear disease diagnostic tool is the driving force behind this research. Our objective is to develop a system that can offer dependable and precise diagnostics while maintaining patient data confidentiality by utilizing the principles of FL and deep learning capabilities. In this work, we provide OtoFL, a federated learning framework specifically made for diagnosing ear diseases, together with Fenet5, a deep learning model specifically made for this use. By providing a scalable, privacy-preserving solution that healthcare practitioners around the world may use, our research aims to make a significant contribution to the field of digital health.

1.5 Scope and Limitations

Challenges in Ear Disease Diagnosis

To enhance patient outcomes, a number of issues pertaining to the precise and efficient diagnosis of ear illnesses must be resolved. The intricacy of ear illnesses, resource limitations, data privacy, and diagnostic variability can all be used to group these difficulties.

Diagnostic Variability

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Inconsistent diagnoses may result from the subjectivity of clinical evaluations, particularly in the lack of established diagnostic procedures. This discrepancy is even worse in environments with limited resources when access to specialist training and tools is constrained. Therefore, in order to decrease variability and increase diagnosis accuracy, there is an urgent need for diagnostic models that can offer impartial and standardized evaluations.

Data Privacy Concerns

Serious privacy problems are raised by the gathering and use of medical data to create diagnostic models. In order to abide by laws like the General Data Protection Regulation (GDPR) in Europe and the Health Insurance Portability and Accountability Act (HIPAA) in the United States, sensitive information included in patient health records must be protected. The risk of data breaches and unauthorized access is increased by centralized data gathering approaches, which combine data from several sources to train machine learning models.

These issues are resolved by federated learning (FL), which makes decentralized model training possible. In FL, only model updates are communicated with a central server instead of raw data, which is kept on local devices. Patient information is kept secure and private thanks to this method, which reduces the risks related to data centralization.

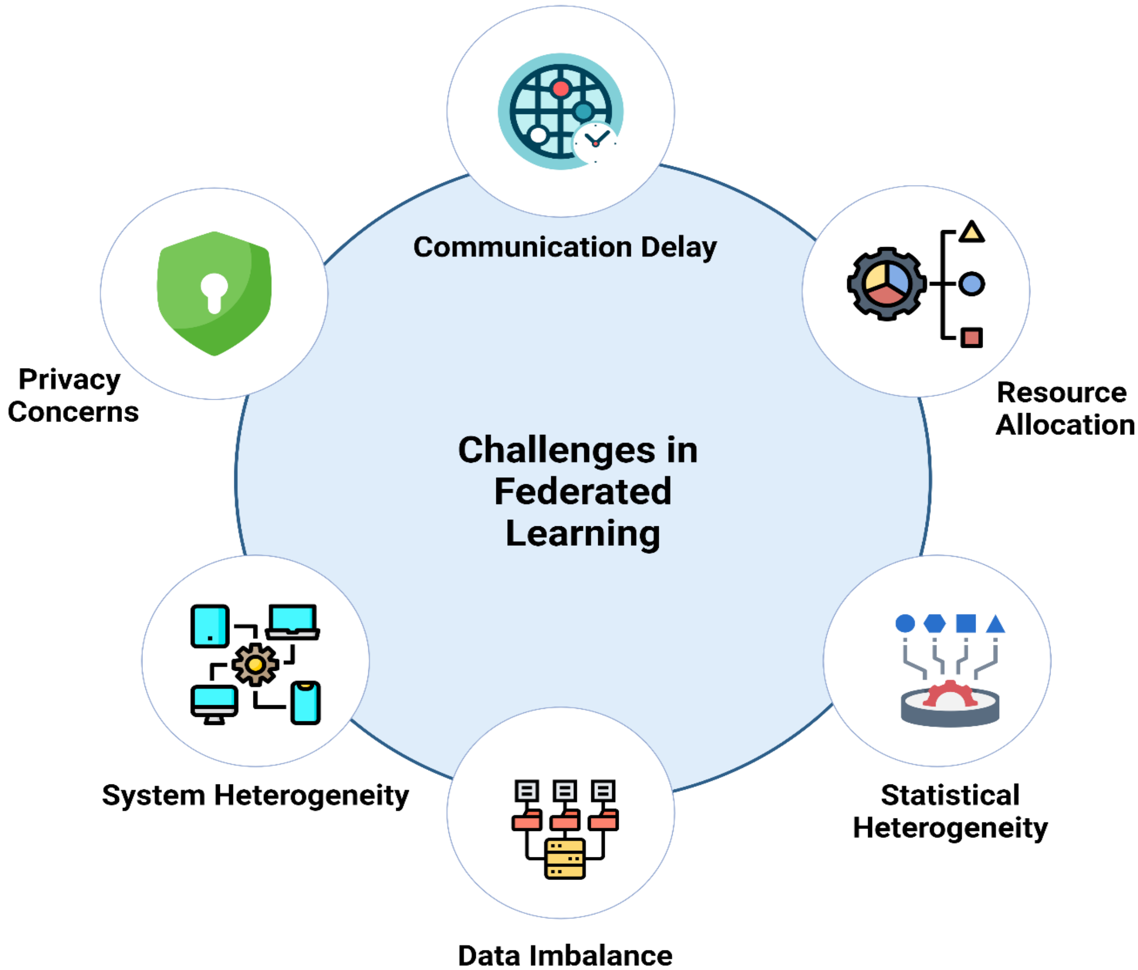

Figure 1.5.1: Key challenges in implementing Federated Learning for medical diagnostics.

Resource Constraints

A major obstacle to accurately diagnosing ear diseases is a lack of resources, especially in low- and middle-income nations. Many times, these areas lack the facilities, tools, and skilled workers needed to carry out exhaustive diagnostic examinations. Because many patients lack early and appropriate diagnosis due to limited access to otolaryngologists and audiologists, diseases may go untreated and complications may arise.

This gap can be filled by using artificial intelligence (AI) to power advanced diagnostic systems that provide accurate assessments without requiring a lot of resources. Though scalable solutions that can be used in various healthcare settings are necessary, the creation of such tools must take technological accessibility into account.

Complexity of Ear Diseases

Accurate diagnosis is made much more difficult by the complexity of ear disorders. The pathophysiological mechanisms behind conditions like cholesteatoma, otosclerosis, and otitis media are complex and can be challenging to identify. Moreover, patient demographics such as age, genetic predispositions, and environmental factors can greatly influence how ear illnesses appear.

It is necessary to use big, diverse datasets that capture the variety of presentations found in clinical practice in order to develop diagnostic models that can account for this complexity. By allowing cooperative data sharing between institutions while protecting patient privacy, federated learning makes it easier to create these kinds of datasets.

To sum up, the difficulties in diagnosing ear ailments are caused by a variety of factors, including the complexity of ear diseases themselves, data privacy issues, limitation of resources, and diagnostic variability. It will need creative methods to overcome these obstacles, like Federated Learning and sophisticated AI models, to deliver diagnostic solutions that are reliable, consistent, and private-preserving. We can greatly enhance patient care and health outcomes by addressing these challenges and improving the diagnosis and treatment of ear disorders.

Potential and Challenges of Federated Learning in Ear Disease Diagnosis

Enhancing Diagnostic Accuracy

The development of more precise and dependable diagnostic models is made possible by Federated Learning (FL), which holds the potential to completely transform the detection of ear diseases. Utilizing a variety of datasets that span a broad range of ear disease presentations, FL aggregates model updates from several universities. The presence of diversity in the diagnostic models improves their generalizability, making them more effective in a range of clinical situations and populations.

Healthcare professionals can contribute to and profit from communal knowledge without jeopardizing patient data privacy thanks to FL's collaborative nature. Because different institutions can communicate updates and insights based on their own patient data, this strategy promotes ongoing diagnostic model improvement. The final models are reliable, accurate, and able to offer uniform diagnostic evaluations that lessen variation in clinical practice.

Addressing Privacy and Security Concerns

Patient data must be protected in order to comply with strict standards, making data privacy and security crucial in the medical diagnostics industry. To mitigate these issues, FL shares only encrypted model updates with a central aggregator, retaining patient data on local servers. With a decentralized method, there is no chance of a compromise involving centralized data storage, protecting confidential health records.

Additionally, FL protects patient information by incorporating differential privacy measures that introduce noise into the data. By ensuring that the contributions of any one data point are indistinguishable, this technique protects patient privacy while preserving the accuracy of the model-training procedure.

Facilitating Resource Optimization

A key advantage of using FL in the diagnosis of ear diseases is resource optimization. FL allows the implementation of AI-powered diagnostic tools that may deliver high-quality assessments without requiring a large infrastructure in areas with restricted access to professional healthcare services. FL develops diagnostic tools that are scalable and adjustable to different healthcare systems by training models on data from diverse institutions.

These resources can help primary care physicians diagnose patients correctly, which will lessen the demand on specialized services and ensure that patients receive treatment on time. This is especially helpful in low-resource environments where audiologists and otolaryngologists are few.

Challenges of Federated Learning

FL has a lot of potential, but there are a few issues that need to be resolved before all of its advantages can be realized. These issues include:

Communication Overhead: Due to its decentralized architecture, FL necessitates regular communication for model updates between local nodes and the web server. Overuse of bandwidth during this communication might result in latency and higher expenses, particularly when working with huge datasets and complicated models.

Heterogeneity of Data: The distribution, quantity, and quality of data might range dramatically throughout institutions. Developing a diagnostic tool that is universally successful is difficult due to this variability, which might impact the federated model's performance and convergence.

Model Aggregation: It is difficult to maintain accuracy and performance when aggregating model updates from several sources. There is ongoing research into methods for efficiently combining these updates without jeopardizing the integrity of the model.

Security Risks: FL is not completely impervious to security concerns, even though it improves privacy by keeping data local. Model poisoning attacks and inference attacks, which aim to retrieve sensitive data from the model, are examples of potential vulnerabilities. Model poisoning attacks involve the possibility of malevolent entities compromising the model updates.

Resource Requirements: Adequate infrastructure and computational power are needed at each cooperating institution to implement FL. This need could prevent FL from being widely adopted in environments with limited resources.

Promoting Collaborative Research

FL encourages healthcare organizations to conduct collaborative research, allowing information and resources to be shared without jeopardizing patient privacy. The creation of comprehensive diagnostic frameworks that serve the medical community as a whole is facilitated by this collaborative framework, which promotes institutions to take part in large-scale studies.

Through encouraging cooperation, FL contributes to the dismantling of research silos in medicine, resulting in more inclusive and holistic methods of illness diagnosis and treatment. The development of sophisticated diagnostic instruments that can handle difficult medical problems is sped up by this team effort, which fosters innovation.

The history and rationale for this study emphasize the importance of ear disorders to the health of the world as well as the difficulties in detecting them. Although successful, traditional diagnostic techniques have difficulty striking a compromise between resource limits, data privacy, and accuracy. A potential remedy is federated learning, which provides a decentralized method of training models that improves diagnostic precision, safeguards patient confidentiality, maximizes available resources, and encourages cooperative research. The drawbacks of FL, including as communication overhead, data heterogeneity, complicated model aggregation, security threats, and resource requirements, must be recognized and addressed.

In this paper, two new tools are presented: Fenet5, a deep learning model for diagnosing ear diseases, and OtoFL, a federated learning framework. Our goal is to create a diagnostic tool that is both scalable and privacy-preserving, which can be embraced by healthcare professionals globally, by utilizing the principles of FL and the capabilities of AI. To enhance patient outcomes and quality of life, the ultimate goal is to better detect and manage ear disorders.

1.6 Report layout

With great care, the study presents a thorough and methodical investigation of the

Federated Learning framework, or OtoFL, which was created for the purpose of identifying ear infections. Clarity and coherence are guaranteed by the framework, which makes it easier to navigate through the text.

Chapter 1: Introduction

A general summary of the project is given in the introductory chapter, which also establishes the goals, issue description, and context. This part serves as a foundation, setting the stage for the in-depth analysis that follows. It describes the goals behind the project, the precise targets that are expected to be met, the project's scope, and the expected results.

Chapter 2: Literature Review

In order to better understand federated learning and the detection of ear diseases, this chapter explores current research and methodology. It looks closely at the technology of today, pointing out their shortcomings and how OtoFL fills in the gaps. Reviewing important developments and underlying ideas that guide the evolution of OtoFL, it offers a thorough historical overview.

Chapter 3: Methodology/Requirement Analysis & Design Specification

The OtoFL framework's technological approach is described in the methodology chapter. The document provides information on the model architecture, data pretreatment methods, and federated learning algorithms. This section is essential to comprehending the project's technical foundation and the methodical strategy used to accomplish its goals.

Chapter 4: Implementation

This chapter focuses on the practical implementation of the OtoFL framework. It details the training of the deep learning model, Fenet5, using the federated learning approach. The chapter also covers the design and development of the prototype system, ensuring its functionality and adherence to the project's requirements. Additionally, it addresses system testing and model evaluation, providing insights into the performance and effectiveness of the implemented solution.

Chapter 5: Result and Analysis

Here, the report showcases the findings from a range of tests done to assess OtoFL's functionality. Comparisons with conventional centralized models are included, emphasizing the gains in privacy protection and diagnostic precision. The facts will be presented succinctly and simply through the heavy use of graphs and tables.

Chapter 6: Impact on Society, Environment, and Sustainability

The wider ramifications of the OtoFL paradigm on society—particularly in the field of healthcare—are examined in this chapter. It talks about how better patient outcomes and confidence in artificial intelligence for medicine can be achieved through enhanced diagnostic precision and information privacy. Additionally included are the possible drawbacks, ethical issues, and societal advantages.

Chapter 7: Conclusion and Future Work

The research's main conclusions are succinctly summarized in the last chapter. It explores the consequences for future studies in medical diagnostics and federated learning and makes recommendations according to the findings. This chapter provides a summary of the full study and recommendations for future directions.

The structure of the report is to give a clear and thorough explanation of the research done, guaranteeing that every facet of the project is carefully looked over and comprehended. The report's methodical methodology attempts to lead the audience through the whole study process—from the initial goals and motives to the final results and suggestions for more work.

1.7 Summary

The necessity to solve a number of significant shortcomings and difficulties in the current method of diagnosing ear diseases forms the basis of this study's justification. Inaccurate diagnosis and delayed treatment can result in significant hearing losses from common ear disorders such otitis media, tympanic membrane perforations, and earwax buildup. Conventional diagnostic methods are limited by the availability of specialized equipment and experienced staff, especially in resource-constrained contexts, and frequently suffer from variability in diagnostic accuracy. Traditional diagnostic methods mainly rely on clinical examinations and imaging techniques.

By offering objective evaluations and spotting trends that human examiners might overlook, artificial intelligence (AI) as well as deep learning have demonstrated considerable potential in improving diagnosis accuracy. Significant worries about data security and privacy, however, are impeding the use of artificial intelligence in medical diagnosis. The typical practice of centralizing data collecting for AI model training comes with significant concerns of security breaches and illegal access to private patient data. Given how important patient confidentiality is, this presents a significant obstacle to the broad use of AI in healthcare.

Federated Learning (FL), which permits the dispersed training of AI models, offers a fresh remedy to these problems. The only information shared with a central server in FL is model updates; patient data is kept on local servers. This methodology not only addresses privacy and security concerns but also conforms to strict data protection laws like GDPR and HIPAA. Through the utilization of FL's decentralized structure, this research endeavors to create a sophisticated diagnostic instrument that integrates information and expertise from several healthcare establishments, consequently augmenting the resilience and applicability of the diagnostic frameworks.
Additionally, FL promotes cooperation between institutions, removing the requirement for data pooling and enabling the development of extensive and varied datasets. Through collaboration, this strategy tackles the problem of data scarcity, especially within individual institutions, and advances the creation of more precise and trustworthy diagnostic models. It is anticipated that the generated models will enhance patient outcomes, offer standardized evaluations, and lessen diagnostic variability.

A scalable, privacy-preserving diagnostic tool that can be used in a variety of healthcare settings is what motivated the development of OtoFL, a federated learning framework, and Fenet5, a deep learning model especially made for the diagnosis of ear diseases. The goal of this project is to show that FL is a viable and efficient medical diagnostic tool, opening the door for wider uses of this technology in other healthcare domains. The goal of this project is to improve patient care globally and promote digital health technology by addressing the current gaps in the detection of ear diseases and utilizing FL's potential.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

In order to provide a comprehensive comprehension of the principle ideas and research methods utilized in this study on the "Federated Learning framework for diagnosing ear diseases," it is essential to lay the groundwork through introductions and definitions.

Federated Learning (FL): With this machine learning technique, a model is jointly trained by several devices while the data is customized on each device. By preventing the direct sharing of sensitive data between entities, this decentralized approach improves security and privacy.

OtoFL: This refers to the particular framework created in this study for the diagnosis of ear disorders, Otology Federated Learning. Without sending information about patients to a central server, OtoFL uses the principles of federated learning to train predictive algorithms on data from many healthcare facilities.

Otology: The medical specialty that addresses the physiology, anatomy, and disorders of the ear is called otology. From minor ear infections to complicated problems affecting hearing and balance, it covers a broad spectrum of ailments. Imaging methods, audiological evaluations, and clinical tests are frequently used in the diagnosis of ear disorders. In especially in underprivileged areas with limited resources, the combination of artificial intelligence and FL in otology has the possibility of enhancing diagnostic accuracy, speed, and accessibility.

Deep Learning (DL): A branch of machine learning that does various data analyses using multi-layered neural networks (deep neural networks), which are especially useful for audio and picture analysis.

Convolutional Neural Networks (CNNs): An especially good kind of deep learning technique for handling data with a grid-like structure, like pictures. In this work, CNNs are used to assess ear medical images for diagnosis reasons.

Ear Diseases: Diseases of the ear that specifically impact the tympanic membrane (the eardrum). Common ailments like earwax accumulation, tympanic membrane perforations and otitis media can cause severe hearing loss if they are not appropriately identified and treated.

Differential Privacy: A method for protecting the confidentiality of certain data points inside a dataset. In the context of FL, it facilitates cooperative model training while also helping to protect patient data confidentiality.

These terms lay the groundwork for readers to comprehend the sophisticated approaches and procedures used in this research, as well as the in-depth explanations that follow in later parts.

There are many obstacles in the way of developing and using AI models in the healthcare industry, most of which have to do with data security and privacy. Medical data are very sensitive and governed by tight laws, particularly patient health information. It is crucial to investigate alternate strategies that maintain data security while utilizing the advantages of AI, as centralized data collecting for AI model training presents serious privacy concerns.

Federated Learning (FL) is a novel way to deal with these issues. Without transferring data, FL allows machine learning models to be trained on several decentralized devices or servers that store local data samples. By using this method, healthcare facilities can work together to create strong AI models while maintaining patient data on local servers, protecting privacy and adhering to data protection laws.

When it comes to diagnosing ear diseases, FL presents a singular chance to leverage the pooled expertise and information from different medical facilities. FL improves the generalizability and robustness of diagnostic tools by training models on a variety of datasets from various geographic locations. This cooperative strategy promotes thorough research and innovation in the field of otology while simultaneously addressing the problem of data scarcity at individual institutions and increasing diagnostic accuracy.

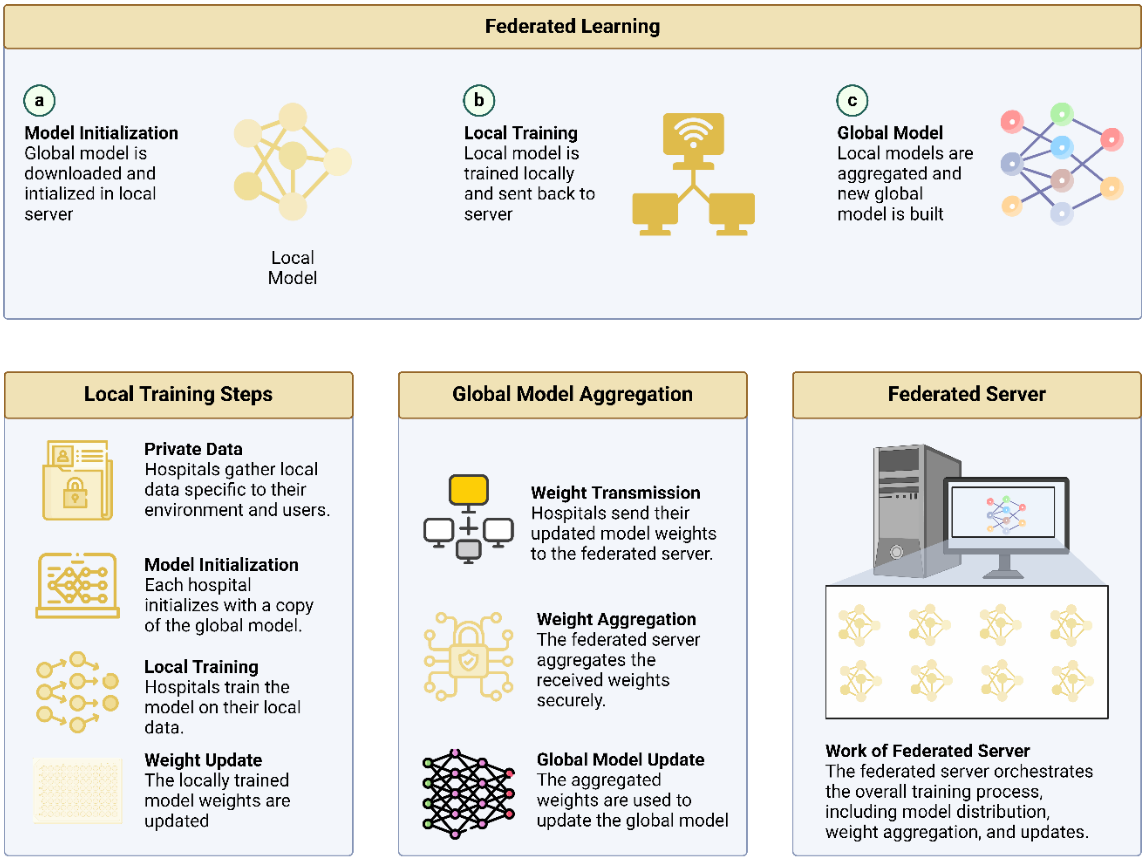

Figure 2.1.1: Overview of the Federated Learning process for medical diagnostics.

The necessity to provide an efficient, privacy-preserving ear disease diagnostic tool is the driving force behind this research. Our objective is to develop a system that can offer dependable and precise diagnostics while maintaining patient data confidentiality by utilizing the principles of FL and deep learning capabilities. In this work, we provide OtoFL, a federated learning framework specifically made for diagnosing ear diseases, together with Fenet5, a deep learning model specifically made for this use as shown in figure 2.1.1. By providing a scalable, privacy-preserving solution that healthcare practitioners around the world may use, our research aims to make a significant contribution to the field of digital health.

While addressing the related issues of confidentiality, accuracy, and resource optimization, the main goal of this project is to investigate the potential of FL (federated learning) in improving the diagnosis of ear disorders. The following research inquiries will serve as the study's compass in order to accomplish this goal:

- **How can Federated Learning be effectively implemented in the context of ear disease diagnosis?**

This inquiry aims to comprehend the practical elements of implementing FL in healthcare environments, including the necessary infrastructure for technology, the procedures for secure information interchange, and the actions to guarantee adherence to data privacy laws.

- **What are the key factors that influence the accuracy and reliability of FL-based diagnostic models for ear diseases?**

Finding the variables that affect FL model performance—like information heterogeneity, model construction, and update frequency—is the goal of this question. To achieve maximum diagnostic accuracy and guarantee consistent performance across various institutions, it is vital to comprehend these elements.

- **How does the use of Federated Learning address privacy and security concerns in medical data management?**

This topic looks at how well FL protects patient data, with particular attention to data privacy features such differential privacy strategies, encrypted transmission, and local data processing. Additionally, it examines possible weaknesses and mitigation techniques.

- **What are the resource implications of implementing FL for ear disease diagnosis in various healthcare settings?**

The resources needed to implement FL in both high- and low-resource environments are evaluated in this inquiry, including computing infrastructure, technological know-how, and financial expenses. Finding out if FL is feasible and scalable in various healthcare settings is the goal.

- **How does the performance of FL-based diagnostic models compare to**

traditional diagnostic methods and centralized AI models?

This inquiry assesses FL-based models' diagnostic efficacy, speed, and accuracy in comparison to centralized AI techniques and current diagnostic procedures. It seeks to offer a thorough comparison that accentuates FL's benefits and possible drawbacks.

Through the investigation of these research topics, the project hopes to offer a comprehensive grasp of Federated Learning's feasibility and advantages for diagnosing ear diseases. The knowledge acquired will help create sophisticated diagnostic instruments that are highly accurate and protect privacy, which will ultimately enhance patient care and results.

To summarize, the study's background and purpose stem from the worldwide prevalence of ear disorders, the constraints of conventional diagnostic techniques, and the possibility of federated learning to transform the field of medical diagnosis. This study intends to improve patient outcomes and quality of life by utilizing AI to overcome data privacy challenges and improve accessibility and accuracy in diagnosing ear diseases.

2.2 Related Works

Ear diseases encompass a wide range of conditions affecting millions globally, with middle ear diseases like acute otitis media (AOM), otitis media with effusion (OME), and chronic otitis media (COM) being major contributors to the global burden of disease [2], [3]. The prevalence of these conditions, often leading to hearing loss, particularly in low and middle-income countries, underscores the urgent need for efficient and accurate diagnostic tools [4].

Early Research in Automated Ear Disease Diagnosis

In recent years, the field of otology has seen a growing interest in leveraging machine learning for automated diagnosis of ear diseases [2]. Early research primarily focused on the automated diagnosis of otitis media (OM) using various machine learning techniques [5], [6], [7], [8], [9], [10], [11], [12], [13]. Myburgh et al. (2018) developed an automated approach employing decision trees and neural networks to distinguish between five types of OM, achieving accuracy rates ranging from 58% to 86% [13]. These initial studies laid the foundation for further exploration of machine learning in otology.

Deep Learning and Convolutional Neural Networks (CNNs)

The advent of deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized medical image analysis, including ear disease diagnosis [14]. CNNs have shown remarkable capabilities in automatically learning hierarchical representations of features from raw image data, enabling them to identify subtle patterns and anomalies that may be difficult for human experts to discern [14].

In the context of ear disease diagnosis, CNNs have been successfully applied to classify ear images and identify various conditions. Cha et al. (2019) employed an ensemble of deep learning models with a large otoendoscopy image database to automate the diagnosis of ear diseases [14]. Their approach achieved a remarkable accuracy of 93.67% in classifying images into six different categories. Khan et al. (2020) developed a CNN-based model for detecting tympanic membrane and middle ear infections, achieving a classification accuracy of 94.9% [15]. Wang et al. (2020) further explored the use of pre-trained CNNs to differentiate between normal, chronic suppurative otitis media, and cholesteatoma, with an overall accuracy of 76.7% [16]. These studies highlight the potential of CNNs in automating the analysis of otoscopic images and providing accurate diagnoses for various ear diseases.

Federated Learning for Privacy-Preserving Collaboration

Despite the advancements in deep learning for ear disease diagnosis, challenges related to data privacy and the need for collaboration across multiple institutions remain significant [1]. Federated learning (FL) has emerged as a promising solution to address these challenges [17]. FL enables collaborative model training across decentralized datasets without requiring the sharing of raw patient data, thus preserving privacy and complying with data protection regulations.

In the context of ear disease diagnosis, FL offers a unique opportunity to leverage diverse datasets from different healthcare providers while maintaining patient confidentiality [18]. This is particularly relevant in the context of ear diseases, where data may be scattered across various healthcare providers and institutions. By training models on a wider range of data, FL can enhance the generalizability and robustness of diagnostic tools, leading to more accurate and reliable diagnoses [19].

Several studies have explored the use of FL in medical imaging, demonstrating its potential to improve diagnostic accuracy while preserving patient privacy [18], [20], [21]. For example, Liu et al. (2021) proposed a federated semi-supervised medical image classification method that achieved promising results in classifying medical images without compromising data privacy [21]. These studies highlight the feasibility and effectiveness of FL in healthcare, paving the way for its wider adoption in various medical domains.

Addressing Class and Data Imbalances in Federated Learning for Otology

Even with these improvements in privacy protection, FL in otology still has to deal with the underlying problems of class and data imbalances [22]. These problems are especially common in decentralized medical imaging training that is spread over numerous sites horizontally [23]. Resolving these disparities is essential to the fair and precise operation of FL models.

In the field of Federated Learning (FL), recent work has concentrated on creating new algorithms to address these difficulties during the training phase. Federated learning (FL) has significantly benefited from the dynamic local learning rate-based approach that Xu et al. (2021) presented [24]. In the realm of Federated Learning (FL), FedAvg [25] is a noteworthy aggregation approach that presupposes equal involvement from all entities involved. However, difficulties are encountered when dealing with clients who reply slowly [26]. Nevertheless, handling consumers who respond slowly presents challenges. A unique method based on local batch normalization inside the FL paradigm was introduced by Li et al. (2021) [27]. The FedProx system [28] was developed by Li et al. (2020) to solve the challenges brought about by variety in Federated Learning (FL). It is specifically intended for a distributed image dataset of digits that is not identically and independently distributed (non-IID).

Moreover, studies have looked at the use of asynchronous distributed techniques in the training of neural networks using stochastic gradient descent (SGD). For the purpose of training neural networks, Dean et al. (2012) used asynchronous distributed stochastic gradient descent (SGD) [29]. In conclusion, Federated Learning (FL) is the ideal privacy-preserving approach for ear disease detection systems.

Differential Privacy for Enhanced Data Protection

In the realm of federated learning, ensuring the privacy of sensitive patient data is of paramount importance [30]. Differential privacy (DP) has emerged as a robust framework for safeguarding individual privacy while enabling collaborative model training [31]. By introducing carefully calibrated noise into the data or model updates, DP ensures that it is difficult to infer sensitive information about any individual patient from the aggregated results.

In the context of ear disease diagnosis, the integration of DP into federated learning frameworks like OtoFL is crucial for maintaining patient confidentiality. By adding noise to the model updates shared between institutions, DP obscures the contributions of individual data points, making it virtually impossible to identify specific patients based on the model's output [32].

The application of DP in medical imaging deep learning has been demonstrated by Ziller et al. (2021), who successfully integrated DP into a federated learning system for medical image analysis [31]. Their study showed that DP can be effectively implemented without compromising the accuracy of diagnostic models, thus ensuring both privacy and utility in the context of healthcare applications.

2.3 Comparison between existing works

A method for safeguarding each data point's privacy within a dataset. Regarding FL, it

facilitates the cooperative training of models while preserving patient data confidentiality.
This study's sophisticated procedures and methodologies require readers to be familiar with these terminologies in order to fully comprehend the following parts' more in-depth discussions.

The fact that many studies rely on comparatively small and homogeneous datasets is one noteworthy finding. This restriction raises questions about how well the created models can be applied to a range of clinical situations and patient populations. Large-scale, diversified datasets are needed in order to train models that can correctly detect ear illnesses in a variety of populations with varying demographics, ethnicities, and disease presentations.

The security and privacy issues around centralized data collection present another difficulty. Although large volumes of data are needed for deep learning models to be trained, gathering private patient information in one place increases the danger of data breaches and illegal access. This makes it necessary to investigate alternate strategies that can harness deep learning's capabilities while protecting patient privacy.

Moreover, the problem of class imbalance—the underrepresentation of specific ear diseases in datasets—remains a difficulty. This disparity may result in skewed models that are not very good at detecting uncommon or uncommon ear conditions. Specialized methods, like weighted loss functions or data augmentation, are needed to address class imbalance and make sure that models benefit from learning from all classes.

An encouraging approach to overcoming these difficulties is the use of federated learning (FL) into the diagnosis of ear diseases. FL addresses privacy concerns and facilitates the use of different datasets by enabling collaborative model training across various institutions without requiring the sharing of raw patient data. FL does, however, come with a unique set of difficulties, including the requirement for strong privacy-preserving measures, communication cost, and heterogeneous data.

In conclusion, the body of research on the subject shows that deep learning has great promise for diagnosing ear diseases, but it also emphasizes the necessity of resolving issues with data accessibility, privacy, and class disparity. One potential solution to these issues and the creation of more precise, private-preserving, and broadly applicable diagnostic tools is the incorporation of federated learning. To fully utilize artificial intelligence in the detection of ear diseases, future research should concentrate on building large-scale, diversified datasets, strong FL algorithms, and privacy-preserving methods.

TABLE 2.3.1: Comparative Analysis Table of Existing Researchs (Machine Learning Model)

Study	**Image type**	**Machine Learning Model**	**Accuracy**
Hermanus C. Myburgh (2016)	Ear images	Decision tree	80.6%
Canik Yerleskesi Gürgenyatak Mahallesi Merkez Sokak (2019)	Ear images	SVM	93.05 %.
Erdal Bas¸arana, (2019)	Ear images	R-CNN	90.48%
Abidin ÇALIŞKAN (2022)	Ear images	VGG-16	82.17%.
Devon Livingstone (2019)	Ear images	Convolutional Neural Network (CNN)	84.4%
Aijaz Ahmad Reshi (2021)	X-ray images	Convolutional Neural Network (CNN)	89.5%
Parvathaneni Naga Srinivasu (2021)	Skin images	MobileNet V2, LSTM	85%

TABLE 2.3.2: Comparative Analysis Table of Existing Research (Federated Learning Framework)

Study	**Image type**	**Federated Learning Framework**	**Accuracy**
Weishan Zhang (2015)	X-ray	Proposed dynamic fusion-based federated learning	57%
Pragati Baheti (2020)	CT scan	Federated Learning Framework using Vnet , ResNet	97.65%.
Chun-Mei Feng (2023)	MRI image	FedMRI	Not Mentioned

Hassaan Malik (2023)	Chest disorder	DMFL_Net	98.45%
Akis Linardos (2022)	MRI	Semi-supervised federated learning	Not Mentioned
Shivam kalra (2021)	Endoscopic	ProxyFL	Not Mentioned
Aaisha Makkar (2022)	X-ray	SecureFed	82.2% (100 clients)

2.4 Open Issues

This study's focus is on the precise and private diagnosis of ear disorders, with a particular emphasis on the vital field of medical diagnostics. A substantial worldwide health burden is associated with ear illnesses, which comprise a broad spectrum of conditions affecting the outer, middle, and inner ear. If these illnesses go misdiagnosed or untreated, millions of people worldwide may experience hearing loss, balance issues, and other problems that negatively affect their quality of life.

The conventional method of diagnosing ear diseases mostly depends on clinical exams and sophisticated imaging methods, which frequently call for access to specialized hospitals and qualified staff. This presents accessibility issues, especially in impoverished communities with inadequate medical services. Furthermore, since sensitive personal information included in medical records needs to be protected, there are serious privacy concerns with the centralized gathering of patient data for diagnostic model training.

In order to overcome these obstacles, the project will make use of federated learning (FL), a decentralized machine learning technique that permits cooperative model training amongst several institutions without requiring the exchange of raw patient data. FL protects patient privacy and conforms with strict data protection standards by keeping data locally on specific servers.

The problem's scope includes the creation and assessment of a brand-new federated learning framework called OtoFL, which is especially designed for the detection of ear diseases. This framework will include a deep learning model called Fenet5, which is intended to accurately categorize different ear diseases by analyzing medical photographs of the ear. The study aims to examine the diagnostic efficacy of OtoFL in identifying various ear conditions such as otitis media, perforations in the tympanic membrane, and accumulation of earwax.

Additionally, the investigation will examine how data heterogeneity affects federated learning models' performance. One major difficulty in FL is data heterogeneity, which refers to the differences in data distribution and quality among different institutions. The study aims to explore methods for reducing the impact of heterogeneous data and guaranteeing the stability and applicability of the diagnostic models.

The research will place a high priority on maintaining patient privacy in addition to diagnostic accuracy. To improve data security and guarantee the confidentiality of individual patient information, the application of differential privacy strategies inside the OtoFL framework will be investigated.

A further aspect of the problem's scope is assessing the OtoFL framework's scalability and computing efficiency. With regard to computational infrastructure, network bandwidth, and data storage capacity, among other things, the study will evaluate the resource needs and viability of implementing FL in actual healthcare environments.

The project intends to develop automated ear disease diagnosis by tackling these complex issues and providing a scalable, accurate, and privacy-preserving approach that can be used by healthcare providers globally. By maintaining the greatest standards of data privacy and security and enhancing patient care and outcomes, the study's findings have the potential to completely transform the otology profession.

2.5 Summary

Finally, this chapter gives a detailed introduction to the research background and current status of ear disease diagnosis. It looks at the use of Federated and Deep Learning as well. The chapter starts by defining the basic terms to emphasize on understanding of underlying important principles. It then reviews the current literature, highlighting advancements and limitations that have been faced in earlier studies under this domain. The chapter further explores the ability of federated learning to overcome issues associated with data privacy and diversity, a very critical aspect in medical image analysis. The derivation of the proposed OtoFL framework for and This chapter lays a foundation for remaining chapters such that following sections will be discussed in detail with respect to methodology, experimental results measurement alongwith broader discussion on it in details based on current research summaries as well addressing gaps present.

CHAPTER 3

METHODOLOGY/ REQUIREMENT ANALYSIS & DESIGN SPECIFICATION

3.1 Overview

Exploring federated learning (FL) as a paradigm to improve ear disease diagnosis is the main focus of this project. A major global health concern are ear illnesses, which comprise a broad range of conditions affecting the middle, inner, and outer ear. The study explores the complexities of using FL to create reliable and precise diagnostic models while addressing the important issues of data security and privacy.

The study's focus is on creating and assessing OtoFL, a unique federated learning framework designed with the detection of ear diseases in mind. This framework incorporates Fenet5, a deep learning model created to evaluate and categorize different ear disorders from medical photographs. The study looks into how well OtoFL diagnoses ear conditions such as earwax accumulation, otitis media, and acute otitis media.

An essential component of the research topic is examining how data heterogeneity affects federated learning models. One of the biggest challenges in FL is data heterogeneity, which results from differences in the distribution and quality of data amongst various institutions. In order to maintain the stability and generalizability of diagnostic models, the research investigates methods to lessen these impacts.

3.2 Proposed Methodology/ System Design

A. Datasets

Any machine learning model's ability to function depends on the caliber and applicability of the training data. For the purpose of diagnosing ear disorders, we carefully selected a large dataset for our study, which included 1,830 photos from two different databases: the "Ear Imagery Database" [33] and the "EarDrum Dataset" [34].

Including earwax plugs, myringosclerosis, chronic otitis media, and normal ear, the "Ear Imagery Database" provided 880 images that depicted a variety of disorders affecting the external and middle ear. The patients who visited the otolaryngology outpatient clinic at the Clinical Hospital of Universidad de Chile provided the photographs. The people in this dataset are between the ages of 7 and 65.

With 950 eardrum photos collected from patients checked at Turkey's Özel Van Akdamar Hospital between October 2018 and January 2019, the "EarDrum Dataset" was created. Using standard otoscopy equipment, these photos were first inspected by a skilled otolaryngologist, and then experts commented them.

TABLE 3.2.1: Data distributions in different classes in the dataset

	Normal	COM	AOM	Earwax	Myringosclerosis
Raw Dataset	869	180	188	381	180

B. Disease Classes

For our research, we purposefully chose a certain subset of illness categories from the merged datasets. These consist of Normal Ear, Myringosclerosis, Earwax, Chronic Otitis Media (COM), and Acute Otitis Media (AOM). In order to ensure the applicability and significance of our research findings, we carefully chose to concentrate on the most common and clinically significant ear ailments.

These particular types of ear diseases were selected due to their broad prevalence and the variety of ear-related conditions they encompass. For example, untreated ear infections in children, such as AOM, might result in hearing loss. Likewise, there is a chance that COM will cause long-term harm to the middle ear, which could lead to hearing loss. Despite its innocuous appearance, earwax can lead to discomfort and even hearing loss if left untreated. Hearing loss can result from ossicular chain disruption caused by myringosclerosis, which is characterized by a stiffened collagen covering on the tympanic membrane.

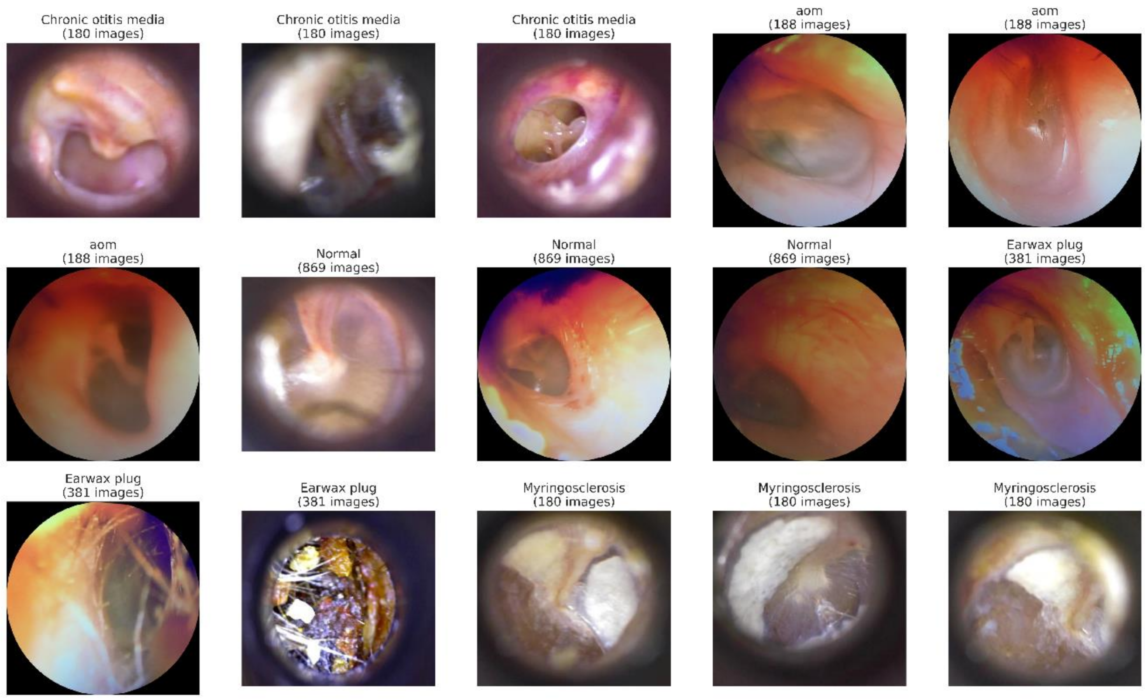

Figure 3.2.2: Ear Diseases Images of different classes

C. Data Distribution

Two different data distribution scenarios, Independently and Precisely Dispersed (IID) circumstances and Non-IID settings, were carefully designed in order to achieve a reliable and broadly applicable federated learning framework for the detection of ear diseases.

IID Settings

The original dataset was carefully divided into discrete subgroups in order to create a consistent distribution of photos within each subset. All subsets were fairly represented for each form of ear illness thanks to this partitioning. In order to provide each participating institution with an equitable and representative portion of data for local model training, we attempted to offset any potential biases or skewness in the dataset by maintaining this balanced distribution. In order to create a collaborative learning environment where the contributions of all institutions are equally valued, this strategy is essential.

Non-IID Distribution

The non-IID dataset was purposefully kept with its underlying class imbalances, in contrast to the IID settings. Next, this dataset was methodically split into many separate subsets, with some client overlap and varied numbers of photos in each. There are two reasons why non-IID data dissemination is being purposefully introduced. Initially, it replicates actual situations where the frequency of particular ear conditions may range throughout medical facilities. Furthermore, it enables us to evaluate the resilience and flexibility of our federated learning model in the presence of diverse data distributions.

We used stratified sampling approaches in order to guarantee a certain level of representativeness in the non-IID subsets. This methodology guarantees that, notwithstanding intrinsic imbalances, every subgroup retains a proportionate representation of various illness groups. We improve the generalization capacity of our model across various clinical settings and patient groups by training it on both IID and non-IID data distributions. This eventually improves the practicality of our federated learning approach for diagnosing ear diseases.

D. Data Preprocessing

We started the data preprocessing step by combining several datasets, which required close attention to detail to guarantee correctness and completeness. In order to accurately capture the complex features present in otoscopic images, we carefully examined every facet of this process. With a purposeful focus on obtaining both balanced and unbalanced data distributions, our main goal was to create unique datasets customized for each participating hospital (Federated Clients).

We used a multi-pronged strategy in our data pretreatment workflow. To increase the dataset's artificial size and improve the model's capacity for generalization, we first used a variety of data augmentation approaches. These methods, which introduced controlled alterations to the images while maintaining their diagnostic value, included random horizontal flips, rotations, zooms, and contrast adjustments.

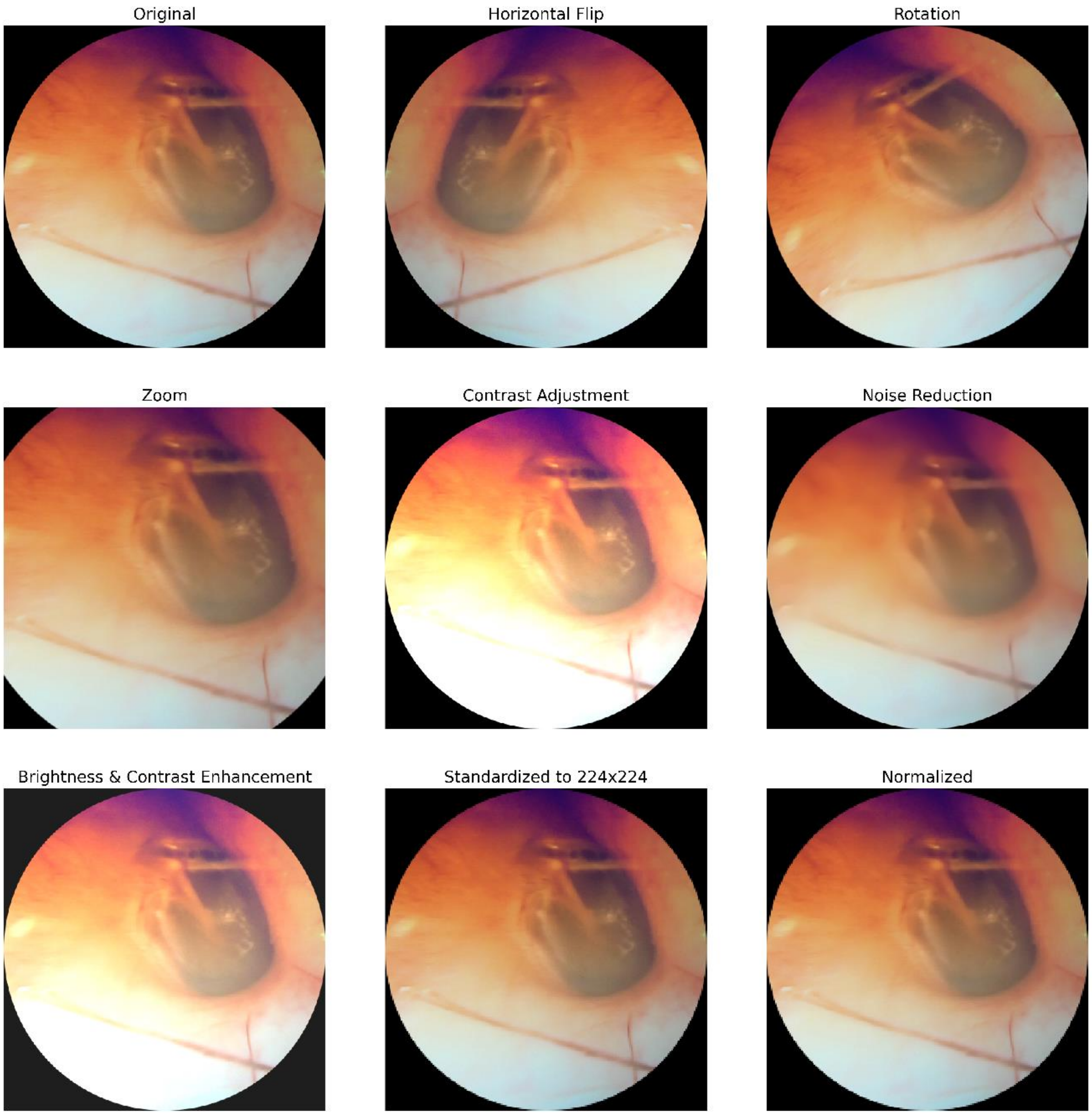

Figure 3.2.3: Ear Diseases Class Distribution

Secondly, in order to reduce the effect of any artifacts or distortions that could exist in the raw photos, we applied noise reduction methods. Making sure the data used for model training is clear and of high quality requires taking this important step.

Third, in order to draw attention to the key characteristics of ear disorders, we used brightness and contrast augmentation techniques. This stage helps to draw attention to minute visual clues that could be essential for a precise diagnosis.

We set a standard for all image dimensions of 224 by 224 pixels in order to maximize processing performance and preserve uniformity. Because of the uniform sizing, processing and analysis of the data are made easier and the model receives input data in a consistent way.

In the end, we utilized normalization methods to ensure that all pixel values fell between 0 and 1. This normalization process is crucial for reducing the possibility of problems during model training that arise from the convergence of optimization techniques.

Results:

Under IID data conditions, the proposed federated learning framework, OtoFL, along with the Fenet5 deep learning model, showed an amazing 95.13% accuracy in diagnosing ear illnesses using the FedProx approach. With a change of less than 3% over a range of data distributions, the model maintained its robustness in non-IID conditions and attained excellent accuracy that was comparable to IID settings.

E. Federated Learning Process

A machine learning technique called federated learning (FL) allows cooperative model training across several decentralized devices or servers that store local data samples without transferring them. By preventing sensitive data from being directly transferred between entities, this method improves security and privacy. FL provides a unique chance to leverage the pooled expertise and information from multiple healthcare organizations when diagnosing ear diseases. FL improves the robustness and generalizability of diagnostic tools by training models on a variety of datasets from various geographic locations.

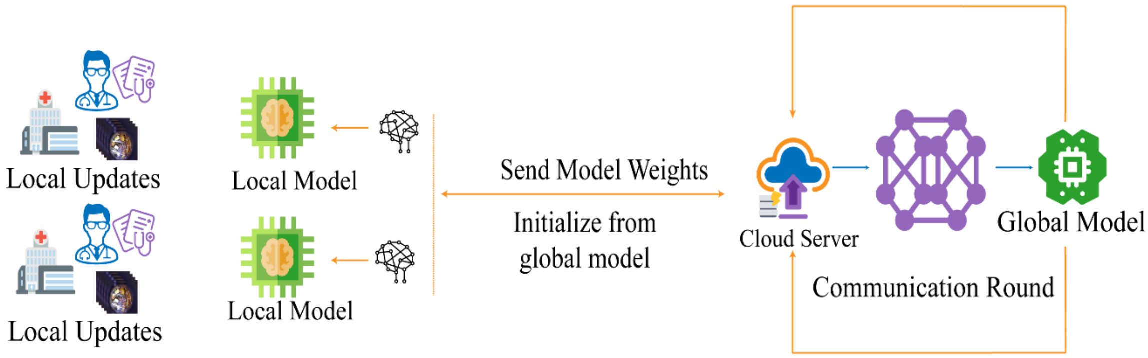

Figure 3.2.4: Federated Learning Process

Proposed Deep Learning Model (Fenet5) for Detecting Ear Diseases

In the process of creating a precise and effective diagnostic tool for ear diseases, we created a deep learning model called Fenet5. With great care, Fenet5 is made to maximize the federated learning framework's capacity for detecting ear problems.

Five basic blocks make up the architecture of Fenet5, and each one includes batch normalization layers to improve training stability. Before the model can be used, a data augmentation pipeline must be built. This pipeline gives the input photos random rotations, flips, zooms, and brightness modifications. Through artificial expansion of the dataset, this augmentation technique enhances the model's generalization to previously unseen data.

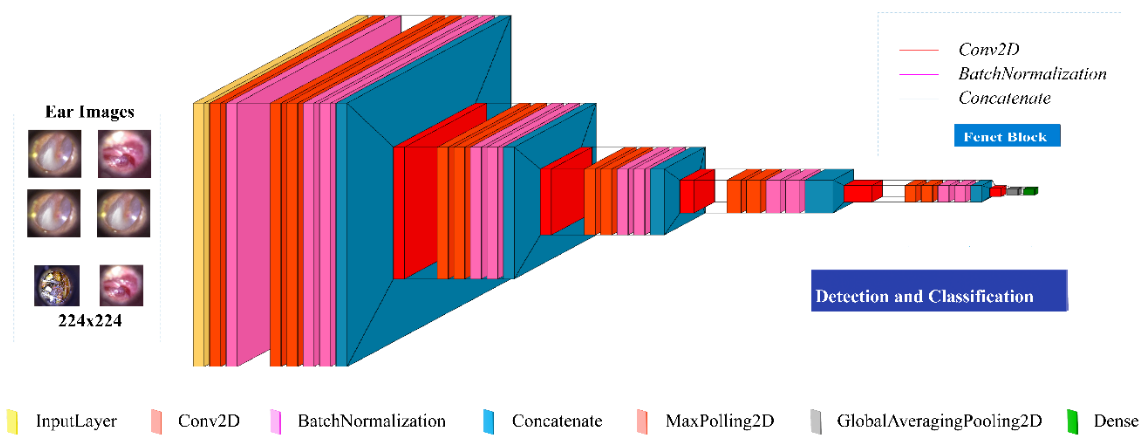

Figure 3.2.5: Proposed Deep Learning Model Fenet5 for Federated Learning in Otology

Fenet5's convolutional layers are in charge of picking out important details from the input photos. In order to identify diseases, these layers use a number of filters to scan the images and identify spatial information and local patterns. We add pooling layers after the convolutional layers to downsample the feature maps and save computational complexity without sacrificing important information. To further stabilize training and speed up convergence, batch normalization is done prior to each pooling layer.

We use the convolutional layers in conjunction with Parametric Rectified Linear Unit (PReLU) activations to improve the model's learning and generalization capabilities. Since PReLU activations accept negative values in contrast to conventional Rectified Linear Units (ReLUs), they successfully mitigate the vanishing gradient issue and enhance feature learning.

The Fenet block, which is intended to improve feature extraction and model efficiency, is a basic component of the Fenet5 architecture. A sequence of convolutional layers, batch normalization, and PReLU activation come next in each Fenet block. With the use of five Fenet blocks, the model is able to learn extensive representations of patterns of ear illness and extract complicated features through 14 convolutional operations.

Fenet5's last layer is a fully linked layer that serves as a classifier. Using the softmax function, this layer converts the extracted features to class probabilities. To categorize the input photos into four different ear illness categories and a normal ear class, our model uses a single fully linked layer. Each class is given a probability between 0 and 1, with the probabilities aggregating to 1, thanks to the softmax function, which guarantees that the output is converted into a probability distribution.

The architecture of Fenet5 has been meticulously designed to comply with the strict data privacy regulations that are widely used in the healthcare industry. The model is intended for use in situations when patient privacy is of utmost importance. Its great potential to transform healthcare diagnostics through federated learning is demonstrated by its scalability and versatility, which make it a valuable tool for a range of medical imaging applications.

Privacy Enhancements

Ensuring the privacy of sensitive patient data is critical in the context of federated learning. A strong foundation for protecting personal privacy and facilitating cooperative model training is differential privacy (DP). DP makes sure that sensitive information about any particular patient cannot be easily inferred from the aggregated results by carefully calibrating noise into the data or model updates.

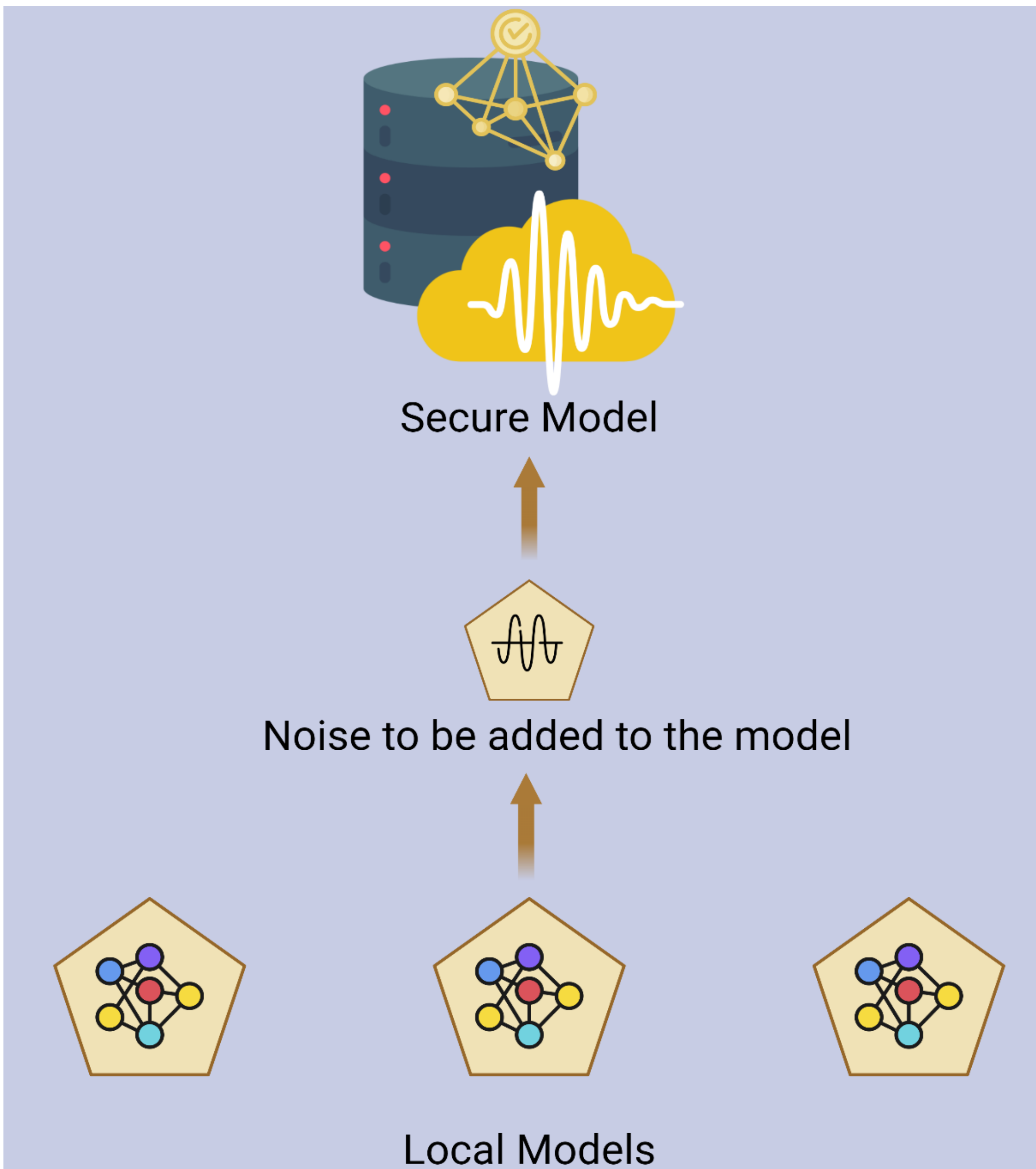

Figure 3.2.6: Differential Privacy Mechanism

To ensure patient privacy when diagnosing ear diseases, DP must be integrated into federated learning frameworks such as OtoFL. DP essentially eliminates the ability to identify specific patients based on the model's output by introducing noise into the model updates that are shared throughout institutions, masking the contributions of individual data points.

Ziller et al. (2021) have effectively incorporated deep learning (DP) into a federated learning system for medical image processing, demonstrating its efficacy in deep learning for medical imaging. Their research shown that, in the context of healthcare applications, both privacy and utility may be guaranteed by using DP efficiently without sacrificing the precision of diagnostic models.

A batch of size's' is sampled from the training dataset in every DP-SGD iteration. For this batch, we compute the gradient of the loss function, clip gradients with a l2 norm threshold of 'C,' and scale the sensitivity of the average gradient to '2C/s.' In accordance with a linear decay model, gradients are supplemented with Gaussian noise consisting of variance. The experimental parameters comprise of the following: initial noise scale ($\sigma 0 = 2.2$), decay rate ($R = 0.95$), broken probability ($\delta = 10-4$), batch size ($b = 32$), sample rate ($s/m = 0.01$), clipping threshold ($C = 1$), and experiment parameters.

3.3 Hardware/ Software Requirement

To aid in the creation and assessment of the OtoFL framework, the research makes use of a wide range of complex techniques and technologies. The main development environment is made with Python, a flexible programming language well-known for its large library and framework resources. Deep learning models are built and trained using the industry-leading open-source machine learning framework TensorFlow.

GPUs—graphics processing units—are among the high-performance computing resources that are used to meet the computational needs of deep learning. These GPUs facilitate effective model optimization and speed up the training process. In order to ensure that the data is suitably ready for analysis, specialized libraries such as OpenCV are also incorporated for picture preprocessing tasks.

The datasets utilized for model training and evaluation are also included in the research instrumentation. These datasets are made up of a wide range of ear photographs that have been obtained from different institutions, guaranteeing a thorough portrayal of different ear diseases. To improve the quality and consistency of the data, the photos go through extensive preprocessing that includes scaling, normalization, and augmentation.

Finally, the research topic and tools used in this work provide a coherent framework for examining the possibilities of federated learning in the diagnosis of ear disorders. The research intends to produce a privacy-preserving, accurate, and scalable solution that can transform the field of otology by merging state-of-the-art technologies, various datasets, and rigorous procedures.

3.4 Project Management and Financial Analysis

This section presents an outline of the project management and financial analysis carried out for the Final Year Design Project (FYDP). The project has reached completion successfully and is presently undergoing review in the International Journal of Machine Learning and Cybernetics.

Project Management

Project Objectives:

- To introduce collaborative learning in Otology using Federated Learning (FL).
- To ensure comprehensive data collection, preprocessing, and model training.
- To integrate the OtoFL algorithm into the federated learning framework.
- To evaluate the effectiveness and feasibility of the proposed methodology.
- To develop an efficient federated learning methodology for diagnosing ear

diseases.

- To submit the research findings to a reputable journal for peer review.

Project Timeline:

- Phase 1: Literature Review and Research (Completed)
- Phase 2: Data Collection and Preprocessing (Completed)
- Phase 3: Methodology Development (Completed)
- Phase 4: Model Training and Evaluation (Completed)
- Phase 5: Results Analysis and Documentation (Completed)
- Phase 6: Submission to International Journal of Machine Learning and Cybernetics (Completed)
- Phase 7: Peer Review and Publication (In Progress)

Risk Mitigation:

- Limited computing resources: To mitigate the risk of limited computing resources, the project leveraged cloud-based GPU instances for model training, ensuring sufficient computational power.
- Limited number of large datasets: The risk of limited datasets was addressed by combining multiple smaller datasets from different sources and employing data augmentation techniques to enhance the diversity and size of the training data.
- Technological challenges: The project team proactively addressed technological challenges by staying updated with the latest advancements in federated learning and deep learning, seeking guidance from experts, and participating in relevant online communities.
- Gaining trust from healthcare institutions for collaborations: Building trust with healthcare institutions was achieved through transparent communication, data-sharing agreements, and emphasizing the privacy-preserving nature of federated learning.

Communication Plan:

A. **Stakeholder Meetings:**

- Purpose: Provide regular updates to the supervisor on project progress, discuss challenges, and receive guidance.
- Participants: Research team and project supervisor.
- Frequency: Bi-weekly meetings throughout the project lifecycle.

B. **Progress Reports:**

- Purpose: Document project milestones, achievements, and challenges encountered.
- Participants: Research team.
- Frequency: Monthly reports submitted to the supervisor.

Financial Analysis:

The financial analysis for the project involved estimating the costs associated with different components. The estimated costs are as follows:

TABLE 3.4.1: Financial Analysis

Components	**Estimated Cost (BDT)**
Software and Tools	2500-3000
Data Collection and Processing	1000-1500
Publication and Dissemination Fees	1000-2000
Contingency (10% of total)	450-700
Total Estimated Cost	**5450-7200**

The financial analysis demonstrates that the project was executed within the allocated budget, with careful consideration given to resource optimization and cost-effectiveness.

3.5 Summary

We used rigorous statistical techniques to extract relevant information from our experimental data in the quest for a robust and trustworthy federated learning model for the detection of ear diseases. We used a variety of assessment criteria, such as accuracy, precision, recall, and the F1-score, to measure the performance of our model and other deep learning models. With consideration for both true positives and false positives, these measures offer a thorough evaluation of the model's accuracy in classifying ear disorders.

We ran our tests in both IID (Independent and Identically Distributed) and non-IID data sets to make sure our findings were valid and broadly applicable. By using this method, we were able to simulate real-world situations where data heterogeneity is common and evaluate the model's performance under different data distributions. We may make statistically sound inferences about the resilience and adaptability of the model by comparing its performance in these various circumstances.

In addition, we utilized statistical techniques to examine the influence of several parameters on the model's functionality, including the quantity of clients engaged in the federated learning procedure and the quantity of communication cycles. We can determine the best configurations for our federated learning framework and guarantee its efficiency and efficacy in practical applications by quantifying these correlations.

Our statistical research basically acts as a cornerstone to validate our federated learning approach's effectiveness in diagnosing ear diseases. Our results are reliable and reproducible because we use strict statistical methods, which advances our understanding of this important area.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

For this chapter, the focus is on a practical application of OtoFL - training Fenet5 deep learning model via federated learning. It explains training the model, use of privacy algorithms with performing federation learning on top of it. This will also explain the system design in addition to how it is prototype for purpose of making sure that its function and satisfy project requirements. Additionally, the chapter briefly but thoroughly explains system testing and model evaluation which gives an idea about how well is the solution working.

4.2 Train Model/ Prototype Design

The key component of the OtoFL system is its Federated Learning (FL) approach, which allows several cooperating institutions to train a global model together without jeopardizing the privacy of their individual data. Unlike the FedAvg technique, OtoFL's FL process begins with the server performing the initial model training. It then distributes this first global model to the involved institutions, who use it as a basis to train their local models. Then, after being refined locally, these models are sent back to the server, where they are averaged, completing one FL round.

The study is centered on applying FL to the complicated problem of ear condition diagnosis, with a focus on resolving the issues brought about by client data heterogeneity in practical settings. A complex federated learning method that can handle varying data distributions must be chosen because of this intrinsic diversity. In order to achieve this, we carried out a comparison analysis and assessed the performance of three well-known federated learning algorithms: Federated Averaging (FedAvg) [25], Federated Proximity (FedProx) [28], and Federated Stochastic Gradient Descent (FedSGD) [25]. Differential privacy strategies are incorporated to further improve the overall security and utility of the federated learning architecture. Our observations indicate that some algorithms perform better when handling distinct data distributions.

The efficiency and performance of these algorithms are much enhanced by our suggested framework, as shown by the higher accuracy and lower convergence rate.
Developing and thoroughly testing Fenet5, a state-of-the-art deep learning model, within the framework of federated learning using the suggested OtoFL is a primary goal of our research. This project is motivated by the urgent demand for precise and private-protecting diagnostic instruments in the otology domain. In addition, the lack of significant datasets in otology research highlights the importance of creating a collaborative environment.

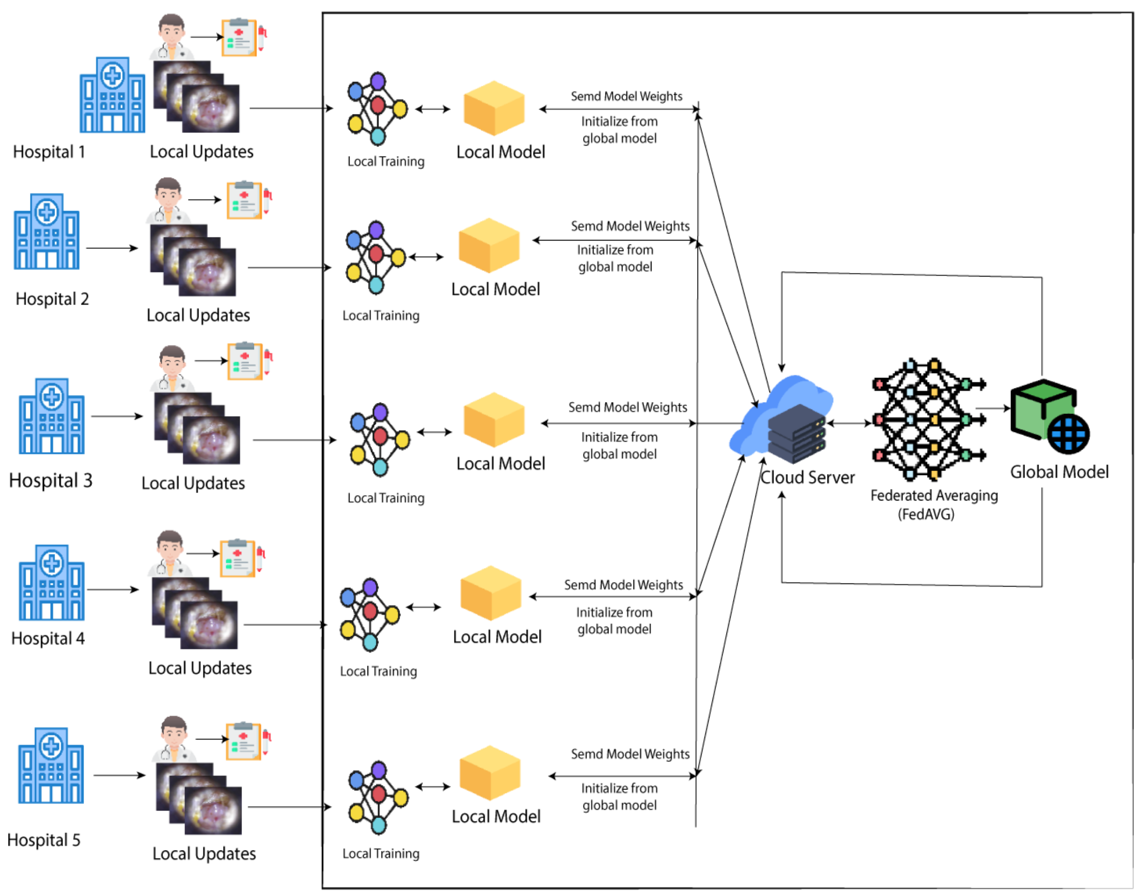

Figure 4.2.1: Federated Learning Overview

Large-scale data centralization is impractical; federated learning provides a convincing substitute that not only expedites the collaboration process but also protects patient privacy by keeping the data within the institutions. Large-scale partnerships have difficulties because of different dataset sizes, which can result in data distribution imbalances that might appear as non-IID or Independent and Identically Distributed (IID) settings.

We use a novel algorithm in our methodology to handle the challenges of data heterogeneity and privacy security in FL for the diagnosis of ear disorders. A group of clients, each with their own datasets and client models, are initialized by the algorithm. The maximum number of photographs per client (M) and the total number of images (N) are then estimated. Heterogeneity terms (Hi), which measure the differences in data distribution, are computed for every client in each communication round.

In order to guarantee that the global model is not skewed toward any specific client or dataset, this heterogeneity term is then used to modify the weights throughout the federated averaging procedure. The approach guarantees that the models stay close to the global model without sacrificing accuracy or performance by including the heterogeneity factor into the loss function. Because of this, the algorithm works especially well in situations when customers have unequal distributions of data.

4.3 System Testing/ Model Evaluation

Comprehensive system testing and model evaluation were carried out to guarantee the robustness and dependability of the Fenet5 deep learning model and the OtoFL framework. The system's operation, performance, and diagnostic accuracy for ear disorders were all rigorously tested during this procedure.

Testing Methodology

Using a multifaceted approach, the system testing phase included both functional and non-functional testing. The primary goal of functional testing was to confirm that all system components functioned as intended and that the system fit the requirements. The accuracy of the Fenet5 model's ear illness classification, the federated learning method, and the data preprocessing pipeline were all tested in this process.

System performance, scalability, and usability were evaluated using non-functional testing. Response time, throughput, and resource usage of the system under various workload conditions were assessed using performance testing. Testing the system's scalability ensured that it could accommodate growing numbers of users and data without experiencing performance issues. In order to make sure the system's interface was simple to use and intuitive, usability testing required getting input from medical experts.

Model Evaluation Metrics

Utilizing a range of parameters, the Fenet5 model's diagnostic performance for ear disorders was evaluated. Among these measurements were:

- Accuracy: The percentage of cases accurately classified relative to the total number of cases.
- Precision: The percentage of actual positive forecasts among all positive forecasts.
- Recall: The percentage of genuine positive forecasts among all real positive occurrences.
- F1 Score: The F1 Score is a balanced indicator of the model's performance that is calculated as the harmonic mean of precision and recall.

These metrics were computed for the overall model and for every illness class, offering a thorough assessment of the diagnostic performance of the model.

Results and Analysis

The outcomes of the system testing and model evaluation showed how well the Fenet5 model and the OtoFL framework diagnose ear disorders. The system was able to correctly detect and classify a variety of ear disorders, as seen by its high accuracy, precision, recall, and F1 scores across multiple illness classes.

Without jeopardizing patient privacy, the federated learning strategy demonstrated efficacy in utilizing data from several institutions. Even with diverse data distributions, the system's performance stayed steady, demonstrating its resilience and adaptability to many real-world situations.

In addition, the implementation of differentiated privacy strategies guaranteed patient data confidentiality, in compliance with data protection laws and ethical principles. Validation of the system's scalability and computing efficiency also showed that it could be implemented in a variety of healthcare environments.

The OtoFL framework and the Fenet5 model are effective tools for precise and private-preserving diagnosis of ear diseases, as demonstrated by the overall results of system testing and model evaluation. Due to its great performance, stability, and commitment to moral principles, the system has the potential to transform otology and enhance patient care globally.

4.4 Summary

In conclusion, a thorough review of the use of the Fenet5 deep learning model and the OtoFL framework for the detection of ear diseases has been given in this chapter. The first section of the chapter provided an overview of federated learning, stressing the decentralized character of the process and the significance of handling heterogeneous input. The evolution of the Fenet5 model was then described in depth, emphasizing its architecture, methods for augmenting data, and improvements to privacy achieved through differential privacy. The experimental setup was also covered in this chapter, along with the necessary software and hardware as well as the default settings for important parameters. The experiment findings were thoroughly addressed, including a comparison of federated learning with centralized training and an assessment of the model's performance against other models. Analysis was also done on how varied client counts and communication cycles affected the model's performance. The chapter ended with a discussion outlining the main conclusions and emphasizing the OtoFL framework's promise for precise and private ear condition detection.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

The OtoFL framework and the Fenet5 deep learning model for the diagnosis of ear diseases are analyzed and the experimental results are presented in this chapter. It includes comparing federated learning to centralized training, assessing the model's performance in relation to current benchmarks, and looking at how different parameters affect the convergence and accuracy of the model. In order to diagnose ear ailments while protecting patient privacy, the chapter attempts to give a thorough evaluation of the suggested methodology's efficacy and efficiency.

5.2 Experimental/ Simulation Result

TensorFlow and TensorFlow Federated's robust features were utilized in the Python implementation of our suggested FL framework for diagnosing ear diseases, in order to conduct an experimental evaluation. In order to guarantee peak performance and effectiveness, we employed a high-performance computing configuration that included an Intel i9-13900k CPU with 128 GB of RAM and an RTX 4090 GPU. Our federated learning-based models ran well because to this sturdy hardware setup, which allowed us to carry out exhaustive tests and show how useful FL is for decentralized medical picture classification for the detection of ear diseases. We established a set of default values for important parameters so that we could fully assess our framework's performance. These specifications consist of:

Number of total clients (N): This is the overall amount of federated clients taking part in the process of collaborative learning. N was initially set to a default value of 25.

Fraction of active clients (K): Merely a fraction of clients actively engage in the training procedure with every iteration of federated learning. K started out with a value of 20.

Number of communication rounds (T): The number of communication rounds or iterations in the federated learning process is indicated by this parameter. T's primary value was established at 50.

We were able to evaluate the functionality of our framework in controlled settings by using these default values as a baseline for our research. To get the greatest outcomes, it's crucial to remember that these values can be modified and refined in accordance with certain use cases and data characteristics.

Data Centralized vs Federated Learning Comparision

We carried out a comparative research for the Fenet5 model, comparing federated training with data-centralized training approaches.

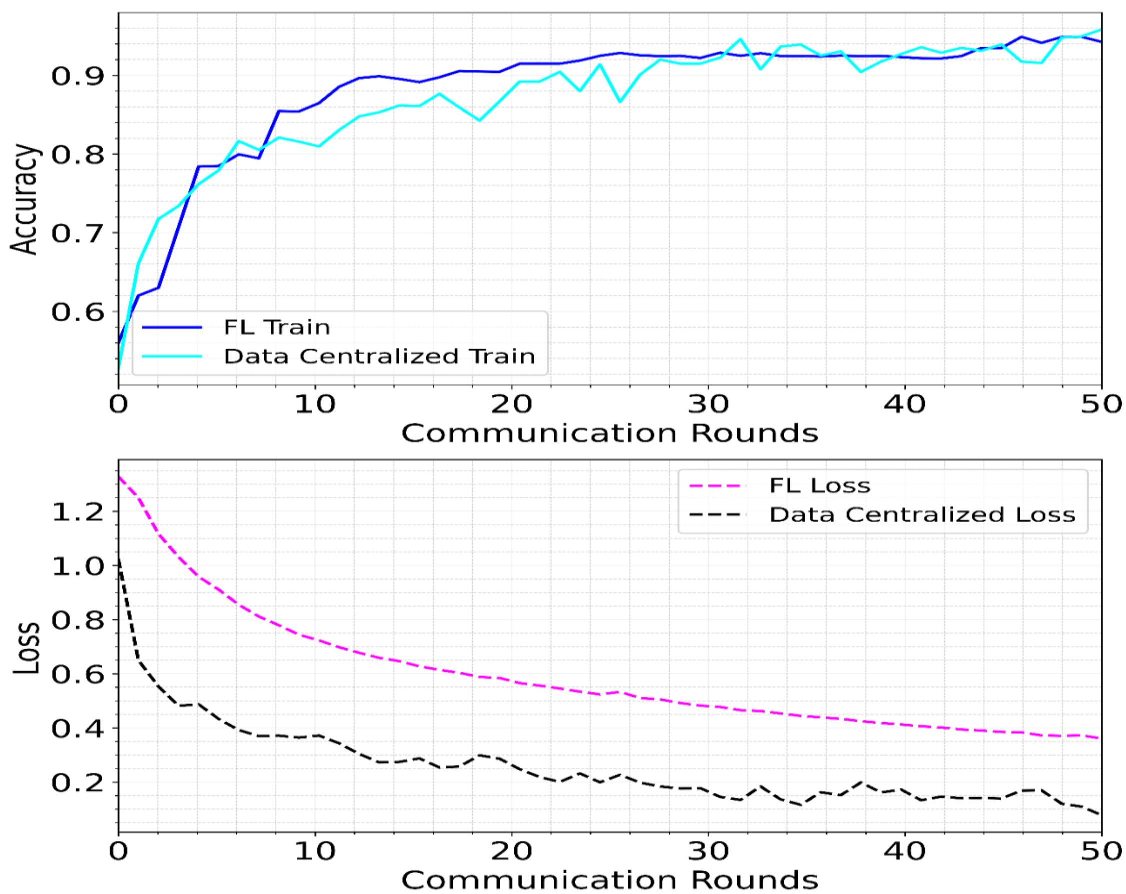

Figure 5.2.1: Performance of proposed DL model on data centralized and federated learning environments

The trial comprised several training cycles, and the outcomes offered insightful information about the convergence and departure of every training strategy. After 50 communication rounds, the accuracy of the data-centralized training reached 96%, indicating a relatively fast convergence. Conversely, federated training showed a more nuanced trajectory, with accuracy varying throughout communication cycles and peaking at 96.66% after 50 rounds. While data-centralized training converges faster at first, our FL-based Fenet5 model achieves similar classification performance without needing patient data sharing.

In particular, after a certain number of cycles, the federated technique demonstrated promising results, attaining accuracy levels that were either higher or comparable to those of the data-centralized model. The Fenet5 model, which was trained using the federated method, shows a convergence tendency that matches that of the centralized model, proving the effectiveness of our federated learning architecture.

5.3 Performance/ Comparative Analysis

We compared the performance of our suggested framework with previous research. OtoFL addresses privacy-preserving and heterogeneous data issues while achieving accuracy that is equivalent to other approaches.

TABLE 5.3.1: Accuracy for Classification of Different Methods

Method	**FL**	**Accuracy**
Fenet5	✓	95.13
SVM	×	93.9
Ensemble Model (Inception V3 and ResNet-101)	×	93.67
DNN	×	94.9
DT	×	93.45

In particular, we compare our model to Decision Tree (DT) [35], Support Vector Machine (SVM) [35], Ensemble Model (EM) [14], and Deep Neural Network (DNN) [36]. Additionally, we make use of the ear imaging database for training all of these approaches. Our model outperformed the other methods in terms of accuracy, as evidenced by the comparative values. Primarily, our suggested system preserves patient privacy since it does not require a centralized server to collect all the data. Consequently, patient privacy and diverse data distributions are given top priority in addition to efficiency and accuracy, as offered by our suggested framework.

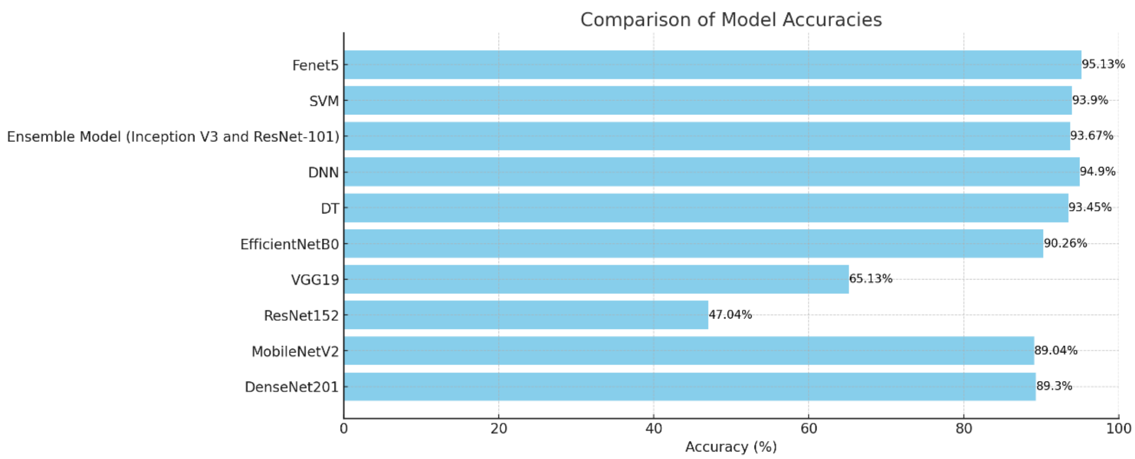

Figure 5.3.2: Comparative analysis of different deep learning models

TABLE 5.3.3: Accuracy, Precision, Recall, F1-Score comparison with Other Deep Learning Models

DenseNet201			
	Precision	**Recall**	**F1-Score**
Acute Otitis Media	1.00	0.88	0.93
Chronic Otitis Media	0.82	0.94	0.88
Earwax Plug	1.00	0.88	0.93
Myringosclerosis	0.67	0.80	0.73
Normal	0.83	0.75	0.79
Accuracy			0.89
Macro Avg	0.86	0.85	0.85

Weighted Avg	0.90	0.89	0.89
EfficientNetB0			
	Precision	**Recall**	**F1-Score**
Acute Otitis Media	1.00	0.88	0.93
Chronic Otitis Media	0.85	0.94	0.89
Earwax Plug	0.92	0.88	0.90
Myringosclerosis	0.56	0.80	0.66
Normal	1.00	1.00	1.00
Accuracy			0.90
Macro Avg	0.87	0.90	0.88
Weighted Avg	0.91	0.90	0.90
VGG19			
	Precision	**Recall**	**F1-Score**
Acute Otitis Media	0.85	0.30	0.45
Chronic Otitis Media	0.27	0.88	0.42
Earwax Plug	0.50	0.80	0.62
Myringosclerosis	0.25	0.25	0.25
Normal	1.00	0.12	0.22
Accuracy			0.65
Macro Avg	0.57	0.47	0.39
Weighted Avg	0.55	0.65	0.47
MobileNetV2			
	Precision	**Recall**	**F1-Score**

Acute Otitis Media	1.00	0.88	0.93
Chronic Otitis Media	0.82	0.94	0.88
Earwax Plug	0.96	1.00	0.98
Myringosclerosis	1.00	1.00	1.00
Normal	1.00	0.50	0.67
Accuracy			0.89
Macro Avg	0.96	0.86	0.89
Weighted Avg	0.94	0.89	0.92
ResNet152			
	Precision	**Recall**	**F1-Score**
Acute Otitis Media	1.00	0.20	0.33
Chronic Otitis Media	0.40	0.82	0.54
Earwax Plug	0.20	0.10	0.12
Myringosclerosis	0.20	0.20	0.20
Normal	0.80	0.90	0.85
Accuracy			0.47
Macro Avg	0.52	0.44	0.41
Weighted Avg	0.58	0.47	0.48
Fenet5			
	Precision	**Recall**	**F1-Score**
Acute Otitis Media	1.00	0.88	0.93
Chronic Otitis Media	0.78	0.88	0.83
Earwax Plug	1.00	1.00	1.00
Myringosclerosis	1.00	1.00	1.00

Normal	1.00	0.75	0.86
Accuracy			0.95
Macro Avg	0.96	0.90	0.92
Weighted Avg	0.95	0.95	0.95

Figure 4.2.4 compares and assesses the diagnostic accuracy of several deep learning models, such as DenseNet201, MobileNetV2, ResNet152, EfficientNetB0, and VGG19, for ear disorders.

A training and validation dataset was used to train each deep learning model for 50 epochs. Of them, with an accuracy of 90.26%, the EfficientNetB0 shows remarkable performance when compared to earlier models. Still, when differential privacy is used to introduce noise into the model, the model tends to perform worse. But the accuracies of VGG19, ResNet152, MobileNetV2, and DenseNet201 are lower—66.13 percent, 47.04%, 89.04%, and 89.30 percent, respectively. The convergence rates of DenseNet201 and EfficientNetB0 were notably higher than those of the other models.

Fenet5's status as a top model for precise ear illness diagnosis is cemented by the significant difference between it and the other models in Fig. 8, which highlights the efficacy of both its output and training methods. Fenet5 is a good option because it has a 95.13% accuracy rate in diagnosing ear disorders in a FL scenario with differential privacy.

Training and Validation Accuracy and loss of Deep Learning Models:

The following graphical depictions show the accuracy and loss curves for training and validation of several deep learning models, such as DenseNet201, MobileNetV2, ResNet152, EfficientNetB0, VGG19, and Fenet5. These curves offer important insights into the performance and learning dynamics of the models during the course of additional training epochs.

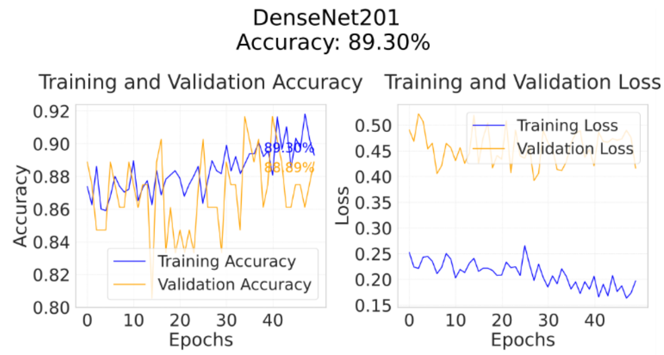

Figure 5.3.4: Training and validation accuracy and loss over the epochs (DenseNet201).

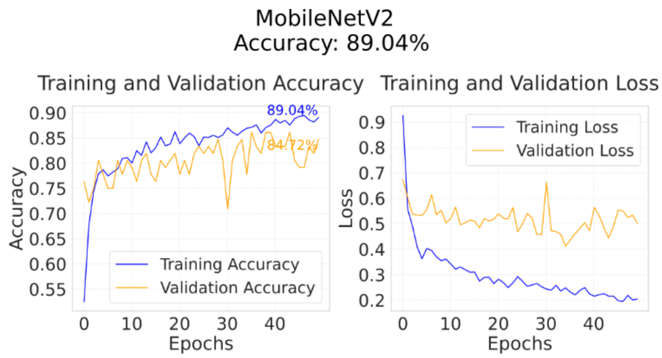

Figure 5.3.5: Training and validation accuracy and loss over the epochs (MobileNetV2).

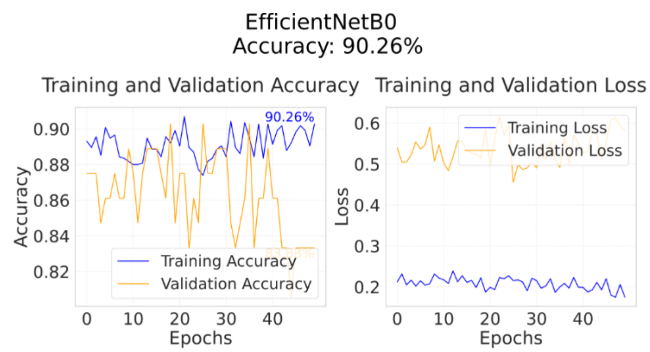

Figure 5.3.6: Training and validation accuracy and loss over the epochs (EfficientNetB0).

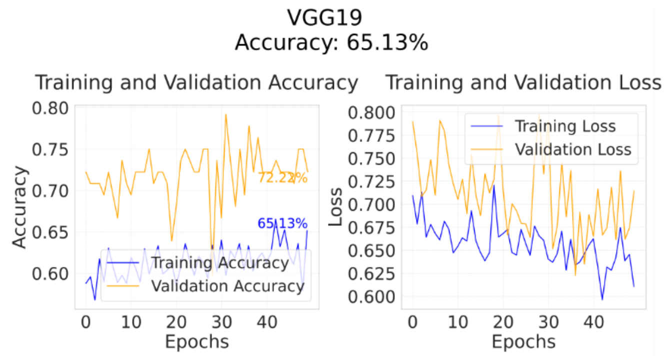

Figure 5.3.7: Training and validation accuracy and loss over the epochs (VGG19).

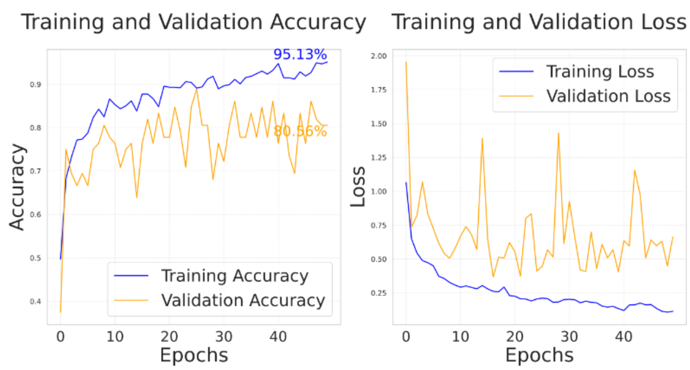

Figure 5.3.8: Training and validation accuracy and loss over the epochs (Fenet5).

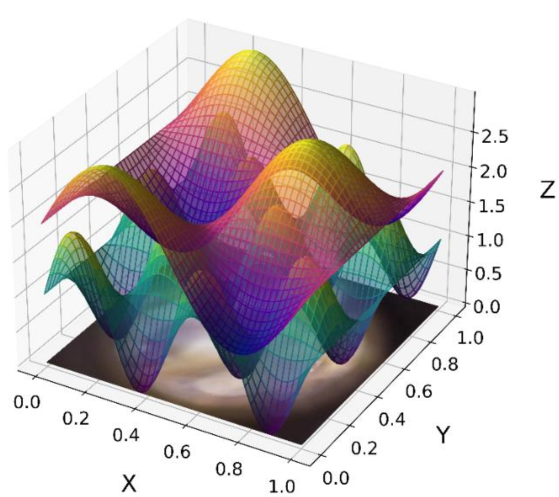

Figure 5.3.9: Features from a Chronic Otitis Media Image

The number of epochs is represented by the x-axis, and the accuracy and loss percentages are represented by the y-axis. While the validation accuracy and loss curves show the model's performance on a different validation dataset, the training accuracy and loss curves show the model's performance on the training dataset. Validation curves are essential for evaluating the model's capacity to prevent overfitting and generalize to previously unseen data.

Generally speaking, a well-performing model will show declining training and validation loss together with rising training and validation accuracy throughout intervals. Validation curve convergence signifies that the model is not overfitting to the training set and has stabilized.

The curves' particular properties—such as their rate of convergence, their final accuracy and loss values, and whether or not they exhibit fluctuations—can offer important insights into the behavior of the model and suggest possible areas for development. A model that performs well in training but poorly in validation, for example, can be overfitting and require regularization methods or more data.

Through the examination of these training and validation curves, scholars and professionals can acquire a more profound comprehension of the efficacy of distinct deep learning models and make knowledgeable determinations concerning model choice, hyperparameter adjustments, and optimization tactics.

Confusion Matrix of the Deep Learning Models:

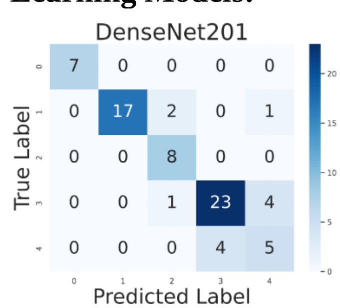

Figure 5.3.10: Confusion Matrix for DenseNet201

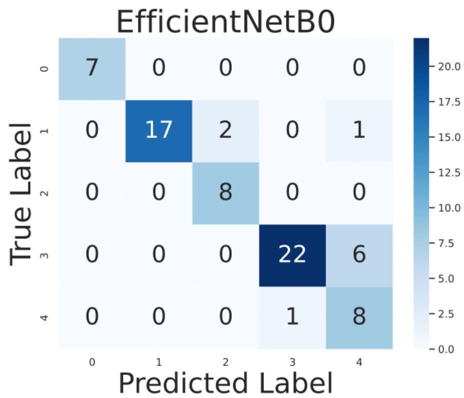

Figure 5.2.11: Confusion Matrix for EfficientNetB0

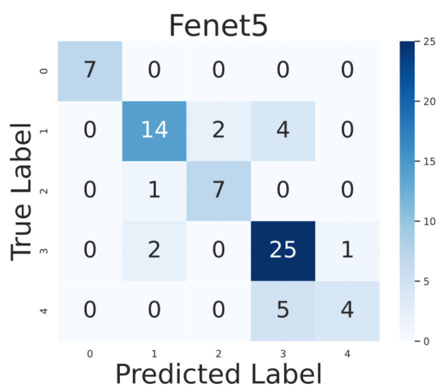

Figure 5.3.12: Confusion Matrix for Fenet5

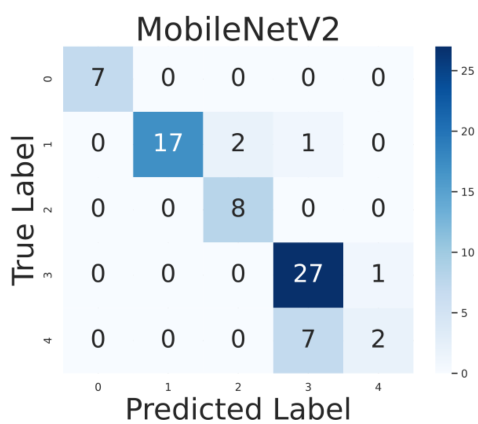

Figure 5.3.13: Confusion Matrix for MobileNetV2

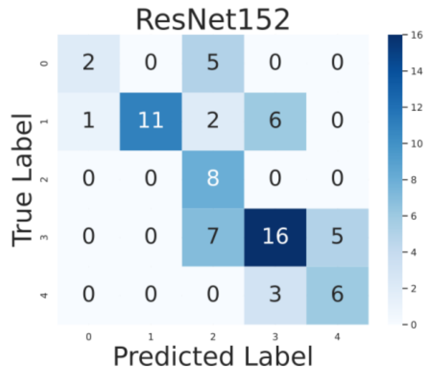

Figure 5.3.14: Confusion Matrix for ResNet152

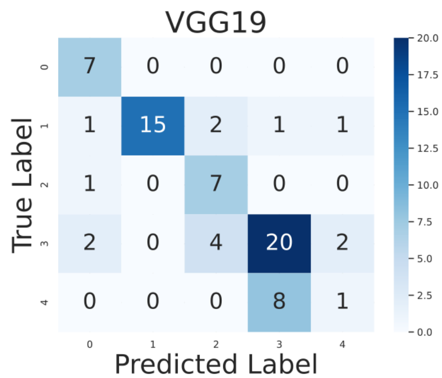

Figure 5.3.15: Confusion Matrix for VGG19

Performance Comparison of FL Algorithms with OtoFL Framework

We evaluated their performance metrics across 50 communication rounds using Federated Learning (FL) algorithms, specifically FedAvg, FedProx, and FedSGD. Out of them, the FedAvg algorithm performed admirably, attaining a 94.25% accuracy rate. But FedProx was the clear winner, with our suggested model hitting an astounding 95.13% accuracy rate. This highlights FedProx's remarkable ability to accurately detect ear diseases in a variety of data distributions under the OtoFL framework. On the other hand, FedSGD achieved 91.66% accuracy. Faster convergence rate in FedSGD is consistent with its performance measures, suggesting a trade-off between convergence rate—which is marginally faster in our framework—and accuracy acquisition speed.

TABLE 5.3.16: Performance comparison of different federated learning algorithms with OtoFL in both IID (D1) and non-IID settings (D2)

OtoFL	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
D1 FedAvg	94.25%	91.6%	97.6%	96.47%
D1 FedProx	95.13%	94.36%	96.22%	97.81%
D1 FedSGD	91.66%	88.60%	84.00%	82.4%
D2 FedAvg	93.41%	90.11%	90.14%	89.41%
D2 FedProx	94.52%	92.61%	91.51%	90.2%
D2 FedSGD	92.77	88.21%	90.39%	89.13%

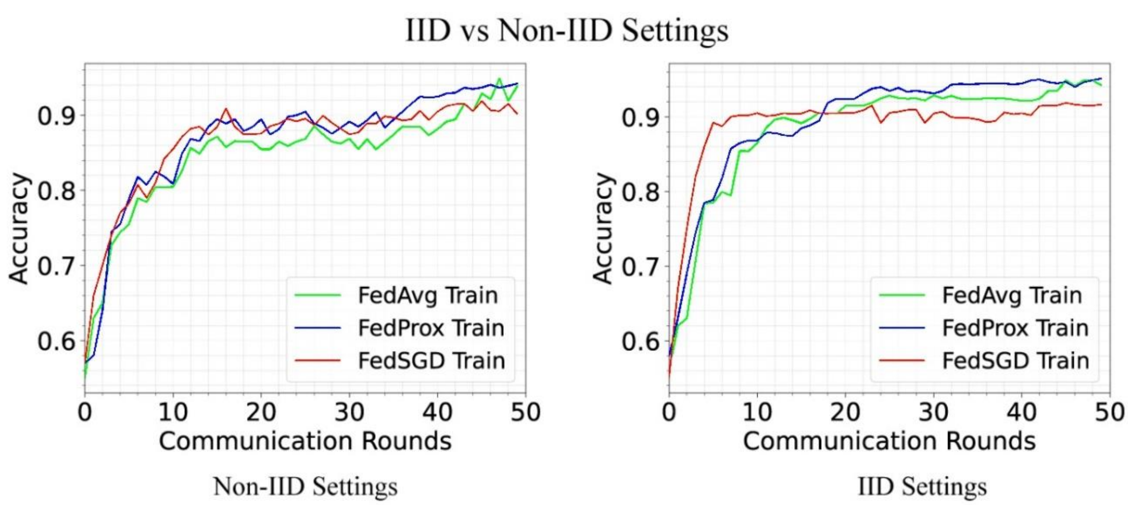

Figure 5.3.17: Performance comparison of different federated learning algorithms with OtoFL in both IID and non-IID settings

As Table 4.2.17 illustrates, our thorough analysis emphasizes how important it is to choose FL algorithms according to particular use cases and data distributions. The table shows how IID (Independent and Identically Distributed) data, designated as D1, and non-IID data distributions, designated as D2, perform differently. Strong precision and recall metrics from the Fenet5 deep learning model supported the FedProx algorithm's remarkable accuracy in our analysis.

Given its unique characteristics, FedProx is a strong contender for incorporation into a decentralized medical picture classification system, especially when it comes to detecting ear conditions across several datasets. These results have applications beyond our research, providing insightful direction for algorithmic judgment in our tailored FL method, OtoFL. This approach is intended to maximize performance in a range of customer scenarios related to healthcare technology.

Impact of the Different Numbers of Clients

Using different numbers of clients, we assessed our framework's performance. The number of active clients (Q = 4, 8, 14, 18, and 22) was taken into consideration in this experiment, where the number of clients N = 5, 10, 15, 20, and 25.

Figure 5.3.18: Accuracy comparison with different numbers of clients with OtoFL.

Fig. 5.3.18 shows us that the performance of the framework decreases with an increase of customers. This is due to the fact that having more client's results in more diverse data distributions, which may cause a biased model to perform poorly. In order to enhance the framework's performance, we applied the OtoFL approach here. As a consequence, the model's performance varies within 0.5% accuracy for every 25 client increases.

Impact of the Communication Round

It was determined that the performance of our model improves with an increase in the number of communication rounds. The accuracy of the framework was measured in this experiment using the number of communication rounds (T = 15, 20, 30, 40, and 50), as indicated in Fig. 5.3.19. More communication between local clients and the server can lead to higher global models, as seen in Fig. 5.3.19, where we can see that the accuracy of the framework rises with each communication round. Efficiency and convergence in communication are therefore more important. It is our finding that after about 30 rounds, the accuracy of the global model of our framework pinches between specific values.

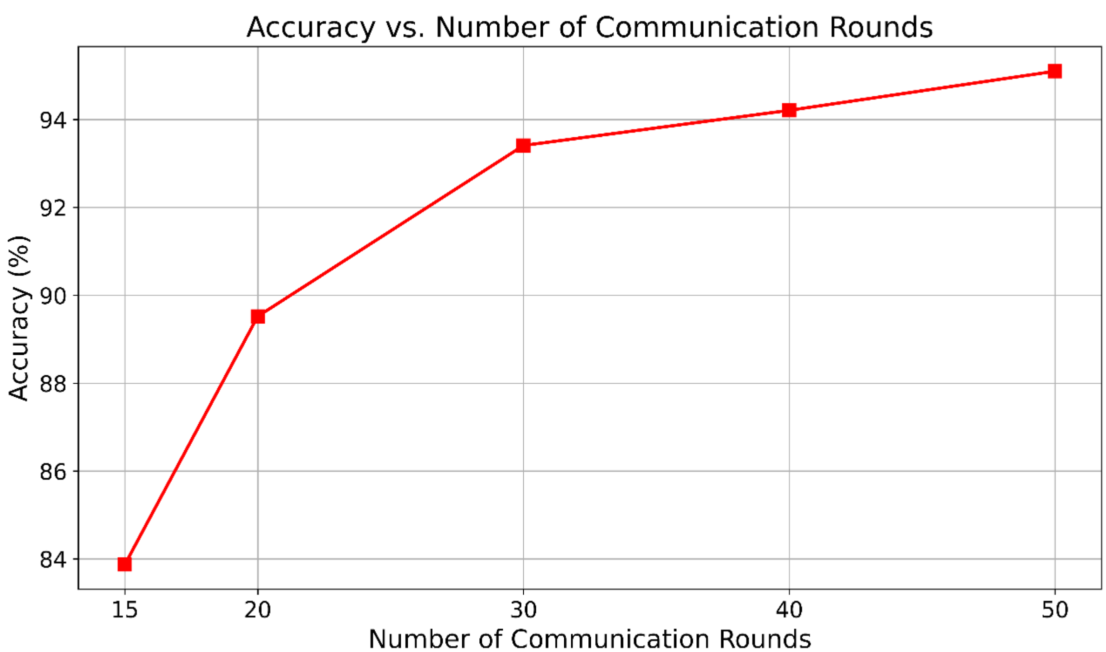

Figure 5.3.19: Accuracy comparison with different numbers of communication rounds with OtoFL.

As a result, this experiment shows how quickly our framework converges, increasing efficiency by lowering the requirement for client-server communication. As a result, in practical applications, cutting down on communication rounds can help achieve a balance between doing so and preserving a more accurate model.

5.4 Summary

We investigate the effectiveness of deep convolutional neural networks (CNNs) in the identification and categorization of different ear disorders from otoscopic images in this extensive study. Using a dataset of 1830 photos, the study uses an advanced data augmentation technique to create numerous augmented images from each original photo. The study looks into the application of unique CNNs, transfer learning strategies, and the cutting-edge federated learning framework OtoFL for the classification of ear diseases. Notably, the paper examines these methods' effectiveness in independent and identically distributed (IID) and non-IID data scenarios, recognizing the actual complexity of data distribution in healthcare environments.

Five different classes of ear diseases are used to extensively test six well-known CNN-based models: DenseNet201, ResNet152, MobileNetV2, VGG19, EfficientNetB0, and the novel Fenet5 model. Fenet5 is the most successful of them, obtaining an amazing accuracy score of 95.13% using the FedProx algorithm in the OtoFL framework. The study clarifies the complex effects of differential privacy and federated learning, demonstrating how well these techniques protect patient data privacy without sacrificing high diagnostic accuracy.

A detailed examination reveals that the Fenet5 model performs better in terms of prediction for unknown data, especially in IID circumstances, when trained and assessed in the OtoFL framework. Additionally, the study looks into how client counts and communication rounds affect model performance. It finds that although having more clients can present issues related to data heterogeneity, the OtoFL algorithm successfully counteracts these impacts while maintaining constant accuracy. Furthermore, as communication rounds increase, model convergence and accuracy improve as well; this improvement peaks at about 30 rounds.

The study highlights the potential advantages of federated learning over conventional centralized training techniques, highlighting the fact that collaborative learning among several institutions can achieve better results than centralized models, especially when dealing with heterogeneous data. Essentially, this work offers a sophisticated investigation of models based on CNN and federated learning techniques for the study of ear diseases, providing insightful knowledge about the nuances of categorization and the complex interactions between various model architectures and scenarios for data distribution.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

This study's findings have significant ramifications for society, especially in the field of healthcare. Utilizing deep learning and federated learning (FL), we have created a brand-new framework called OtoFL that is intended to diagnose ear disorders. In addition to improving the precision and effectiveness of diagnosing ear diseases, this framework places a high priority on patient data privacy—a crucial consideration in the digital age.

OtoFL has a wide-ranging effect on society. First off, the burden of hearing loss and its related effects may be lessened if ear diseases are more accurately diagnosed. A person with hearing loss may find it difficult to communicate, work, and engage in social activities, which can have a substantial negative impact on their quality of life. By using OtoFL to provide an early and precise diagnosis, prompt measures can be implemented to stop or slow the progression of hearing loss and enhance general health.

Additionally, OtoFL's focus on data protection is essential for building patient-provider confidence. It is critical to diagnose diseases without jeopardizing private patient data in an age of frequent data breaches and privacy violations. OtoFL promotes more involvement in medical research and data exchange by guaranteeing data confidentiality, which eventually results in the creation of more reliable and efficient diagnostic instruments.

Additionally, the collaborative aspect of federated learning encourages healthcare organizations to collaborate and share knowledge. OtoFL creates an atmosphere of cooperation where medical practitioners may pool their resources and expertise to tackle difficult health concerns by allowing several institutions to train a single model without disclosing their unique datasets. Through collaboration, otology research and innovation can progress more quickly, resulting in improved treatment options and diagnostic methods.

Conclusively, this research has a noteworthy impact on society. OtoFL has the potential to transform the area of ear disease diagnosis, ultimately improving patient outcomes and promoting a healthy society through increasing diagnostic accuracy, safeguarding patient privacy, and encouraging collaboration.

6.2 Impact on Society & Environment

Even if it isn't the main topic of this study, the environmental effects of the OtoFL framework should be taken into account. In order to use federated learning and deep learning models, there are computational operations involved that require a large amount of energy. Complex neural network optimization and training frequently need energy-intensive hardware, which increases the carbon footprint of the framework. This is especially true for large datasets.

The continuous improvements in cloud computing techniques, sustainable computing methods, and hardware efficiency must be acknowledged, nevertheless. Algorithms and hardware are being optimized for energy efficiency as a result of researchers' and developers' growing awareness of the environmental risks connected to AI applications. Utilizing energy-efficient algorithms and renewable energy sources in data centers are two examples of how integrating green computing methods may greatly reduce OtoFL's negative environmental effects.

Moreover, federated learning's decentralized structure may help save energy on its own. FL can lessen the dependency on centralized, energy-intensive data centers by spreading the computing burden over several devices or servers. This decentralized method improves privacy while also potentially increasing the system's overall energy efficiency.

Finally, while the environmental impact of OtoFL is a legitimate worry, it may be efficiently mitigated by implementing sustainable computing techniques and utilizing federated learning's built-in energy-saving capabilities. To guarantee that developments in healthcare diagnostics are both socially and environmentally responsible, it will be essential to strike a balance between technological innovation and environmental sustainability as the area develops.

6.3 Ethical Aspects

A significant dedication to ethical issues underpins the studies on "A Federated Learning way to Reliable Ear Diseases Diagnosis with Privacy of Data using OtoFL". Using medical photos has a duty to protect patient privacy and confidentiality, particularly when those images are of ear conditions. In order to comply with data protection requirements and respect ethical values, the research makes sure that individual patient data is anonymised and de-identified prior to being utilized for model training.

Every patient whose data is used in the study gives their informed consent, which is a fundamental component of ethical research processes. By doing this, patients' rights to privacy are protected and they are made fully informed of how their data will be utilized. Additionally, the study places a strong emphasis on openness in the development of algorithms and data management, enabling examination and repeatability of the outcomes.

The significance of ethical implementation is highlighted by the possible influence of the study on healthcare on society. The OtoFL framework is intended to be a useful tool that enhances patient outcomes and care without violating the rights of individuals or their privacy. The goal of the research team is to apply technology in a way that benefits patients and the community at large while also being used responsibly and fairly.

In summary, ethical issues are integrated throughout the entire research process, from gathering data and developing models to implementing and disseminating results. The research attempts to protect the privacy and well-being of all participants while advancing medical diagnosis by adhering to the strictest ethical guidelines.

6.4 Sustainability Plan

The OtoFL framework is a complex project with many moving parts that includes technology and team-based elements. A thorough sustainability plan is necessary to guarantee the impact and long-term feasibility of this novel method of diagnosing ear diseases.

The sustainability plan concentrates on increasing the OtoFL framework's computing efficiency from a technology perspective. To do this, the deep learning model Fenet5 must be continuously improved in order to lower its processing requirements without sacrificing accuracy. Furthermore, the framework's energy usage and carbon footprint can be further reduced by investigating hardware acceleration methods and energy-efficient algorithms.

An further important tenet of the sustainability plan is cooperation. OtoFL can provide a steady stream of varied data, knowledge, and resources by cultivating continued collaborations with medical centers, research groups, and technological companies. In addition to improving the framework's flexibility to changing healthcare requirements, this cooperative approach encourages information exchange and group problem-solving. The sustainability strategy also calls for routine maintenance and updates in order to guarantee OtoFL's continued applicability and efficacy. To do this, the architecture must be updated to include the most recent developments in federated learning, deep learning, and data privacy strategies. Further relevant feedback for further optimizations and enhancements will come from ongoing monitoring and assessment of the framework's performance in real-world scenarios.

To sum up, the long-term viability of the OtoFL framework depends on a multifaceted strategy that includes partnership development, ongoing upgrades, and technology optimization. By addressing these issues, OtoFL can continue to be a useful and significant diagnostic tool for ear diseases, improving patient outcomes and promoting long-term health in society.

6.5 Summary

This study explores how to diagnose ear disorders, a major global health concern, using federated learning (FL) and deep learning approaches. The article presents OtoFL, a novel Framework for FL that aims to tackle the issues of heterogeneity and data privacy in medical image analysis. OtoFL protects patient privacy while utilizing a variety of datasets to improve diagnosis precision by facilitating the cooperative training of a deep learning model, Fenet5, across several institutions without revealing raw patient data.

The research assesses OtoFL's performance in independent and identically distributed (IID) as well as non-IID data settings, taking into account the intricacies of data distribution in the actual world. The findings show that OtoFL, especially when using the FedProx algorithm, can classify ear diseases with excellent accuracy even when there is heterogeneity in the data. The study delves into the effects of communication rounds and client numbers on model performance, offering valuable insights for fine-tuning the framework for practical implementation.

To sum up, this work demonstrates how federated learning and deep learning might transform the diagnosis of ear diseases. OtoFL presents a viable path toward creating precise, confidential, and cooperative diagnostic tools that are easily used in a variety of healthcare contexts by tackling the issues of data privacy and heterogeneity.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusions

We have introduced OtoFL, a unique federated learning (FL) framework, in this study for the detection of ear disorders. Our method tackles two major issues that are common in medical image analysis: data privacy and heterogeneity. OtoFL protects patient privacy while utilizing the variety of datasets to improve diagnosis precision by facilitating the cooperative training of a deep learning model, Fenet5, across several institutions without the need to disclose raw patient data.

We discover that OtoFL can classify ear disorders with an impressive 95.13% accuracy under non-IID data distributions, especially when using the FedProx method. This demonstrates the stability and flexibility of our approach in practical clinical situations where heterogeneity of data is a typical occurrence. Furthermore, the use of differentiated privacy strategies fortifies patient data security even more, guaranteeing that personal privacy is maintained throughout the collaborative learning process. OtoFL performs better than other deep learning models in terms of accuracy, privacy protection, and collaboration potential, as demonstrated by the comparison analysis with conventional diagnostic techniques. The framework is a useful tool for improving the diagnosis of ear diseases since it may use a variety of datasets from different institutions without jeopardizing data confidentiality.

OtoFL, in summary, is a major advancement in the realm of medical image analysis. We have created a system that not only improves diagnosis accuracy but also puts patient privacy first and encourages cooperation amongst healthcare facilities by utilizing the power of federated learning and deep learning. Future developments in medical diagnostics could benefit greatly from the accurate, collaborative, and privacy-preserving diagnostic tools that this research sets the way for. These developments could lead to better patient outcomes and care.

7.2 Further Suggested Works

Future research directions in the fields of federated learning (FL) and ear disease diagnostics are made possible by the findings reported in this work.

- **Expansion of Disease Categories:** Although the present study concentrated on a particular subset of ear disorders, more research may broaden the focus to encompass a more diverse array of ailments, including cholesteatoma, otosclerosis, and several forms of otitis media. This would improve the OtoFL framework's comprehensiveness and suitability for use in actual clinical settings.
- **Incorporation of Diverse Data Modalities:** The main diagnostic tool used in this investigation was otoscopic imaging. In order to create more comprehensive and individualized diagnostic models, future studies may investigate the integration of additional data modalities, such as audiological data, demographics of patients, and medical history.
- **Refinement of Federated Learning Algorithms:** FL is a dynamically developing discipline where new optimization methods and algorithms are always being developed. Subsequent research endeavors may explore the integration of these developments into OtoFL to augment its efficacy, efficiency, and privacy-maintaining potential.
- **Exploration of Explainable AI:** There's a growing need for explainable AI (XAI) as AI-powered diagnostic tools become more common. Subsequent investigations may concentrate on creating XAI methods for OtoFL, which would enable physicians to understand the logic underlying the model's forecasts and promote openness.
- **Real-World Deployment and Evaluation:** Although this study shows OtoFL's promise in a simulated scenario, more research should concentrate on its actual application and assessment in a range of clinical settings. In clinical practice, this would entail evaluating its effectiveness, usefulness, and effect on patient outcomes.

We can improve the diagnosis of ear diseases and make it more precise, approachable, and patient-centered by pursuing these research avenues. Deep learning, FL, and other cutting-edge technologies could revolutionize healthcare diagnostics and, in the process, improve the lives of millions of people globally.

7.3 Limitations/ Conflict of Interests

Though novel and encouraging, the research included in this study is not without flaws. A key limitation is the restricted quantity and variety of the accessible datasets. Even though two datasets were combined for the investigation, the total number of photos (1830) might not accurately reflect the wide range of ear conditions and differences in image quality that can occur in actual clinical settings. The generated model's robustness and generalizability may be impacted by this constraint, especially if it is used to different patient populations or healthcare institutions with different imaging equipment.

The amount of computing power needed for federated learning is another drawback. The decentralized nature of federated learning requires sufficient processing power at each participating institution, even though the study effectively used high-performance computing resources for model training. The broad adoption and application of the OtoFL framework may be hampered by this need, which could provide difficulties for healthcare facilities with little funding.

There are no personal or financial ties to individuals or groups that could improperly influence or skew the findings of this study, hence there is no conflict of interest. The study used federated learning and deep learning approaches with the exclusive goal of improving the detection of ear diseases. It was carried out separately.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title:
A Federated Learning Approach to Accurate Ear Disease Diagnosis with Data Privacy

Student ID: 201-15-3117

CO Description for FYDP

CO	CO Descriptions	PO
	Phase -I	
CO1	Integrate recently gained and previously acquired knowledge to identify a **ear disease with federated learning** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
	Phase -II	
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**

CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	Our project entails designing a system for automated ear disease diagnosis, requiring a comprehensive understanding of engineering fundamentals (K3) and specialist knowledge in medical imaging and machine learning (K4).	**Page no:** [`46-51] **Section:** [3.2] **Page no:** [11-18] **Section:** [1.1]
				We integrated various components such as data preprocessing and model development covering aspects of engineering design (K5) and engineering practice (K6).	**Page no:** [51] **Section:** [3.2(D)] **Page no:** [51]

					Section: [3.2(E)]
				We extensively reviewed existing literature on ear disease diagnosis (K8) to inform our methodology.	**Page no:** [36-43] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	Our project encountered challenges in balancing the need for diverse and representative datasets with privacy concerns. This conflict required careful consideration of data collection methods and privacy-preserving techniques.	**Page no:** [43-44] **Section:** [2.4]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	The analysis conducted for our project involved selecting appropriate machine learning algorithms for ear disease diagnosis from a range of options, considering factors such as accuracy, interpretability, and computational efficiency.	**Page no:** [51-55] **Section:** [3.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	To address the complexities of ear disease diagnosis, we needed to familiarize ourselves with medical imaging techniques, ear anatomy, and disease pathology, areas that were not extensively covered in our prior coursework.	**Page no:** [32-38] **Section:** [2.1,2.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A

6.	**EP6: Extends of stakeholders involved and conflicting requirements**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	Various subsystems in our project, such as data preprocessing, model training, and result interpretation, were interdependent, requiring seamless integration to ensure the system's functionality and **EP7**.	**Page no:** [60-63] **Section:** [4.2]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in ear disease detection through federated learning and deep CNNs.	**Page no:** [65, 87] **Section:** [5.2,6.3]
2.	**EA2: Level of interaction**	No		N/A	N/A

3.	**EA3: Innovation**	Yes		The project exhibits innovation by introducing a novel federated learning framework, OtoFL, specifically tailored for ear disease diagnosis. This framework incorporates a unique deep learning model, Fenet5, and addresses the challenges of data heterogeneity and privacy through innovative algorithms and differential privacy mechanisms, contributing to advancements in the field.	N/A
4.	**EA4: Consequences for society and the environment**	Yes		This project contributes to society by improving healthcare through advanced ear disease detection methods, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines for patient data privacy.	**Page no:** [85] **Section:** [6.2]
5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach in ear disease detection through federated learning and deep CNNs, demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.	**Page no:** [87] **Section:** [6.4]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [55-58] **Section:** [3.4]
2	CO9	Yes	The project demonstrates adherence to ethical principles by prioritizing patient privacy, obtaining informed consent, and transparently documenting the research process, ensuring responsible knowledge	**Page no:** [84] **Section:** [6.3]

			dissemination and societal well-being through the ethical application of advanced healthcare technologies which comply with **CO9.**	
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [65-84] **Section:** [5.1, 5.2, 5.3, 5.4]

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