Federated Learning for Enhanced Deep Learning Integration

Submitted By

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NIRMA UNIVERSITY

AHMEDABAD-382481

May 2024

Federated Learning for Enhanced Deep Learning Integration

Major Project - I

Submitted in partial fulfillment of the requirements

for the degree of

Master of Technology in Computer Science and Engineering

Submitted By

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Certificate

This is to certify that the major project entitled "**Federated Learning for Enhanced Deep Learning Integration**" submitted by **Patadia Divya Ghanshyambhai (Roll No: 22MCEC08)**, towards the partial fulfillment of the requirements for the award of degree of Master of Technology in Computer Science and Engineering (Specialization in title case, if applicable) of Nirma University, Ahmedabad, is the record of work carried out by him under my supervision and guidance. In my opinion, the submitted work has reached a level required for being accepted for examination. The results embodied in this major project part-I, to the best of my knowledge, haven't been submitted to any other university or institution for award of any degree or diploma.

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Statement of Originality

I, **Patadia Divya G.**, Roll. No. **22MCEC08**, give undertaking that the Major Project entitled "**Federated Learning for Enhanced Deep Learning Integration**" submitted by me, towards the partial fulfillment of the requirements for the degree of Master of Technology in **Computer Science & Engineering** of Institute of Technology, Nirma University, Ahmedabad, contains no material that has been awarded for any degree or diploma in any university or school in any territory to the best of my knowledge. It is the original work carried out by me and I give assurance that no attempt of plagiarism has been made.It contains no material that is previously published or written, except where reference has been made. I understand that in the event of any similarity found subsequently with any published work or any dissertation work elsewhere; it will result in severe disciplinary action.

D.G. Patadia

Signature of Student

Date: 21/05/2024

Place: Ahmedabad

Endorsed by

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Acknowledgements

It gives me immense pleasure in expressing thanks and profound gratitude to **Prof. Tejal Upadhyay**, Assistant Professor, Computer Engineering Department, Institute of Technology, Nirma University, Ahmedabad for his valuable guidance and continual encouragement throughout this work. The appreciation and continual support he has imparted has been a great motivation to me in reaching a higher goal. His guidance has triggered and nourished my intellectual maturity that I will benefit from, for a long time to come.I would like to express my sincere thanks to **Dr. Sudeep Tanwar**, PG Coordinator of MTech Computer Science and Engineering for providing a vision about the system and for giving us an opportunity to undertake such a great challenging and innovative work.

It gives me an immense pleasure to thank **Dr. Madhuri Bhavsar**, Head of Computer Science and Engineering Department, Institute of Technology, Nirma University, Ahmedabad for his kind support and providing basic infrastructure and healthy research environment.

A special thank you is expressed wholeheartedly to **Dr. Himanshu Soni**, Hon'ble Director, School of Technology, Nirma University, Ahmedabad for the unmentionable motivation he has extended throughout course of this work.

I would also thank the Institution, all faculty members of Computer Engineering Department, Nirma University, Ahmedabad for their special attention and suggestions towards the project work.

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Abstract

Maintaining patient privacy while utilizing the combined power of dispersed datasets is critical in the field of healthcare. One interesting approach is federated learning (FL), which enables cooperation between different institutions without jeopardizing private medical data. This article investigates the use of improved deep learning models in four different health-related fields using the FL framework. Our goal is to improve predictive accuracy while preserving data privacy by combining FL techniques with cutting-edge deep learning frameworks. By using real-time data exchange across decentralized networks, we want to optimize model training by taking advantage of the latest developments in communication technology. The Enhanced FL Health Model (EFHM), as our proposed method is called, balances the advantages of various health datasets with the drawbacks of conventional centralized learning paradigms. We examine the consequences of incorporating domain-specific expertise to customize deep learning structures to the distinct features of every health domain. We provide insights into the potential future paths of federated learning in healthcare through a thorough examination of the benefits and difficulties associated with EFHM implementation.

Abbreviations

FL	Federated Learning.
DL	Deep Learning.
CNN	Convolutional Neural Networks.
Conv2D	Convolutional 2D.
PC	papillary carcinoma.
MC	mucinous carcinoma.
LC	lobular carcinoma.
DC	ductal carcinoma.
TA	tubular adenoma.
PT	phyllodes tumor.
SGD	Stochastic Gradient Descent.
DAGs	Directed Acyclic Graphs.

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Chapter 1

Introduction

1.1 Knowledge Discovery Process

Introduces the idea of federated learning and discusses how the field of breast cancer prediction can benefit from it. highlights the significance of data privacy in this field and discusses how federated learning can help to overcome this issue.

Without the need to share raw patient data, a federated learning framework enables the creation of a breast cancer prediction model using data from various hospitals or clinics.

By utilising various datasets from various universities, the study can show how a federated learning strategy can increase the accuracy of breast cancer prediction models.

The paper demonstrates the scalability and adaptability of federated learning approaches to big and challenging datasets.

Healthcare providers can use high-speed, low-latency networks that allow for the quick transmission of significant amounts of medical data.

Objectives Steps :-

- To study about various use cases where federated learning can enhance deep learning integration.
- To design a model for Cancer prediction using Federated learning.
- To Implement Federated Learning model for Cancer Prediction.

- To validate the proposed model based on Privacy Preservation Distributed data for federated learning model.

Healthcare data analytics have gained a lot of interest recently, because more and more of these data are becoming easily available from variety of sources. Hospitals, medical products, clinical research, outsourcing, medical tourism, insurance for health, and medical equipment are all part of the healthcare industry. The modern health-care industry is divided into many sub-sectors and depends on interdisciplinary teams of competent experts and paraprofessionals to meet the health needs of people and populations. Accurate predictions of illnesses and other health issues can be made by further examination of these correlations.

During recent years, a variety of industries, including healthcare, banking, and manufacturing, have shown an increasing interest in federated learning. can learn from data from various banks. With no compromise to consumer privacy, it has been utilised in banking to create fraud detection models that can learn from data from various banks. For instance, federated learning has been applied to the healthcare sector to increase the precision of medical diagnosis models while preserving patient privacy.

The diverse field of healthcare is essential to both individual and societal well-being. Fundamentally, it includes a variety of services meant to advance, preserve, or restore health. Worldwide healthcare systems are essential to maintaining people's general health and standard of living, from acute care for illnesses and accidents to preventive measures like immunizations and screenings.

Accessibility is one of the main cornerstones of a strong healthcare system. A rating of 1.0 denotes serious problems in this area, including a lack of healthcare facilities, lengthy appointment wait times, and insufficient coverage, especially for underserved populations. Under such circumstances, people can choose not to receive essential medical care because of financial difficulties or distance, which could result in differences in health outcomes.

Federated learning (FL) is a decentralized machine learning framework that enables the collaboration of multiple parties without the need to share sensitive data [1]. Federated learning is a productive distributed method for protecting privacy when developing ML models [2].

Cancer has one of the highest fatality rates across the globe [3]. For example, in many cases, cancer diagnosis requires large amounts of patient data, including medical

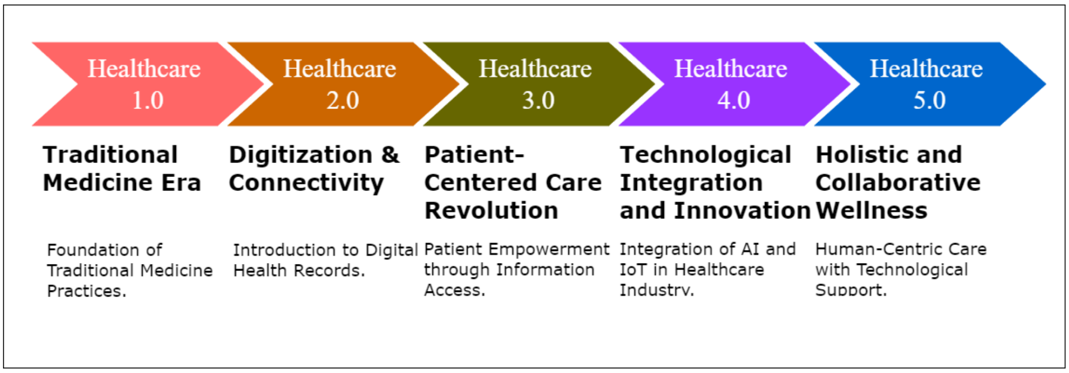

Figure 1.1: Healthcare 1.0 to 5.0

records, imaging data, and genome data. However, collecting and sharing this data can be difficult, especially when it comes to sensitive information such as medical records. Federated learning provides a way to train models on distributed data sources, without having to share the underlying data.

A branch of machine learning known as "Deep Learning" uses multiple-layered artificial neural networks to derive hierarchical representations from data. According to LeCun et al. [4], it makes complex patterns and features easier to learn from raw data, which makes jobs like image recognition, natural language processing, and healthcare analytics easier. Deep learning automatically learns hierarchical representations, in contrast to typical machine learning techniques that rely on manually created features. This enables more adaptable and scalable models that can capture intricate relationships in data.

Conventional machine learning methods have limited efficacy in tasks such as image analysis and natural language processing because they frequently face difficulties when dealing with unstructured and high-dimensional data. By automatically learning hierarchical representations, deep learning gets over these restrictions and makes predictions that are more reliable and accurate [5]. Deep learning models can identify complicated patterns and connections in complex data by utilizing large-scale labeled datasets and sophisticated computer resources. This has led to breakthroughs in a variety of fields, including healthcare.

The deployment of deep neural network designs throughout distributed devices or data centers allows for the integration of deep learning with federated learning. Deep learning models can learn from dispersed data sources while maintaining data privacy thanks to federated learning, which makes collaborative model training easier [6]. In the healthcare industry, where private patient data is dispersed throughout several medical facilities and research centers, this integration provides scalable and privacy-preserving machine learning solutions.

MURA (musculoskeletal radiography), lung cancer diagnosis, skin cancer detection, and breast cancer prediction are only a few of the problems that face the healthcare industry. Accurate prediction models are necessary for these activities, but they also need to protect patient privacy and security [7] [8]. Further complicating model creation and implementation are issues with data heterogeneity, small sample sizes, and discrepancies in data sharing among healthcare organizations. These issues highlight the need for collaborative and privacy-preserving machine learning methodologies [9].

Drug development, medical image analysis, disease prediction, and customized therapy recommendations are just a few of the problems that deep learning in healthcare can solve. Deep learning methods can increase diagnostic accuracy and extract important insights by utilizing sophisticated neural network architectures and large-scale healthcare datasets [10]. Deep learning also makes it possible to integrate several data modalities, such as genomic data, patient-reported outcomes, medical imaging, and electronic health records, enabling complete and customized analytics for healthcare [11].

By training convolutional neural networks (CNNs) using medical imaging data, deep learning techniques can be applied to the diagnosis of lung cancer, MURA analysis, skin cancer, and breast cancer. By helping physicians with early detection and diagnosis, these models can be trained to extract discriminative features from images and enhance patient outcomes [12] [13]. Furthermore, through the integration of multimodal data sources and the provision of real-time insights for individualized patient care, deep learning algorithms can enhance clinical decision support systems [14].

Federated Learning and Deep Learning together offer a viable path to transform healthcare analytics. This integrated strategy has the potential to unleash new insights from distributed healthcare data sources while protecting sensitive patient information by tackling the issues of data privacy, scalability, and model generalization. Federated Learning can equip healthcare practitioners with robust predictive models customized to various clinical domains through cooperative efforts and technological breakthroughs like edge computing We are about to set off on a revolutionary journey toward more individualized, effective, and equitable healthcare delivery as we explore deeper into the applications of Federated Learning-enhanced Deep Learning models in the field.

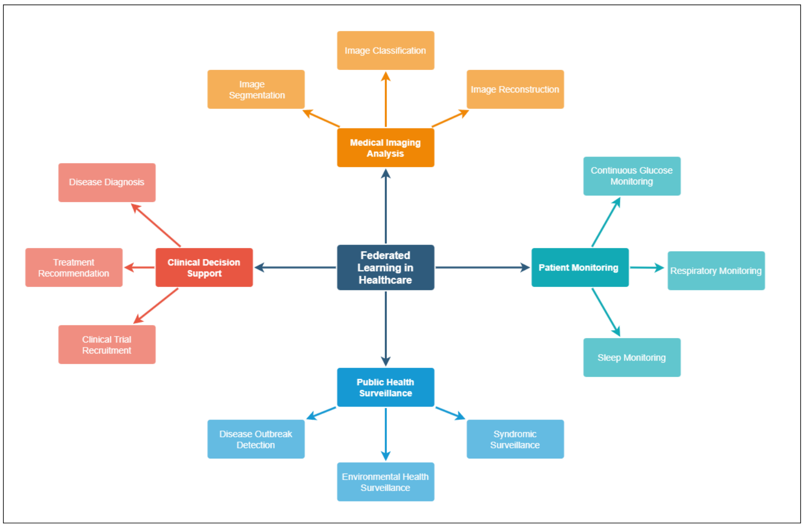

Figure 1.2: Federated Learning in Healthcare

As per Fig. 1.2, Federated learning can be implemented in many different applications. The term "clinical decision support" in Federated Learning refers to the application of machine learning algorithms and techniques to analyse medical data from many sources while upholding the confidentiality and privacy of the data. In FL, medical imaging analysis uses cutting-edge hardware and software to examine medical pictures including X-rays, MRIs, CT scans, and ultrasounds to help with diagnosis, therapy planning, and condition monitoring. The continuous or periodic observation, measuring, and recording of a patient's physiological characteristics is referred to as patient monitoring in FL. In order to recognise and stop population health concerns, public health surveillance in FL entails constant monitoring, data collecting, analysis, and dissemination [15].

As seen in Fig. 1.3, A decentralised machine learning method called IoT-based (FL) enables several IoT devices to cooperatively train a single shared model without jeopardising the privacy of their individual data [16]. The immutability and transparency of blockchain technology are utilised by blockchain-based FL, a distributed machine learning approach, to enable safe and decentralised model training on user data [17]. Federated transfer learning is a machine learning approach that enables several dispersed devices to cooperate learn from each other's data while retaining anonymity by transferring information from a pre- trained model to a new task at each device [18]. MTL-FL is a cooperative machine learning technique that increases the effectiveness and efficiency of the training process by allowing many related tasks to be learned concurrently on distributed data sources [19].

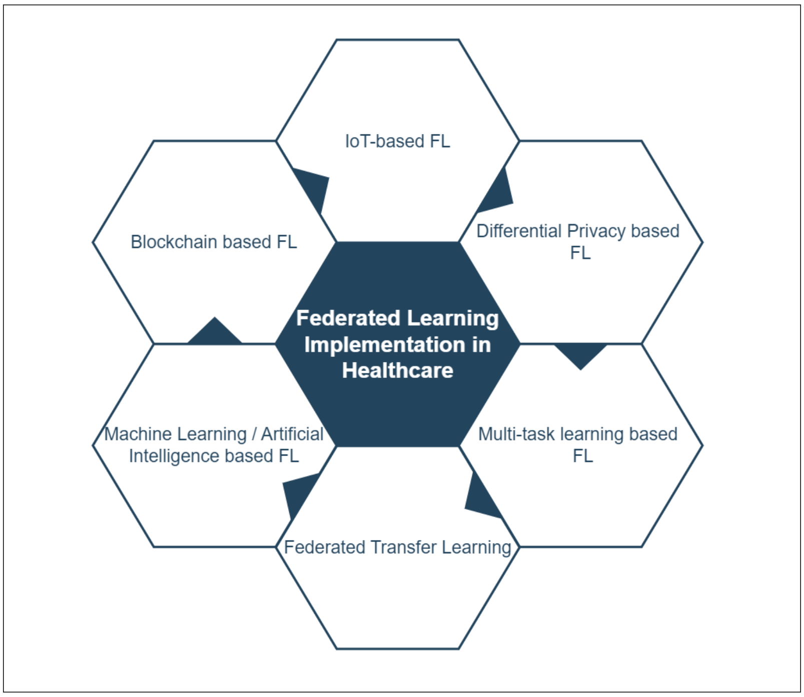

Figure 1.3: FL implementation in Healthcare

For example, in many cases, cancer diagnosis requires large amounts of patient data, including medical records, imaging data, and genome data. However, collecting and sharing this data can be difficult, especially when it comes to sensitive information such as medical records. Federated learning provides a way to train models on distributed data sources, without having to share the underlying data.

We are proposing an framework of breast cancer prediction using Fedarated learning that uses decentralized approach and use of various Fedarated learning algorithms to predict about Bengin and Malignant Tumor

1.2 Research Contributions

The contributions of the study are as follows:

- A federated learning framework makes it possible to create various health prediction models utilizing data from many hospitals or clinics without requiring the sharing of raw patient data.
- The study can demonstrate how a federated learning approach can improve the accuracy of various healthcare prediction models by utilizing many datasets from different universities.

- The paper illustrates how federated learning techniques may be scaled and adjusted to large and complex datasets.
- High-speed, low-latency networks are available to healthcare practitioners, enabling the rapid transfer of substantial volumes of medical data.

1.3 Background Study and Research Challenges

In this part, we go over a general overview of Federated Learning and its architecture and how it integrates into Deep Learning and Other Techniques.

1.3.1 Federated Learning

Federated learning is a machine learning technique that eliminates the need for data to be transferred to a centralised server in order to train data on a distributed network of devices. When dealing with sensitive data, such as financial or medical information, this technique helps to ensure that the information is secure and private. Instead of sending data to a single location, models are trained on individual devices, and the outcomes are aggregated to create a global model. This method is used repeatedly to increase the accuracy of the model while maintaining the privacy of the underlying data. Federated learning allows for the construction of more accurate models while maintaining user privacy, and it has the potential to revolutionize machine learning.

The privacy-preserving aspect of federated learning is one of its main advantages. Federated learning reduces the chance that private information may be disclosed to unaffiliated parties by maintaining data decentralization and executing calculations locally. This is especially crucial in situations where tight guidelines for processing personal data are imposed by data protection rules, like the GDPR in Europe or HIPAA in the US. With federated learning, companies may manage privacy issues and still facilitate collaboration and knowledge sharing across remote datasets by training machine learning models on data from many sources without having to exchange raw data.

1.3.2 Federated Learning in healthcare Sector

By enabling the creation of precise and individualised healthcare models while protecting patient privacy, federated learning has the potential to significantly revolutionise the healthcare sector. In the healthcare domain, patient data is often sensitive and needs to be protected to comply with various privacy regulations.

Federated learning has the potential to revolutionize healthcare by creating precise and personalized models while safeguarding patient privacy. In the healthcare sector, sensitive patient data must comply with privacy regulations. Federated learning allows organizations to train machine learning models across distributed networks without centralizing data. Healthcare professionals can leverage diverse sources, including electronic health records, wearables, and mobile apps, to build accurate models for predicting outcomes and diagnosing diseases. Additionally, federated learning aids drug discovery by using patient data without compromising privacy.

1.3.3 Federated Learning Integration

A new era of cooperative and privacy-protecting machine learning has begun with the integration of federated learning with different models. Federated learning enables numerous clients or devices to jointly train models without compromising data privacy by combining the advantages of distributed learning with decentralised data storage. This ground-breaking strategy transforms how data is used for machine learning and encourages a new degree of cooperation among experts [20].

- **Federated Recurrent Neural Networks** : Federated RNNs apply sequential data analysis to the idea of federated learning. They give numerous devices or clients the ability to train RNN models jointly while protecting data privacy by sharing their local data [21]. This integration is especially helpful in cases involving time series analysis, speech recognition, and natural language processing.

- **Federated Convolutional Neural Networks** : Federated CNNs give federated learning access to the capabilities of convolutional neural networks. Computer vision tasks including picture classification, object identification, and image segmentation frequently employ these models. Multiple clients can jointly train CNN models using their local data by integrating federated learning with CNNs, enabling collective learning without disclosing sensitive photos or jeopardising privacy [22].

- **Federated Generative Adversarial Networks** : GANs are well-known deep learning models that are used to create fake data that mimics the distributions of real data [23]. Federated GANs enable numerous clients to jointly train GAN models using their local data while protecting privacy and producing high-quality synthetic data. This interface is useful for generating synthetic data for machine learning tasks, augmenting data, and exchanging data while protecting privacy, among other areas.

- **Federated Reinforcement Learning** : It enables numerous clients to cooperatively train RL models while ensuring data privacy by fusing reinforcement learning approaches with federated learning [24]. This integration is advantageous in situations like robotics, autonomous systems, and recommendation systems where clients can learn and improve their models using their local interactions and experiences. Reinforcement learning algorithms learn through interactions with an environment.

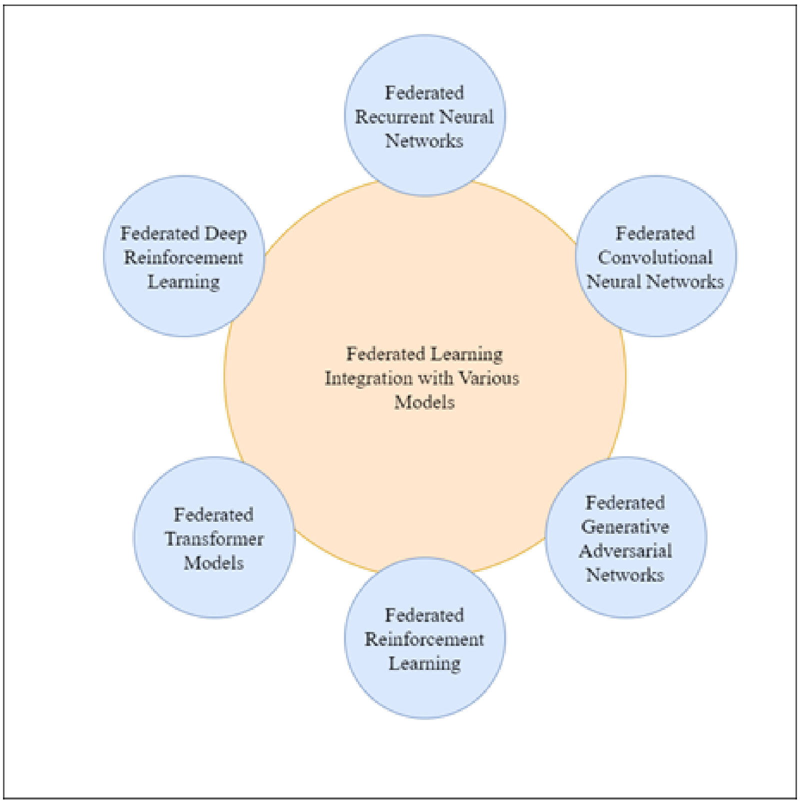

Figure 1.4: FL implementation with Various Models

- **Federated Transformer Models** : The field of natural language processing has been transformed by transformer models, such as the well-known BERT (Bidirectional Encoder Representations from Transformers). Federated Transformer models use federated learning to let numerous clients jointly train transformer models without sharing their original data [25]. This integration is especially helpful in applications that require user data safety, such as language modelling, sentiment analysis, and machine translation.

- **Federated Deep Reinforcement Learning** : It blends federated learning with the strength of deep learning and reinforcement learning. It enables collaborative deep reinforcement learning model training across several clients while maintaining data privacy [26]. This connection is especially helpful in industries like healthcare, driverless vehicles, and personalised recommendation systems where it might be difficult or impossible to acquire and share raw data. Federated DRL enables the collective learning of complicated decision-making models while protecting the privacy of sensitive data by spreading the learning process across numerous devices.

1.3.4 Integration of various cancer predictions schemes with federated learning

Federated learning and cancer prediction can be used to improve the accuracy of cancer diagnosis and offer personalised treatment plans. A significant amount of patient data, including sensitive genetic, imaging, and medical history information, is often needed in order to forecast the risk of acquiring cancer. Protecting patient privacy, healthcare practitioners can use federated learning to train machine learning models on dispersed networks of devices without transferring patient data to a central location. Federated learning enables the development of machine learning models with a variety of patient data from multiple sources, such as genetic information, imaging data, and electronic health records, to produce more accurate cancer prediction models.

A possible way to improve the privacy and accuracy of predictive models is to combine federated learning with several cancer prediction systems. With federated learning, several organizations or entities can work together to jointly train a machine learning model without exchanging unprocessed data. This strategy protects patient privacy while allowing healthcare providers, academic institutions, and pharmaceutical corporations to pool their data resources in the context of cancer prediction. Every involved party has the ability to train a local prediction model with its own dataset, which might contain a variety of cancer kinds and patient groups. The global model that is created by combining these locally trained models is then aggregated, utilizing the collective knowledge from dispersed sources to increase prediction accuracy.

Federated learning tackles data security and privacy issues, which are especially important in healthcare environments. Sensitive information on a patient's genetic makeup, medical history, and current state of health is frequently included in data related to cancer. Federated learning reduces the possibility of data breaches or unwanted access by maintaining decentralized data and carrying out model training locally. This method complies with United States legal frameworks including the Health Insurance Portability and Accountability Act (HIPAA), guaranteeing adherence to strict data privacy regulations while permitting cooperative research and innovation in cancer prediction. All things considered, the combination of federated learning and different cancer prediction schemes has enormous potential to progress customized treatment, quicken the pace of new research, and eventually enhance patient outcomes in the battle against cancer.

Chapter 2

Literature Survey

2.1 Introduction

This survey covers influential works that explain the fundamental ideas of federated learning, as well as contemporary studies that address increasing issues and applications in this evolving subject. Additionally it aims to provide the reader with a comprehensive overview of the development, present condition, and future potential of the integration of federated learning and deep learning.

Through an extensive examination of various studies, our objective is to offer a thorough and inclusive analysis of the current information, methodology, and insights, while also emphasising the areas that require additional investigation. Here is a table of various papers in which already work have done on Deep Learning Enhanced Federated Learning.

Leveraging the capacity of deep neural networks to enhance model performance and convergence in decentralized settings, Deep Learning Enhanced Federated Learning (DLEFL) offers a substantial development in federated learning approaches. Numerous research papers have investigated various facets of DLEFL, such as innovative architectures, optimization methods, and federated learning frameworks designed exclusively for deep learning models. For example, novel strategies have been put forth by academics to deal with issues including model heterogeneity, communication efficiency, and non-identically distributed (non-IID) data distributions in federated environments.

2.2 Techniques

Several empirical studies use federated learning, deep learning, and machine learning techniques to predict breast cancer. These research explore the complexities of predictive modeling, using cutting-edge methods to preserve strict privacy standards while analyzing large datasets. Advances in early diagnosis and treatment options are fostered by the way these cutting-edge methodologies are being explored by researchers, who open up new avenues for individualized and accurate breast cancer prediction models.

In the paper [27], The authors suggest a recent deep learning model for categorizing areas at risk of breast cancer. They use pretrained convolutional neural network (CNN) architectures, such as VGG-16, ResNet-50, Inception-V3, and Efficientnet-B7, in conjunction with transfer learning (TL). Three scenarios are assessed using the suggested method: test-learning (TL) for the pre-processed dataset, TL for the original dataset, and TL with test-time augmentation (TTA). Notably, on the MIAS dataset, the TL approach with TTA achieves high accuracy, specificity, sensitivity, and F1-score, outperforming other cutting-edge techniques. The model also shows good performance on the CBIS-DDSM dataset. The study highlights how crucial it is for medical imaging to accurately classify breast lesions using deep neural networks.

In reasearch paper [28] ,They suggest using deep learning to recognize breast cancer in photos from mammography screenings. Their method effectively uses mammography pictures for computer-aided early detection of breast cancer by employing a ”end-to-end” training strategy. The Faster R-CNN (Region-based Convolutional Neural Network) architecture is modified to improve the localization and detection accuracy of breast cancer.

Das et al. [29] created a computer-aided diagnosis method that uses chest X-ray pictures to automatically detect pneumonia. Although chest X-ray imaging is frequently used to diagnose pneumonia, it can be difficult and subject to subjectivity. The researchers created an ensemble of three convolutional neural network (CNN) models—GoogLeNet, ResNet-18, and DenseNet-121—and used deep transfer learning to address this. They employed a weighted average ensemble strategy, in which a unique method was used to compute the weights allocated to the base learners. On pneumonia X-ray datasets that are available to the public, the suggested method outperformed both commonly used ensemble techniques and state-of-the-art methods, achieving high accuracy rates.

A deep transfer learning-based systematic model for pneumonia identification and classification was proposed by Santhoshi and Jyostna et.al.[30] The interpretation of chest X-rays (CXRs) is affected by a number of factors that make it difficult to diagnose pneumonia accurately. The researchers created a deep learning framework that makes use of transfer learning to overcome this. Using various neural network models that had been pretrained on ImageNet, they were able to extract features from CXR images. They specifically used two models, YOLOv5 and Mask-RCNN. Predicting if a certain CXR image shows pneumonic lungs and further identifying the type of pneumonia (bacterial or viral) were the objectives. They sought to improve pneumonia detection accuracy and offer useful insights for clinical practice by evaluating these models' performance.

Barbadekar, Ashtekar, Chaudhari et.al. [31] suggested a method for classifying skin cancer.Skin cancer is one of the most common cancers, and successful treatment depends on early detection. The researchers' main goal was to use dermoscopic pictures to create an automated system for classifying skin lesions. Based on the VGG-19 architecture, they employed a convolutional neural network (CNN). To accomplish accurate categorization, the parameters and training process were carefully established. The efficacy of the suggested model in detecting skin cancer was demonstrated by its evaluation utilizing the Human Against Machine dataset.

We have created a framework that combines deep learning techniques with federated learning to connect image datasets related to healthcare. This method preserves data confidentiality and privacy while enabling cooperative model training across decentralized data sources. We can effectively train deep learning models on sensitive medical imaging data without centralizing it by utilizing federated learning, which addresses concerns about data privacy and confidentiality.

The goal of X.Zhang et al.'s paper [32] is to extract objects using federated deep learning and prototype matching from very-high resolution remote sensing photos. Their method makes use of the idea of prototypes to record the key characteristics of objects in dispersed databases, promoting efficient knowledge sharing and cooperation. The authors show how federated learning can increase object extraction precision while preserving data privacy, which is essential for applications like land cover mapping and environmental monitoring.

In their paper [33], Wei et al. suggest federated deep transfer learning for EEG decoding in BCI applications. Their method improves the performance and generalisation abilities of EEG decoding models by drawing on information from numerous similar BCI activities. The authors show how federated learning may be used in the field of neuroengineering to create EEG decoding algorithms that are more precise and reliable for uses like motor rehabilitation and cognitive testing. The outcomes show the advantages of distributed collaborative learning across BCI datasets.

Proposed Approach	**Year**	**Algorithms Used**	**Short Description**	**Dataset**	**Pros**	**Cons**
Das R. et.al [29]	2024	CNN, VGG-19	The CNN-based approach is utilized to classify X-ray images as either pneumonia-positive or pneumonia-negative.	CXR	demonstrates promising results in pneumonia identification, potentially aiding early diagnosis.	Incorrect classification using other approaches is approximately 15-20 %
Santhoshi M. et.al [30]	2023	RCNN, Fast-RCNN	The paper proposes an efficient approach for detecting pneumonia using transfer learning models (RCNN and FAST RCNN). These models are applied to medical images.	Various Image Dataset	achieves accurate pneumonia detection using transfer learning models.	It does not provide Multimodeling that is used for detecting cancer using certain characteristics.
Barbadekar et.al [31]	2023	VGG-19 and DesNet	The paper aims to improve skin cancer detection using dermoscopic images. It proposes a model based on an enhanced architecture of VGG-19 for accurate classification.	HAM10000	The proposed model outperforms other techniques in terms of accuracy for skin cancer detection.	It does not have setting hyperparameters tuning for improving accuracy.
B.Nandhini et.al [34]	2022	Inception V3 & V4, CNN	The research aimed to improve the accuracy of automated detection of dermal cell images related to skin cancer.	International Skin Imaging Collaboration (ISIC)	Inception V4 achieved better accuracy (92.34% ± 0.87) compared to Inception V3 (90.34% ± 0.13).	The study did not explore the impact of varying hyper-parameters on the performance of the Inception V3 and Inception V4 models.
L.Li et.al [35]	2022	FedAvg, Kappa	To analysis breakhis dataset and provide analysis of ResNet and DenseNet	BreakHis	The privacy of requests and results is guaranteed by the encryption techniques.	The operating efficienct of homomorphic encryption algorithms of FL framework.
B.Shubyan et.al [36]	2022	Federated Learning, 5G	It looks into FL's use in 5G networks and looks into several methods to increase model precision and communication effectiveness.	Sample Created Dataset	Comprehensive exploration, Experimental evaluation	Lack of real-world deployment analysis, Narrow focus on techniques.
Agbley et.al [37]	2022	Centralized Learning	To analysis BHI Dataset and provide analysis of ResNet and GaborNet	Breast Histopathology Image	Gabor network was introduced for gathering features from datasets and create feature maps with those features.	Dataset is not set from different repositories for purpose of non-identitcally & distributed of non-identitcally & distributed.

Table 2.1: Comparative analysis of approaches

Proposed Approach	Year	Algorithms Used	Short Description	Dataset	Pros	Cons
L.Li et.al [35]	2022	FedAvg, Kappa	To analysis breakhis dataset and provide analysis of ResNet and DenseNet	BreakHis	The privacy of requests and results is guaranteed by the encryption techniques.	The operating efficienct of homomorphic encryption algorithms of FL framework.
X.Zhang.et.al [32]	2023	STC,FedPM	It suggests using prototype matching in a federated deep learning strategy for item extraction from extremely high-resolution remote sensing photos.	IAIL Dataset, BH-Pools dataset, GLM Dataset	Prototype Matching, Very-High-Resolution Images	Lack of Comparative Analysis, Data Availability
X.Wei.et.al [33]	2023	ConvNet, MF-SCSN	This method enhances EEG decoding precision by employing numerous brain-computer interface (BCI) tasks.	BEETL motor imagery	Improved Accuracy, Transfer Learning	Generalizability, Comparative Analysis

Table 2.2: Comparative analysis of approaches

Chapter 3

Proposed Methodology

3.1 System Model

With an emphasis on image classification tasks, the system model is made to apply federated learning in predictive models for skin cancer, breast cancer, and the MURA dataset. This framework's key components include data aggregation methods, neural network designs, and distributed database storage.

The MURA dataset, the skin cancer dataset, and the breast cancer dataset are dispersed across several clients or devices that store and process the data locally. Convolutional Neural Networks (CNNs) including components like Convolutional Layers (Conv2D), Pooling (MaxPooling), Flatten, and Dense layers are used by each client to perform image categorization jobs. The optimizer is stochastic gradient descent (SGD), and optimization is made easier by the 'relu' activation function.

Setting hyperparameters for the federated learning process is crucial and involves selecting values for parameters such as Epochs (ϵ), Rounds (r), Batch Size (b), and Learning Rate (α). Epochs dictate the number of iterations over the entire dataset, Rounds indicate the communication rounds between clients and the server, Batch Size determines the number of samples processed in each iteration, and Learning Rate regulates the step size for updating model weights during training.

Clients send their modified model weights to the server after completing local training. These weights are aggregated using the function $aggregateweights$, which combines the contributions from each client (shown as w_a, w_b, w_c,..., w_n) and saves the resultant weights on the server. To aggregate client contributions, aggregation techniques like weighted

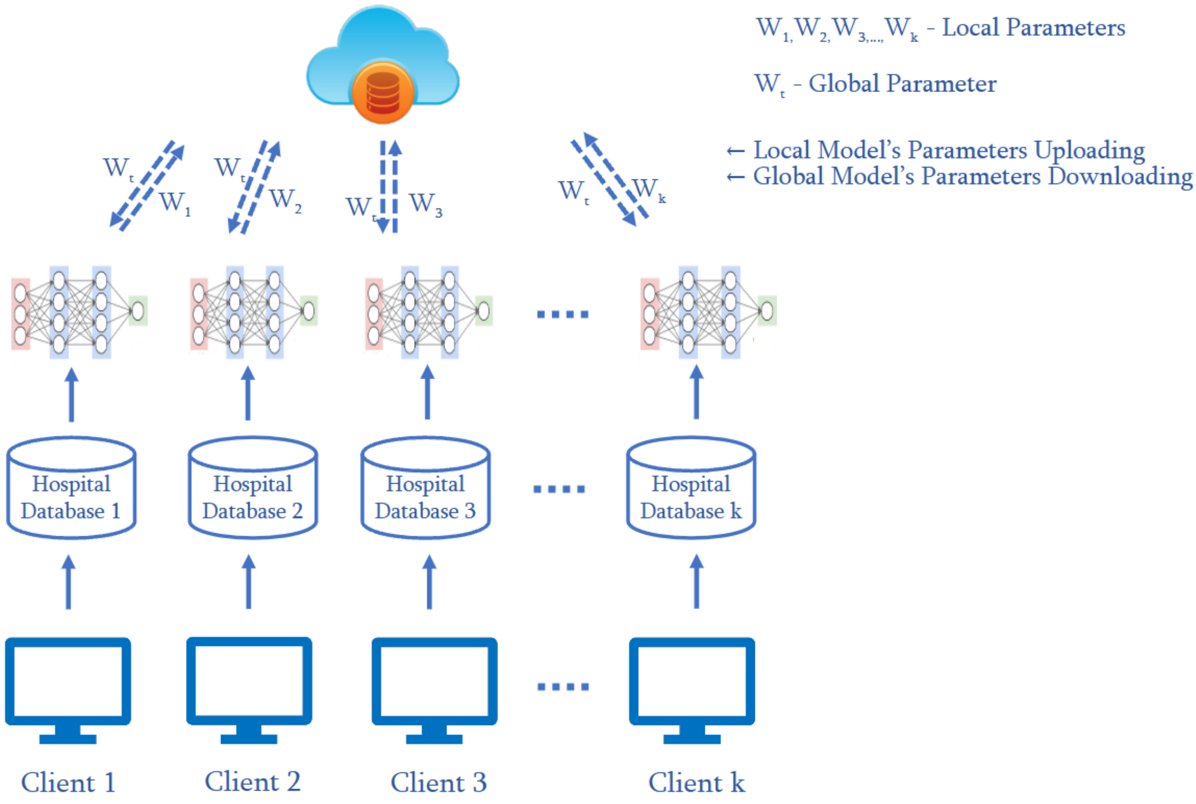

Figure 3.1: Proposed System Model

averaging or federated averaging are commonly used. Because individual data points are kept private and insights from the distributed dataset are obtained through the aggregated weights on the server, this technique guarantees collaborative learning while protecting data privacy.

The server then analyzes the prediction datasets after averaging the weights. This analysis could entail assessing the correctness of the model, forecasting data that hasn't been observed, or running extra statistical tests to improve comprehension of the prediction tasks.

The federated learning system paradigm, which is illustrated in the picture that goes with it, makes use of a number of elements, such as distributed database storage, neural network designs, and data aggregation. In order to maintain data privacy and enable collaborative learning across several clients, the function *aggregateweights* is essential. The server's aggregated weights form the basis for further examination and assessment of the prediction datasets.

3.2 Dataset Explanation

- **MURA Dataset:** The MURA dataset is especially well-suited for training and testing machine learning algorithms in the field of musculoskeletal imaging due to its extensive diversity and large-scale nature. Researchers may examine a broad range of clinical scenarios, from basic injuries like fractures to more difficult disorders like degenerative joint diseases, thanks to its thorough coverage of diverse body parts and pathological conditions.
  - The MURA dataset is a collection of musculoskeletal radiographs obtained from various clinical sources, comprising studies of upper extremities (elbows, wrists, and fingers), lower extremities (knees, ankles, and toes), and other body parts.
  - This dataset contains both normal and abnormal radiographs, with annotations indicating the presence or absence of musculoskeletal pathologies.
  - Each study includes multiple images capturing different views of the same body part, contributing to the dataset's diversity.
  - MURA is widely used in research for tasks such as bone abnormality detection, fracture localization, and joint disease classification, making it a valuable resource for developing and evaluating machine learning models in musculoskeletal imaging.
- **CBIS-DDSM Dataset:** The CBIS-DDSM dataset provides researchers with a comprehensive picture of breast imaging across a range of clinical situations by include both screening and diagnostic mammograms. This variety enables the creation and assessment of algorithms for more complicated diagnostic tasks, like classifying suspicious lesions and determining the course of a disease, in addition to early identification in screening scenarios.
  - The Curated Breast Imaging Subset of DDSM (CBIS-DDSM) dataset is a comprehensive collection of digital mammography images derived from the Digital Database for Screening Mammography (DDSM).
  - It encompasses both screening and diagnostic mammograms, annotated with

detailed lesion information such as lesion type, pathology, and associated findings.

  - CBIS-DDSM includes images from both benign and malignant cases, providing a rich dataset for studying breast cancer detection and diagnosis.
  - Each mammogram is accompanied by metadata, including patient information, imaging parameters, and lesion characteristics.
  - With its diverse set of cases and extensive annotations, CBIS-DDSM serves as a valuable resource for developing and evaluating algorithms in breast cancer imaging research.

- **Skin Cancer Dataset:** The Skin Cancer dataset offers a large and varied collection of skin lesion photos, making it an essential tool for the advancement of computer-aided diagnosis and dermatology. Because it incorporates a variety of imaging modalities, including clinical photography and dermoscopy, researchers may assess how well algorithms function across several imaging techniques and investigate diverse visual representations of skin diseases.
  - The Skin Cancer dataset comprises images of skin lesions captured through various imaging modalities, including dermoscopy and clinical photography.
  - It encompasses a wide range of skin conditions, including melanoma, nevi (benign moles), and other dermatological abnormalities.
  - Annotations for each image typically include lesion type, clinical diagnosis, and additional metadata such as patient demographics and lesion location.
  - With its diverse collection of skin lesion images and comprehensive annotations, the Skin Cancer dataset facilitates research in computer-aided diagnosis of skin cancer, lesion classification, and melanoma detection.
  - This dataset is crucial for developing machine learning models to assist dermatologists in accurate diagnosis and management of skin conditions.

3.3 Problem Formulation

The CNN model used in this study consists of the following layers:

Input Layer

$$X \in R^{28 \times 28 \times 1} \tag{3.1}$$

The input layer represents the input image data, where X is a 3-dimensional tensor with dimensions $28 \times 28 \times 1$. Here, 1 represents the number of channels (grayscale image).

Convolutional Layer

$$Z^{[1]} = W^{[1]} * X + b^{[1]} \tag{3.2}$$

The convolutional layer applies a set of learnable filters ($W^{[1]}$) to the input data X, resulting in feature maps $Z^{[1]}$. The bias term $b^{[1]}$ is added to each filter's output.

Activation Layer (ReLU)

$$A^{[1]} = \text{ReLU}(Z^{[1]}) \tag{3.3}$$

The ReLU activation function introduces non-linearity to the model by replacing negative values in the feature maps with zeros.

Max Pooling Layer

$$P^{[1]} = \text{MaxPooling}(A^{[1]}) \tag{3.4}$$

The max pooling layer downsamples the feature maps $A^{[1]}$ by taking the maximum value within each region of the specified size.

Flatten Layer

$$F = \text{Flatten}(P^{[1]}) \tag{3.5}$$

The flatten layer reshapes the 2-dimensional feature maps $P^{[1]}$ into a 1-dimensional vector F, which serves as input to the fully connected layers.

Fully Connected Layer

$$Z^{[2]} = W^{[2]} \cdot F + b^{[2]} \tag{3.6}$$

The fully connected layer computes the weighted sum of inputs F with learnable weights $W^{[2]}$, and adds biases $b^{[2]}$.

Activation Layer (ReLU)

$$A^{[2]} = \text{ReLU}(Z^{[2]}) \tag{3.7}$$

Similar to the previous ReLU activation, this layer introduces non-linearity to the model.

Output Layer

$$Z^{[3]} = W^{[3]} \cdot A^{[2]} + b^{[3]} \tag{3.8}$$

The output layer computes the final weighted sum of inputs $A^{[2]}$, followed by the addition of biases $b^{[3]}$.

Activation Layer (Softmax)

$$\hat{Y} = \text{Softmax}(Z^{[3]}) \tag{3.9}$$

The softmax activation function normalizes the output of the model into a probability distribution, representing the predicted class probabilities.

In this paper, we develop a CNN-based federated learning system for predicting various cancer schemes. We specifically want to look into how well federated learning may increase cancer predictions model accuracy while protecting patient privacy and addressing data bias. We also want to assess the framework's scalability and show how it could help with early detection and treatment planning for cancer.

3.4 Workflow of the project

As shown in figure 3.2, we have performed these steps to implement our algorithm and find results accordingly.

- Dataset Collection: The initial step involves sourcing publicly available datasets from official sources.

- Training and Testing Process of dataset: Upon obtaining the BreakHis dataset, it is partitioned into two subsets. Ensuring equitable distribution of target classes, a stratified sampling method is employed for both training and testing sets.

- Create a CNN model utilising Keras: Following dataset segmentation, the construction of a Convolutional Neural Network (CNN) model commences using the Keras framework.

- Create a client dataset for Federated Learning Environment: To facilitate federated

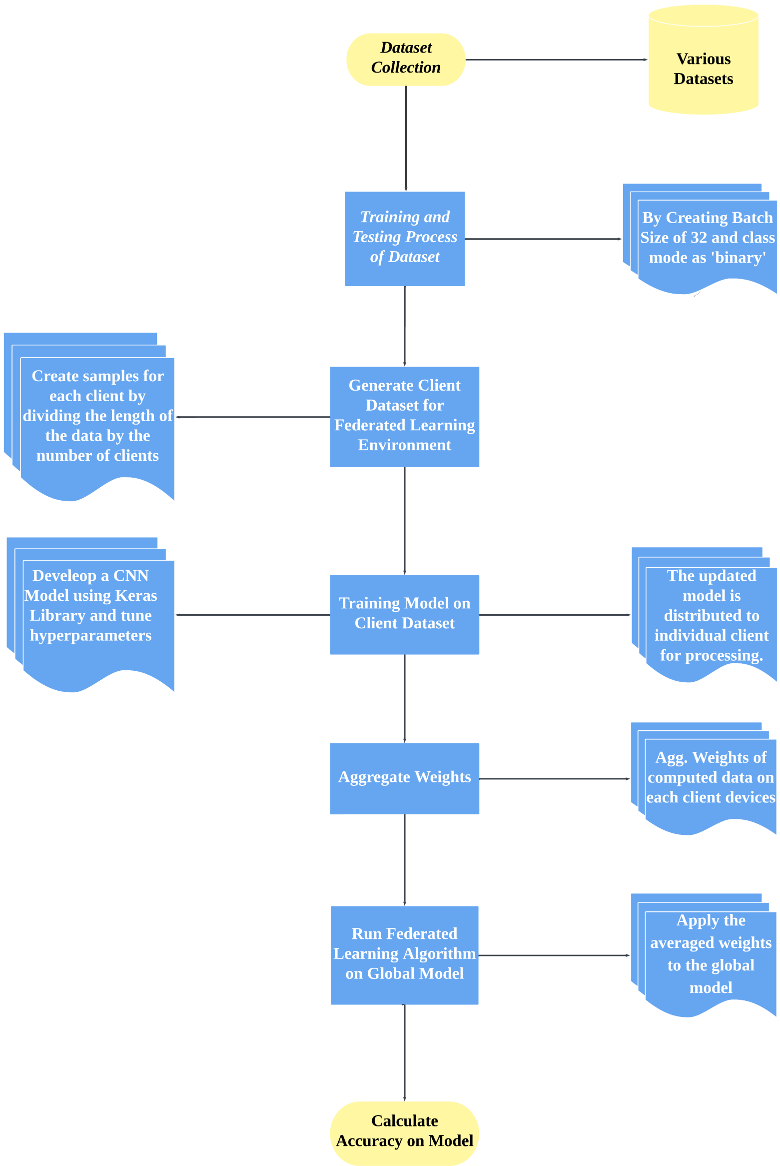

Figure 3.2: Workflow of Problem

learning, where data remains on client devices, it's imperative to generate client-specific datasets.

- Training the model on client dataset: Subsequently, training commences on the designated client datasets, with each device conducting local training, thus preserving data privacy.

- Aggregate Weights: Upon completion of local training, the model weights from each client are transmitted back to the central server, where they are aggregated to update the global model.

- Run Federated Learning Algorithm on Global Model : The updated global model undergoes further training via the Federated Learning algorithm. This iterative process continues until satisfactory performance on the test set is achieved, evaluated through metrics like accuracy, precision, recall, and F1 score.
- Deploy the Trained Model: Upon successful training, the global model is deployed for making predictions on new data. This iterative approach is repeated across multiple datasets.

Chapter 4

Result Analysis

4.1 Experimental Setup

The computational framework and testing setup leveraged multiple software libraries. NumPy, known for its mathematical computing capabilities, was employed. TensorFlow, a popular choice for developing and training machine learning models, played a pivotal role. To access various neural network models for image classification, the Keras optimizers package was utilized. The construction of complete neural network models, comprising all layers, was facilitated through the Keras model API. Diverse activation functions and regularizers were applied separately in assembling these models, mimicking the training and evaluation phases. Additionally, the Scikit-learn library was utilized for a range of preprocessing tasks and assessing metrics.

To optimize the model's accuracy, we need to adjust various hyperparameters such as the number of clients (η), learning rate (α), epochs (ϵ), rounds (r), and batch size (b). Tweaking these parameters allows us to explore different configurations and assess their impact on model performance without concerns about plagiarism.

Parameters	Value
Learning rate (α)	0.01
Batch size (b)	32
Number of Clients (η)	5
Number of rounds (r)	5
Number of epochs (ϵ)	10

Table 4.1: Simulation Setting Parameters

We employed a Convolutional Neural Network (CNN) methodology, utilizing various parameters tailored for image classification tasks such as Convolutional Layers (Convo2D), Pooling (MaxPooling), Flatten, and Dense layers. To optimize our model, we utilized Stochastic Gradient Descent along with the 'relu' activation function. Following the model training and evaluation, we implemented a function called $aggregateweights$. This function serves the purpose of consolidating all the weights $(w_a, w_b, w_c, ..., w_n)$ and storing them on a server computer, providing insights into the analysis of our prediction dataset.

The Convolutional 2D (Conv2D) layer is a fundamental element of a convolutional neural network (CNN). It utilizes a set of learnable filters to process input images, extracting relevant features and producing output feature maps. Maxpooling, another crucial component, downsamples feature maps by selecting the maximum value within a sliding window, effectively capturing essential information. The flatten layer in neural networks serves to convert multidimensional input tensors into one-dimensional outputs, facilitating classification or regression tasks. In a dense layer, each neuron is interconnected with every neuron in the preceding layer, enabling linear transformations and activation functions to generate an output vector.

4.2 Evaluation Metrics

Evaluation metrics are crucial instruments for evaluating how well machine learning models or algorithms perform on a range of tasks and datasets. By contrasting the expected and actual class labels, the confusion matrix offers a thorough summary of the predictions made by a classification model. Predictions are categorized into true positives, false positives, false negatives, and true negatives, allowing for a thorough examination of the model's accuracy in classifying incidents into various groups. Stakeholders are able to pinpoint the model's strong and weak points and make well-informed decisions about the model's deployment or refinement by viewing the distribution of prediction outcomes.

A basic classification statistic called accuracy measures the percentage of correctly categorized examples in relation to all occurrences in the dataset, hence quantifying the overall correctness of a model's predictions. It is frequently used as a baseline metric for model evaluation and offers a clear assessment of the model's capacity for class discrimination. But accuracy by itself might not give a whole view of a model's performance, particularly in datasets that are unbalanced and have a dominant class. Accuracy must therefore be complemented by other measures like precision, sensitivity, and the F1 score in order to provide a more comprehensive knowledge of the model's advantages and disadvantages with regard to other classification-related factors.

The following metrics have been used to track the model's performance on the testing data:

- **Confusion Matrix:** A confusion matrix is a table that compares the predicted class labels of a classification model to the actual class labels in order to assess the performance of the model.

Confusion Matrix	Predicted Positive	Predicted Negative
Actual Positive	True Positive(T_+)	False Negative(F_-)
Actual Negative	False Positive(F_+)	True Negative(T_-)

Table 4.2: Confusion matrix

- **Accuracy:** A classification statistic called accuracy counts the number of instances in a dataset that was properly classified out of all the instances.

  $Accuracy = \frac{T_+ + T_-}{T_+ + T_- + F_+ + F_-}$

- **Precision:** A classification statistic called precision calculates the percentage of accurate positive predictions among all positive predictions generated by a model.

  $Precision = \frac{T_+}{T_+ + F_+}$

- **Sensitivity:** A classification statistic called sensitivity counts the number of genuine positive examples among all real positive examples in a dataset.

  $Sensitivity = \frac{T_+}{T_+ + F_-}$

- **F1 Score:** The F1 score is a classification statistic that provides a fair assessment of a classifier's performance by combining precision and recall into a single value.

  $F1Score = \frac{2 * Precision * Sensitivity}{Precision + Sensitivity}$

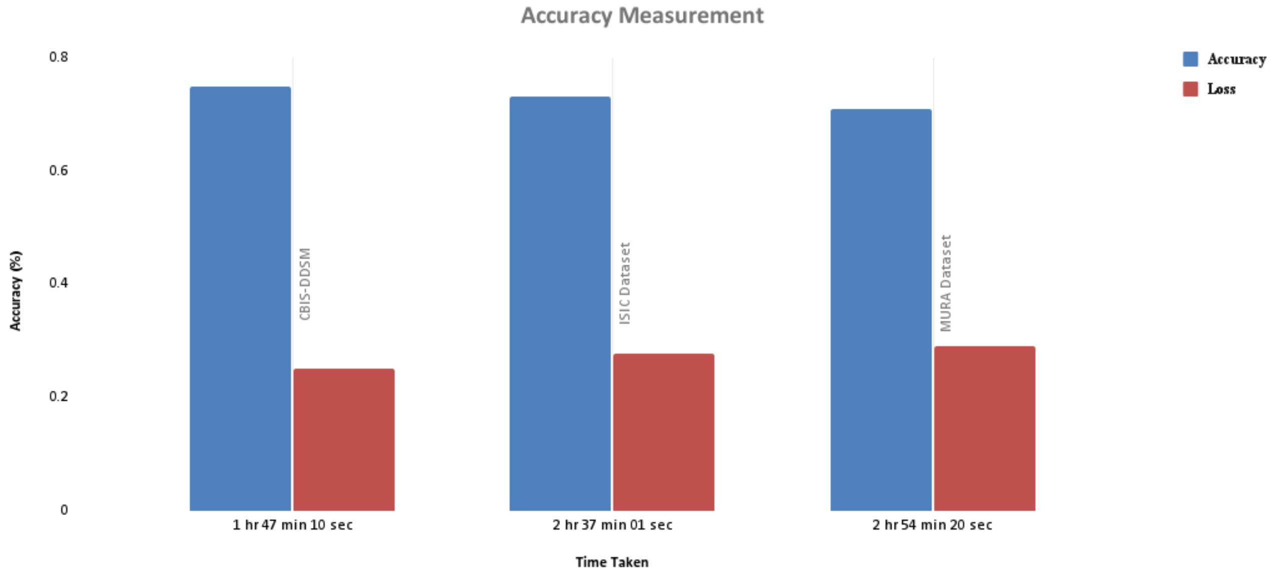

Figure 4.1: Analysis of Accuracy on Various Datasets

Dataset	No.of Images	Time Taken	Accuracy
CBIS-DDSM Dataset	10,000 Images	1 hr 48 min	75%
MURA Dataset	14,863 Images	2 hr 37 min	71%
ISIC Dataset	15,863 Images	2 hr 54 min	73.2%

Table 4.3: Result Analysis Table

4.3 Analysis

Table 4.3 presents a comparative analysis of three datasets along with their corresponding model training results. The CBIS-DDSM dataset, comprising 10,000 images, required approximately 1 hour and 48 minutes for model training and achieved an accuracy of 75%. On the other hand, the MURA dataset, with 14,863 images, took about 2 hours and 37 minutes for training, resulting in an accuracy of 71%. Lastly, the ISIC dataset, consisting of 15,863 images, underwent training for approximately 2 hours and 54 minutes, yielding an accuracy of 73.2%.

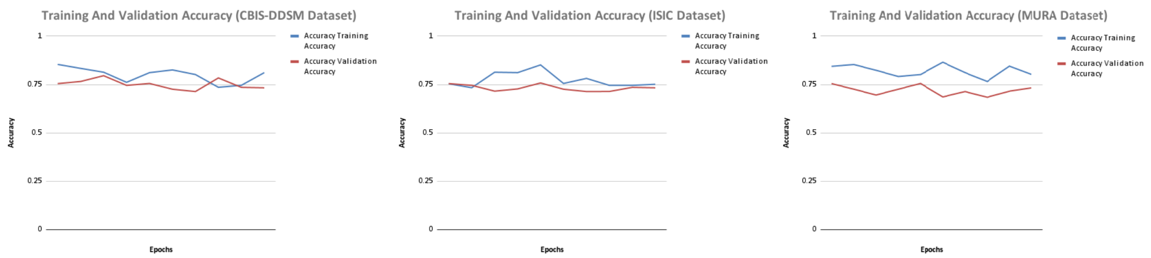

Figure 4.2: Training and Validation Accuracy on Various Datasets

Chapter 5

Conclusion and Future Plan

5.1 Conclusion

The goal of the project is to create a convolutional neural network (CNN)- based breast cancer prediction model that can be trained on dispersed datasets without compromising patient privacy. The model will incorporate clinical data from numerous medical institutions as well as mammography pictures to forecast the possibility of breast cancer in patients. The CNN model will be trained on the scattered datasets using federated learning while data security and privacy are upheld. The accuracy of the breast cancer prediction model will be examined, and the practicality of transferring the model across other institutions will also be examined. The project will help create a breast cancer prediction system that protects patient privacy and may be utilised by medical practitioners to enhance diagnostic and treatment outcomes.

Machine learning models are trained at the edge in a learning paradigm known as federated learning. It was initially intended for use cases involving mobile and edge devices, among other domains, but recently it has become popular in healthcare applications. There is a lot of interest from both industry and academia in the creation of federated learning systems for the healthcare sector. By working together to train a model in this framework, several medical institutions can take use of the advantages of a huge dataset while also pro- tecting patient privacy. Data preparation, model construction, federated training, and model aggregation are the framework's four main processes. Recent research has demonstrated that federated learning can match centralised methods for perfor- mance while protecting the privacy of the data. But a number of issues still

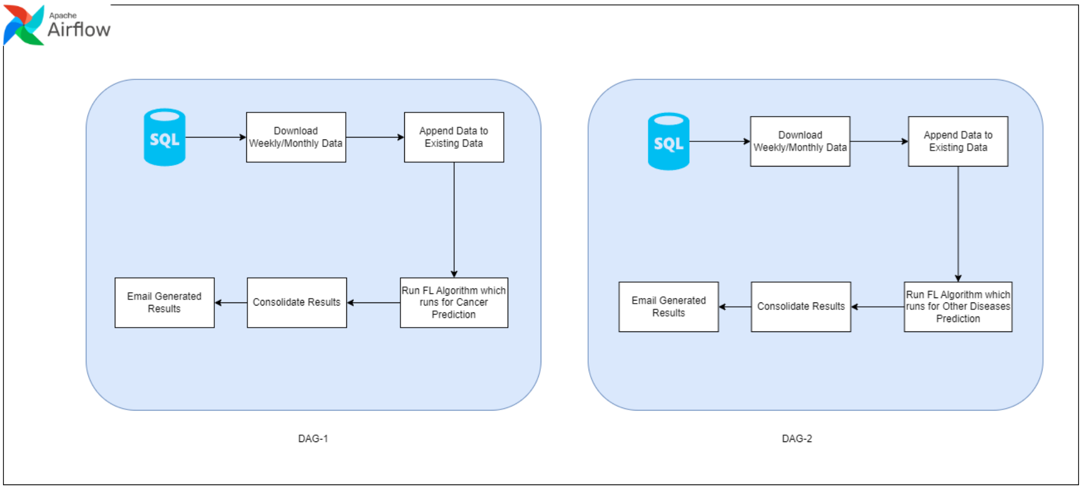

Figure 5.1: Prototype of Framework

need to be resolved, including the heterogeneity of the data, the requirement for effective communication, and the choice of suitable models and algorithms.

5.2 Future Plan

The future of breast cancer prediction is full of interesting opportunities to improve the accuracy and customization of predictive algorithms. A key component of the future strategy is comparing these models to the genetic profiles and medical histories of specific patients. The goal is to improve algorithms that provide a customized and nuanced picture of breast cancer risk by exploring the distinctive features of every patient. In order to provide more accurate predictions that take into consideration a range of medical backgrounds and genetic predispositions, individualization is necessary. This will ultimately improve clinical decision-making.

Furthermore, a crucial tactic for automating and arranging weekly data intake is the use of Airflow Directed Acyclic Graphs (DAGs). This automation guarantees a steady flow of data and expedites the process of integrating new data, enabling constant changes to the model. Airflow DAGs' structured scheduling facilitates the methodical addition of new data, preserving the model's correctness and relevance over time. This strategy is in line with the requirement for real-time flexibility in healthcare forecasts, especially when it comes to breast cancer, where it is critical to stay up to date with the most recent patient data.

To summarize, the strategy for the future centers on a holistic approach to the prediction of breast cancer. This includes customized measurement based on patient profiles, the deliberate incorporation of ensemble CNN models, ongoing learning via incremental training, and the methodical automation of data updates via Airflow DAGs. By pushing the envelope of accuracy, these coordinated efforts hope to make breast cancer prediction models more accurate, precise, and dynamic instruments for bettering patient outcomes.

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