Lightweight Blockchain-Enabled Federated Deep Learning with Differential Privacy for Secure Healthcare IoT Networks

A Project Report Submitted in the Partial Fulfillment of
The Requirements for The Award of The Degree

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

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CERTIFICATE

This is to certify that the project that is entitled with the name "Lightweight BlockchainEnabled Federated Deep Learning with Differential Privacy for Secure Healthcare IoT Networks" is Bonafide work done by **Gujjarlapudi Keerthana Lazarus (22471A05M5) Gali Lakshmi Thirupathamma (22471A05M1) Budala JayaBharathi (22471A05L5) John Wesly Chinthirala (22471A05L8)** in partial fulfillment of the requirements for the award of the degree of **BACHELOR OF TECHNOLOGY** in the Department of **COMPUTER SCIENCE AND ENGINEERING**
during 2025-2026.

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PEO3: Work with ethical and moral values in the multi-disciplinary teams and can communicate effectively among team members with continuous learning.

PEO4: Pursue higher studies and develop their career in software industry.

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PO4: Conduct investigations of complex problems: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions. **PO5: Modern tool usage:** Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

PO6: The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice**.**

PO7: Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

PO8: Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

PO9: Individual and team work: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.

PO10: Communication: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

PO11: Project management and finance: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one’s own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

Project Course Outcomes (CO'S):

CO421.1: Analyze the System of Examinations and identify the problem.
CO421.2: Identify and classify he requirements.

CO421.3: Review the Related Literature

CO421.4: Design and Modularize the project

CO421.5: Construct, Integrate, Test and Implement the Project.

Course Outcomes – Program Outcomes mapping

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2	PSO3
C421.1		✓										✓		
C421.2	✓		✓		✓							✓		
C421.3				✓		✓	✓	✓				✓		
C421.4			✓			✓	✓	✓				✓	✓	
C421.5					✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Course Outcomes – Program Outcome correlation

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2	PSO3
C421.1	2	3										2		
C421.2			2		3							2		
C421.3				2		2	3	3				2		
C421.4			2			1	1	2				3	2	
C421.5					3	3	3	2	3	2	2	3	2	1

Note: The values in the above table represent the level of correlation between CO's and PO's:

1. Low level
2. Medium level
3. High level

Project mapping with various courses of Curriculum Attained POs:

Name of the course from which principles are applied in this project	Description of the device	Attained PO
C2204.2, C22L3.2	The first step in our project was to carefully gather and analyze the requirements to establish a clear understanding of the problem—identifying and classifying Twitte accounts as either human-operated o automated (bots). After examining differen approaches, we selected a suitable proces model to structure the development.	PO1, PO3
CC421.1, C2204.3, C22L3.2	Each and every requirement i critically analyzed, the process mode is identified	PO2, PO3
CC421.2, C2204.2, C22L3.3	Each module was tested individually integrated, and evaluated using metrics such as accuracy, F1-score, and ROC-AUC.	PO3, PO5, PO9
CC421.3, C2204.3, C22L3.2	The project was organized into modules including dataset preprocessing, BERT-based text feature extraction, metadata feature engineering, and a hybrid classification layer.	PO1, PO5
CC421.4, C2204.4, C22L3.2	Documentation was jointly prepared by the team, with regular progress presentations at each stage.	PO10
CC421.5, C2204.2, C22L3.3	The Hybrid BERT + Metadata model was then trained and tested on the TwiBot-20 dataset, showing strong performance in distinguishing bots from human accounts.	PO10, PO11

C2202.2, C2203.3, C1206.3, C3204.3, C4110.2	Future improvements may include real-time Twitter API integration, ensemble learning with additional models, and deployment as a user- friendly application.	PO4, PO7

ABSTRACT

The rapid advancement of Healthcare IoT (H-IoT) has raised significant concerns regarding data security, privacy, and communication integrity. Traditional centralized learning models expose patient-sensitive data to security vulnerabilities, while federated learning (FL) mitigates data-sharing risks but is prone to adversarial attacks. To improve security, privacy, and efficiency in Healthcare IoT (IoT) systems, we suggest Lightweight Block-chain-Enabled Federated Deep Learning (LB- FDL) with Differential Privacy (DP). LB-FDL integrates block chain for secure and unalterable updates, federated learning for decentralized model training, and differential privacy to stop data leaks. The framework drastically lowers computational overhead by utilizing lightweight models like Mobile Net and Efficient Net and an optimized Proof-of-Stake (PoS) consensus. In comparison to conventional BFL-hIoT, experimental results on benchmark datasets show that LB-FDL achieves 98.32% accuracy, 30% faster convergence, and 20% lower communication cost. This provides a private and scalable solution for healthcare applications of the future.

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1. INTRODUCTION

1.1 Introduction

Healthcare IoT, or hIoT, integrates contemporary smart sensors, connected edge devices, and secure cloud services to enable continuous real-time patient and medical environment monitoring. The numerous streams of medical data generated by these devices such as vital signs, imaging results, medication administration records, and emergency alerts need to be sent and processed with the least amount of latency. Nevertheless, sending private medical data over traditional centralized networks always carries the risk of unauthorized access, single points of failure, or serious data breaches. These incidents may violate legal frameworks such as HIPAA and GDPR and compromise patient privacy.

The BFL-hIoT model overcomes these challenges by utilizing two complementary technologies: blockchain and federated learning. Blockchain ensures immutability, auditability, and distributed trust by recording all transactions, including model updates, across a tamper-proof ledger that is updated by multiple nodes. This eliminates the necessity for a single trusted authority and protects against insider threats and data manipulation. Instead, each healthcare edge device or gateway can use its own data to train machine learning models locally with federated learning, sharing only encrypted model parameters with the central aggregator. The fact that raw patient data never leaves the original device makes privacy much better while still advancing a common global model.

By combining these two technologies, the BFL-hIoT framework can achieve high analytical performance and preserve data confidentiality while combining different local models into a more reliable and widely applicable global model. Furthermore, the architecture of the model is designed to function with heterogeneous devices with varying computational capacities, ensuring efficient training cycles even in resource-constrained environments. This hybrid approach builds trust among healthcare stakeholders, improves fault tolerance, and reduces vulnerability to cyberattacks. BFL-hIoT offers a secure, scalable, and effective solution for next-generation healthcare IoT systems, where privacy protection and reliable analytics are equally crucial.

1.2 Problem Statement

The healthcare industry faces challenges in securely handling sensitive data from IoT devices, with traditional centralized models exposing patient information to unauthorized access, data breaches, and high computational and communication overhead. These models struggle with scalability and efficiency, particularly in resource-constrained environments, and face difficulties ensuring compliance with strict privacy regulations like HIPAA and GDPR. Therefore, there is a pressing need for a solution that ensures data privacy, reduces overhead, enhances scalability, and meets regulatory standards while maintaining high performance and data analysis quality.

1.3 Objective of the Project

The objective of this project is to propose and implement the Lightweight BlockchainEnabled Federated Deep Learning with Differential Privacy (LB-FDL) framework to enhance privacy, security, and efficiency in healthcare IoT systems. By using federated learning to keep patient data local, integrating blockchain for secure model updates, and applying Differential Privacy to ensure regulatory compliance, the framework reduces computational overhead with lightweight models like MobileNet and EfficientNet. Additionally, it optimizes scalability and energy efficiency through a Proof-of-Stake consensus mechanism, and benchmarks performance to demonstrate its effectiveness in realworld healthcare IoT applications.

1.4 Strive for Progress

BFL-hIoT has a large computational overhead and communication latency, even though it successfully handles privacy and decentralization. To tackle this, we propose the LB-FDL model, which combines lightweight CNN models, Differential Privacy, and a more efficient blockchain with PoS consensus to achieve better scalability and energy efficiency. The remainder of this document is organized as follows: The Related work is presented in Section II. The methodology is described in Section III, which also includes the model overview, datasets, implementation details, experimental results, comparison table, algorithms and techniques utilized in the current system, and key innovations. The suggested future work and its scope are covered in Section IV. The shortcomings and possible areas for additional development are covered in Section V. Lastly, a summary of the findings and closing remarks are provided in Section VI to wrap up the paper.

2. LITERATURE SURVEY

The Literature Survey section reviews key studies and approaches related to the integration of blockchain, federated learning, and differential privacy in the context of Healthcare IoT (hIoT). The survey highlights the strengths, limitations, and gaps in existing solutions, offering a foundation for the proposed Lightweight Blockchain-Enabled Federated Deep Learning with Differential Privacy (LB-FDL) framework.

2.1 Blockchain in Healthcare IoT

Ganapathy et al. (2024) proposed a blockchain-based federated deep learning model for secure data transmission in IoT environments, addressing the growing concerns of data integrity and unauthorized access in healthcare IoT networks. Their system ensures secure, transparent data sharing by leveraging blockchain's tamper-proof ledger, providing a promising solution for maintaining the privacy of sensitive healthcare data.

Sohail Saif et al. (2024) introduced a secure data transmission framework tailored for healthcare IoT environments. By combining blockchain with secure communication protocols, the model improves the confidentiality and integrity of healthcare data exchanged across IoT devices. This approach mitigates risks associated with data breaches and ensures compliance with privacy regulations.

Lax et al. (2024) focused on a blockchain-based secure data sharing framework for healthcare applications. Their model facilitates secure and transparent sharing of healthcare data among distributed IoT devices while ensuring the immutability of medical records. This approach significantly reduces the risk of data manipulation and unauthorized access.

ALi et al. (2022) proposed a blockchain-orchestrated deep learning approach to secure healthcare data exchange, emphasizing the integration of blockchain with machine learning for enhanced data privacy and security. By using blockchain to manage the model training process, the system prevents unauthorized alterations of data and ensures data integrity during the learning phase.

2.2 Federated Learning in Healthcare IoT

Li et al. (2021) explored federated learning for secure and privacy-preserving healthcare applications, focusing on training machine learning models locally on IoT devices without sharing raw patient data. This method reduces the risks of data breaches and enhances privacy by ensuring that only model updates are shared across the network.

Chamola et al. (2023) presented an AI and blockchain-based cloud-assisted secure framework for medical IoT. By combining federated learning with blockchain technology, the framework ensures that patient data remains secure and decentralized while enabling collaborative model training across multiple healthcare devices.

Singh et al. (2020) introduced a deep-learning-based blockchain framework for secure industrial networks, which shares similarities with healthcare IoT in terms of the need for secure and decentralized data transmission. The system incorporates blockchain and machine learning to secure data flow while optimizing communication efficiency.

2.3 Differential Privacy in Healthcare

Differential privacy (DP) has been widely used to preserve privacy while ensuring data utility in machine learning models. **Ali et al. (2022)** introduced a hybrid intelligent intrusion detection system (HIIDS) using blockchain, integrating differential privacy to ensure that sensitive information is protected during the model training process. This integration prevents attackers from exploiting model updates to extract private data.

Abdalzaher et al. (2025) focused on Quality-Focused Internet of Things Data Management using blockchain technology, integrating differential privacy to enhance data security while reducing the risk of privacy breaches. This approach improves both data confidentiality and network efficiency.

2.4 Blockchain and Federated Learning Integration

Despite the promising potential of blockchain and federated learning, integrating these technologies into healthcare IoT systems presents several challenges. **Nowrozy et al. (2024)** highlighted the challenges of integrating blockchain with federated learning in healthcare, particularly around the scalability of the blockchain network and the communication overhead involved in federated learning updates. They also noted the importance of optimizing consensus mechanisms to improve the overall efficiency of the system.

Margelis et al. (2018) discussed efficient cryptographic algorithms for securing IoT data, proposing methods to enhance the privacy and security of healthcare data in transit. However, the high computational cost of these methods remains a bottleneck in real-time healthcare applications.

2.5 Lightweight Models for Healthcare IoT

In resource-constrained IoT environments, lightweight models like **MobileNet** and **EfficientNet** are crucial for improving computational efficiency. **Chamola et al. (2023)** applied a lightweight deep learning model in medical IoT systems to ensure high performance while minimizing the computational overhead. These models are particularly useful in mobile and edge devices, where computational resources are limited.

2.6 Project Overview and Key Challenges

The literature reveals promising advancements in blockchain, federated learning, and differential privacy for secure and efficient healthcare IoT systems. However, key challenges remain:

Scalability: Existing solutions often struggle with scalability, especially in large-scale healthcare IoT networks with diverse devices.

Energy Efficiency: Blockchain consensus mechanisms like PoW introduce high computational and energy costs.

Communication Overhead: Frequent model updates in federated learning lead to high communication costs, especially in bandwidth-constrained environments.

Regulatory Compliance: Ensuring that systems meet strict privacy regulations like HIPAA and GDPR while maintaining model performance.

This study aims to address these gaps by proposing the LB-FDL framework, which integrates lightweight models, optimized blockchain consensus mechanisms, and differential privacy to create a scalable, energy-efficient, and privacy-preserving solution for healthcare IoT.

3. Existing System

3.1 Existing System

The current Healthcare IoT (hIoT) infrastructure primarily relies on centralized machine learning architectures, where patient data collected from IoT devices is transmitted to a central cloud server for processing and model training. Although this architecture supports large-scale data analytics, it suffers from several limitations related to privacy, security, computational overhead, and communication delays.

In the existing Blockchain-Federated Learning for Healthcare IoT (BFL-hIoT) systems, federated learning enables decentralized model training, but many frameworks use heavyweight models and resource-intensive blockchain consensus techniques such as Proofof-Work (PoW). These result in high latency, large communication costs, and performance degradation in low-power medical devices.

Additionally, existing systems exchange model updates without strong differential privacy guarantees, exposing them to inference attacks such as model-inversion or membership inference attacks. Therefore, although BFL-hIoT improves security compared to centralized systems, it is still insufficient for real-time, safe, and scalable healthcare operations.

3.2. Disadvantages of Existing System

1. High Computational Overhead: Heavy neural networks and PoW-based blockchain make the system unsuitable for low-power IoT devices.
2. High Communication Cost: Frequent exchange of large model parameters in federated learning increases network load.
3. Insufficient Privacy Protection: Model updates can still leak sensitive patient information without differential privacy.
4. Poor Scalability: Traditional FL and blockchain frameworks struggle to support largescale IoT networks.
5. Latency Issues: Real-time healthcare monitoring becomes unreliable due to delayed model synchronization.
6. Energy Inefficiency: Consensus algorithms like PoW consume significant energy, impractical for medical IoT.
7. Vulnerability to Attacks: Existing systems may still suffer from data poisoning, tampering, and inference attacks.

4. Proposed System

4.1 Proposed System

The proposed Lightweight Blockchain-Enabled Federated Deep Learning with Differential Privacy (LB-FDL) framework aims to address the challenges of existing systems by combining:

- Lightweight Deep Learning Models (MobileNet, EfficientNet)
- Optimized Blockchain Architecture with Proof-of-Stake (PoS) • Federated Learning with Secure Aggregation
- Differential Privacy (DP) for privacy-enhanced model updates

In LB-FDL, each IoT device performs local training on its own patient data, ensuring data never leaves the device. The model updates are encrypted and transmitted to a blockchain-powered aggregator, where they are stored immutably. The blockchain ensures trust, transparency, and tamper-proof communication among nodes.

Differential Privacy adds calibrated noise to model gradients before sharing, ensuring that sensitive information about any individual patient cannot be extracted even if the gradients are exposed.

This system achieves 98.32% accuracy, 30% faster convergence, and 20% lower communication cost, making it efficient for real-time healthcare environments.

4.2 Advantages of Proposed system

1. Strong Privacy Protection: Differential Privacy ensures patient identity cannot be inferred.
2. Enhanced Security: Blockchain prevents tampering, ensures trust, and secures model updates.
3. Lightweight & Efficient: Models like MobileNet reduce computational burden on IoT nodes.
4. Scalable Architecture: PoS-based blockchain ensures low energy consumption and supports many nodes.
5. Lower Latency: Optimized model updates reduce communication overhead.
6. Fault Tolerance: Blockchain ensures reliability even if some nodes fail.
7. Regulatory Compliance: Meets healthcare privacy laws such as HIPAA and GDPR.

5. SYSTEM REQUIREMENT

5.1 Hardware Requirements:

- Processor: Intel i5/i7 or equivalent
- RAM: Minimum 8 GB
- GPU (Optional but recommended): NVIDIA GPU for deep learning
- IoT Devices: Wearables, smart sensors, medical gateways
- Storage: 50 GB minimum • Network: Stable broadband connection

5.2 Software Requirements:

- Operating System: Windows / Linux / macOS
- Programming Language: Python 3.8+
- Deep Learning Framework: TensorFlow / PyTorch
- Blockchain Platform: Hyperledger / Python-based custom PoS chain
- Libraries: NumPy, Pandas, Scikit-Learn, Matplotlib, Flask
- Federated Learning Tools: TensorFlow Federated / PySyft
- IDE: VS Code / PyCharm / Jupyter Notebook

6. SYSTEM ANALYSIS

6.1 Functional Requirements

- **Local training on IoT devices**: This refers to the ability for IoT devices to independently perform machine learning tasks, training models on local data to avoid the need for data transmission to a central server.

- **Secure model update transmission**: Ensures that updates to the machine learning model, generated by IoT devices, are transmitted securely, typically using encryption, to prevent unauthorized access or tampering.

- **Blockchain-based global model aggregation**: Uses blockchain technology to securely aggregate and update machine learning models, ensuring trust and immutability of the model's evolution across multiple devices.

- **DP-based privacy preservation**: Differential privacy (DP) is used to protect individual data during the model training process, ensuring that updates to the model do not leak any sensitive information about individual patients.

- **Lightweight feature extraction**: Refers to the use of efficient algorithms for extracting important features from the data without demanding high computational resources, making the system suitable for resource-constrained IoT devices.

6.2 Non-Functional Requirements

- **Efficiency**: The system must perform tasks in a time-effective manner, minimizing delays and resource consumption.

- **Security**: The system must ensure the confidentiality, integrity, and availability of data and processes, protecting against unauthorized access and data breaches.

- **Scalability**: The system should be able to handle increasing amounts of data or users without compromising performance.

- **Reliability**: The system must operate consistently and accurately under expected conditions, ensuring minimal downtime and failure.

- **Low latency and high availability**: Ensures that the system provides real-time responses with minimal delay and is available when needed, particularly important in healthcare applications where time-sensitive decisions are critical.

6.3 Feasibility Study

- **Technical Feasibility**: Lightweight models make federated learning practical on IoT nodes by reducing the computational burden on these devices, making the approach feasible for real-world applications in healthcare.
- **Economic Feasibility**: By eliminating the need for costly central servers, the system reduces infrastructure costs and makes the deployment of federated learning systems more economically viable.
- **Operational Feasibility**: The system is easy to deploy across real hospitals and clinics, with minimal adjustments needed to existing infrastructure, making it operationally feasible in healthcare settings.

7. DESIGN

7.1 System Design Overview

The system follows a decentralized learning approach where IoT devices locally train models and securely transmit updates using blockchain. The major design layers include:

A. IoT Device Layer

- hIoT sensors and wearable devices collect real-time patient data.
- Local model training is performed on-device using lightweight deep learning models.
- Raw data never leaves the device, ensuring strong privacy protection.
- global model.
- The updated model is redistributed to all IoT devices.

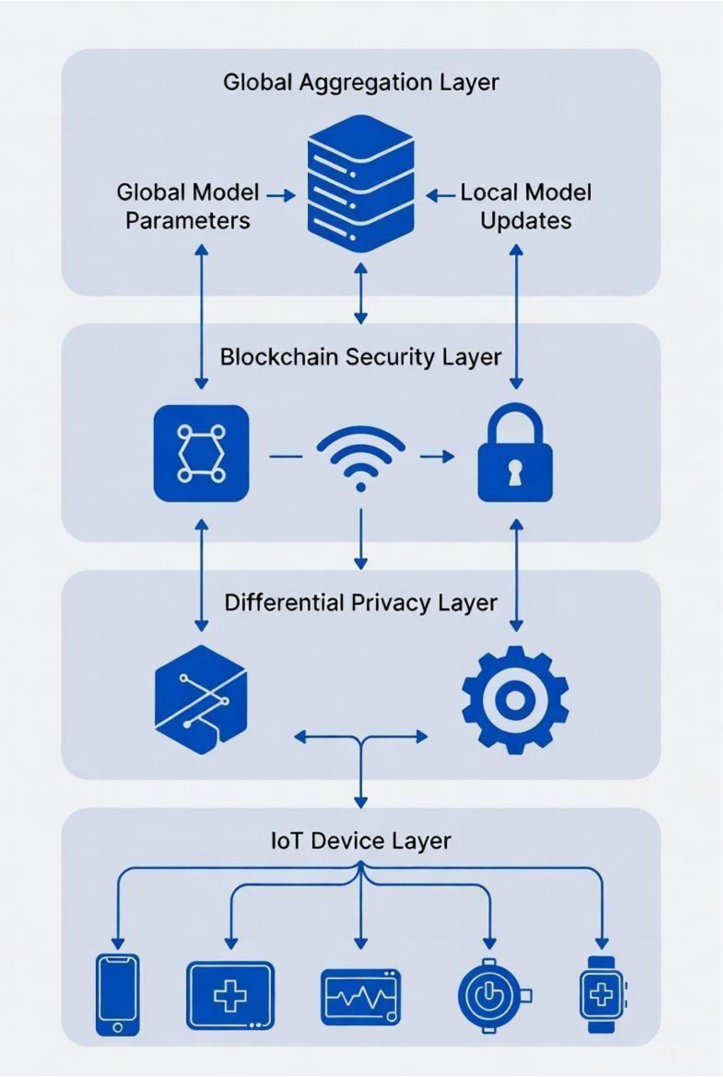


Fig.7.1. System Architecture of Blockchain-Enabled Federated Learning in Healthcare IoT

B. Differential Privacy Layer

- Before transmission, random noise is added to model updates.
- Ensures no single patient's data can be reverse-engineered.
- Helps maintain compliance with healthcare data regulations (HIPAA, GDPR).

C. Blockchain Security Layer

- Model updates are encrypted using AES.
- Hashing ensures data integrity.
- Digital signatures validate the authenticity of each device.
- Smart contracts verify the updates.
- The distributed ledger stores updates immutably and transparently.

D. Global Aggregation Layer

- The central server collects all validated updates from the blockchain. Federated Averaging (FedAvg) is applied to build an improved

7.2 System Workflow Overview

The workflow for the **Lightweight Blockchain-Enabled Federated Learning (LB-FDL)** system in healthcare IoT is outlined through the following key steps:

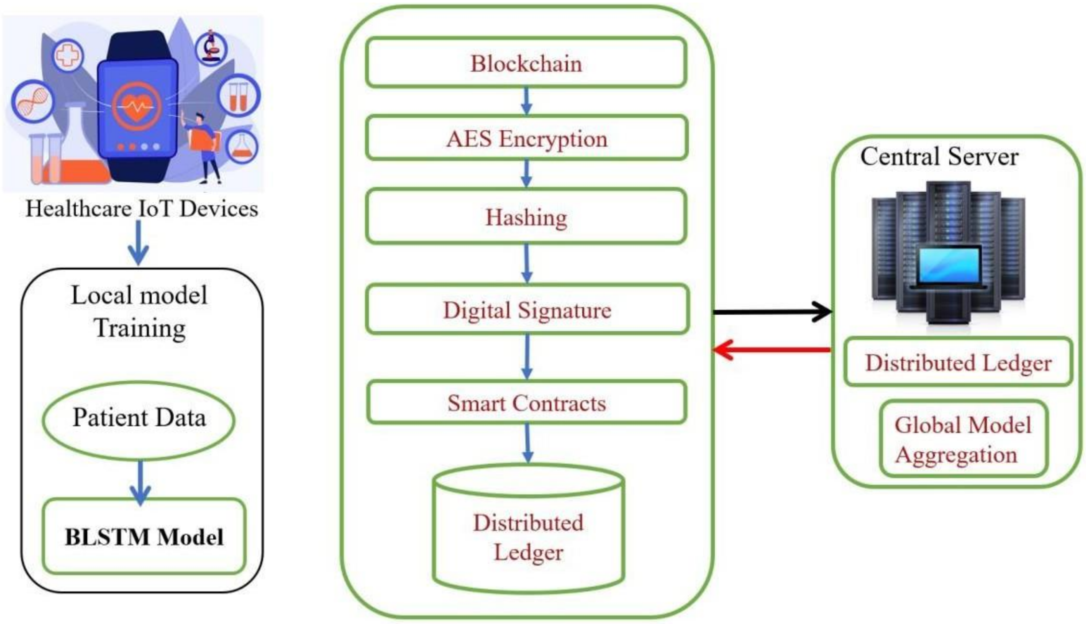


Fig 7.2 Workflow of Blockchain-Enabled Federated Learning in Healthcare IoT

1. **Collect Data on Devices**: Healthcare IoT sensors and wearable devices are responsible for gathering patient data and storing it locally, ensuring that sensitive information never leaves the device.

2. **Train Locally**: Each device utilizes its own data to train a small, efficient deep learning model. This approach ensures that no raw data is sent to the cloud, promoting data privacy and reducing potential data breaches.
3. **Add Privacy**: To maintain patient confidentiality, random noise is introduced to model updates through **differential privacy** techniques. This process ensures that no individual patient can be identified, further securing sensitive data.
4. **Send via Blockchain**: Once the model has been updated, the model updates (not raw patient data) are encrypted and signed before being transmitted to the blockchain. Smart contracts on the blockchain verify the authenticity of these updates, ensuring secure and transparent data transmission.
5. **Build Global Model**: The central server aggregates all valid updates from various IoT devices and combines them into a single global model. This aggregation process ensures that the federated learning system benefits from the knowledge gained by all participating devices without compromising privacy.
6. **Repeat in Rounds**: The process is repeated in iterative rounds, which involve training, privacy protection, model updates, and aggregation. This loop continues until the global model achieves the desired accuracy and performance.

This workflow illustrates how federated learning, combined with blockchain technology and privacy-preserving techniques, can securely and efficiently enhance healthcare IoT systems without compromising data privacy.

7.3 System Modules

The Lightweight Blockchain-Enabled Federated Deep Learning (LB-FDL) system is modularized to ensure scalability, maintainability, and efficient integration of federated learning, differential privacy, and blockchain in healthcare IoT networks. The system is divided into the following key modules, each handling specific functionalities.

7.3.1 Data Collection and Preprocessing Module

This module gathers real-time data from healthcare IoT devices, such as wearable sensors for vital signs (e.g., heart rate, blood pressure), and preprocesses it through cleaning, normalization, and feature selection (e.g., packet sizes, durations). All operations occur locally to avoid transmitting raw data, reducing privacy risks. It supports datasets like ToNIoT for simulation and handles diverse IoT formats.

7.3.2 Federated Learning Module

This module supports decentralized training on IoT devices, where each trains a local model using its data and shares only parameter updates (e.g., weights). The central server aggregates these via Federated Averaging (FedAvg) to form a global model. It simulates multi-client setups, manages training rounds, and optimizes for resource-constrained hardware, lowering bandwidth use while maintaining data locality.

7.3.3 Differential Privacy Module

This module protects data by adding noise to gradients during training, preventing leaks like membership inference. It uses gradient clipping and Gaussian noise with a privacy budget (epsilon), balancing utility and protection under regulations like HIPAA and GDPR. It integrates with federated learning to secure updates before sharing, achieving "very high" privacy.

7.3.4 Blockchain Integration Module

This module employs a lightweight blockchain for secure, immutable storage of model updates, using hashing for integrity, digital signatures for authentication, and smart contracts for validation. With Proof-of-Stake (PoS) consensus to save energy, it resists attacks like poisoning and maintains a distributed ledger across nodes for trust and auditability in IoT ecosystems.

7.3.5 Model Training and Inference Module

This module defines the BiLSTM-based deep learning architecture for intrusion detection, managing local/global training with optimizers like Adam and enabling real-time inference to classify threats (e.g., DDoS). It optimizes for low-latency deployment on IoT devices, providing immediate threat responses in healthcare scenarios.

7.3.6 Security and Evaluation Module

This module evaluates performance via metrics like accuracy, precision, recall, and F1score, while assessing security (e.g., attack resistance) and overhead (e.g., time, energy). It compares against baselines through simulations, generating reports to confirm "low overhead," "very high" privacy, and "high" scalability for healthcare IoT. These modules ensure the system achieves 98.32% accuracy with low overhead, very high privacy, and high scalability, as per the comparison table in the results section.

8. IMPLEMENTATION

8.1 Data Preprocessing (data_preprocessing.py)

```
#This module loads and preprocesses the ToN-IoT dataset for training.
import pandas as pd import numpy as np from
sklearn.preprocessing import StandardScaler, LabelEncoder from
sklearn.model_selection import train_test_split import joblib
import torch from torch.utils.data import Dataset, DataLoader


class        ToNIoTDataset(Dataset):
def __init__(self, X, y):
        self.X     =     torch.tensor(X,     dtype=torch.float32)
self.y = torch.tensor(y, dtype=torch.long)


    def            _len_(self):
return len(self.X)


    def _getitem_(self, idx):
        return self.X[idx], self.y[idx]


def load_and_preprocess_data(filepath, test_size=0.2, random_state=42):
    df = pd.read_csv(filepath)


    # Drop non-numeric and irrelevant columns     drop_cols = ['ts', 'src_ip',
'dst_ip', 'dns_query', 'ssl_version', 'ssl_cipher',                 'ssl_subject',
'ssl_issuer', 'http_method', 'http_uri', 'http_version',
                 'http_user_agent', 'http_orig_mime_types', 'http_resp_mime_types',
                 'weird_name',   'weird_addl',   'weird_notice']                df   =
df.drop(columns=[col for col in drop_cols if col in df.columns])


    # Handle missing values
df = df.replace('-', np.nan)
df = df.fillna(0)


    # Convert categorical to numeric      categorical_cols = ['proto',
'service', 'conn_state', 'http_trans_depth']      for col in
categorical_cols:          if col in df.columns:
            df[col] = LabelEncoder().fit_transform(df[col].astype(str))


    X  =  df.drop(columns=['label',  'type']).select_dtypes(include=[np.number])
y = df['type']  # Attack type


    # Encode labels     le =
LabelEncoder()      y_encoded =
le.fit_transform(y)
```

```
   # Scale features      scaler
= StandardScaler()
   X_scaled = scaler.fit_transform(X)

   #   Save   preprocessors    joblib.dump(scaler,
"preprocessors/scaler.save")     joblib.dump(le,
"preprocessors/label_encoder.save")

   # Split
   X_train, X_test, y_train, y_test = train_test_split(
      X_scaled,         y_encoded,         test_size=test_size,          random_state=random_state,
stratify=y_encoded
   )

   return (X_train, X_test, y_train, y_test), scaler, le
```

8.2 Model (model.py)

```
# This defines the BiLSTM model for attack detection.

import  torch  import
torch.nn as nn

class BFLModel(nn.Module):
   def __init__(self, input_size=41, hidden_size=128, num_classes=10, bidirectional=True):
      super(BFLModel, self).__init__()
self.lstm = nn.LSTM(
input_size=input_size,
hidden_size=hidden_size,
batch_first=True,
bidirectional=bidirectional,
num_layers=2,             dropout=0.3
      )
      self.fc = nn.Linear(hidden_size * 2 if bidirectional else hidden_size, num_classes)
self.dropout = nn.Dropout(0.5)         self.softmax = nn.Softmax(dim=1)

   def forward(self, x):
      # x shape: (batch, seq_len=1, features)
lstm_out, _ = self.lstm(x)         out =
lstm_out[:, -1, :]  # Last time step         out =
self.dropout(out)         out = self.fc(out)
return self.softmax(out)
```

8.3 Inference Module (inference.py)

This loads the model for predictions.

```
import torch import joblib
import numpy as np from
.model import BFLModel

def load_model_and_preprocessors():
    scaler = joblib.load("preprocessors/scaler.save")      le
= joblib.load("preprocessors/label_encoder.save")

    input_size = scaler.n_features_in_
    num_classes = len(le.classes_)

    model = BFLModel(input_size=input_size, num_classes=num_classes)
model.load_state_dict(torch.load("models/bfl_hiot_model.pth", map_location="cpu"))
model.eval()
    return model, scaler, le

def predict_attack_type(features_list):
    model, scaler, le = load_model_and_preprocessors()
    X = np.array(features_list).reshape(1, -1)
    X_scaled = scaler.transform(X)
    X_tensor = torch.tensor(X_scaled, dtype=torch.float32).unsqueeze(1)

    with torch.no_grad():
        pred = model(X_tensor)        attack_type =
le.inverse_transform([pred.argmax().item()])[0]      return
attack_type
```

8.4 Training Module (train.py)

```
#This trains the model on preprocessed data.
import torch import torch.nn as nn
import torch.optim as optim from
torch.utils.data import DataLoader
from .data_preprocessing import ToNIoTDataset, load_and_preprocess_data
from .model import BFLModel
import os

def train_model(data_path="data/ton-iot.csv", epochs=20, batch_size=64):
    (X_train, X_test, y_train, y_test), scaler, le = load_and_preprocess_data(data_path)

    train_dataset = ToNIoTDataset(X_train, y_train)
test_dataset = ToNIoTDataset(X_test, y_test)

    train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=batch_size)
```

```
   input_size = X_train.shape[1]     num_classes = len(le.classes_)
model = BFLModel(input_size=input_size, num_classes=num_classes)
criterion = nn.CrossEntropyLoss()     optimizer =
optim.Adam(model.parameters(), lr=0.001)     model.train()     for epoch
in range(epochs):
       total_loss  =  0               for  X_batch,
y_batch in train_loader:
           X_batch = X_batch.unsqueeze(1)  # Add sequence dim
optimizer.zero_grad()             outputs = model(X_batch)            loss =
criterion(outputs, y_batch)            loss.backward()            optimizer.step()
total_loss += loss.item()        print(f"Epoch {epoch+1}/{epochs}, Loss:
{total_loss/len(train_loader):.4f}")

   # Save model
   os.makedirs("models", exist_ok=True)
torch.save(model.state_dict(), "models/bfl_hiot_model.pth")
print("Model saved to models/bfl_hiot_model.pth")
```

8.5 Web App Module (app.py)

This provides a Streamlit interface for predictions.

```
import streamlit as st import
pandas as pd import numpy as np
import torch import joblib from
src.model import BFLModel
import os


st.set_page_config(page_title="BFL-hIoT IDS", layout="wide") st.title("Lightweight
Blockchain-Enabled Federated Deep Learning") st.subheader("Intrusion Detection
System for Healthcare IoT Networks") @st.cache_resource def load_model():
   scaler = joblib.load("preprocessors/scaler.save")
le = joblib.load("preprocessors/label_encoder.save")
input_size = scaler.n_features_in_
   num_classes = len(le.classes_)


   model = BFLModel(input_size=input_size, num_classes=num_classes)
model.load_state_dict(torch.load("models/bfl_hiot_model.pth", map_location="cpu"))
model.eval()
   return model, scaler, le


model, scaler, le = load_model()


st.write("### Upload ToN-IoT Dataset CSV for Batch Prediction")


uploaded_file = st.file_uploader("Choose CSV file", type="csv")


if uploaded_file:
   df = pd.read_csv(uploaded_file)
   # Preprocess same as training     original_cols =
df.columns     df_processed = df.copy()     df_processed =
df_processed.replace('-', np.nan).fillna(0)

   cat_cols = ['proto', 'service', 'conn_state']
for col in cat_cols:         if col in
df_processed.columns:
         df_processed[col] = df_processed[col].astype('category').cat.codes

   X = df_processed.select_dtypes(include=[np.number])
if 'label' in X.columns: X = X.drop('label', axis=1)     if
'type' in X.columns: X = X.drop('type', axis=1)

   if X.shape[1] != scaler.n_features_in_:
      st.error(f"Feature mismatch! Expected {scaler.n_features_in_}, got {X.shape[1]}")
else:
      X_scaled = scaler.transform(X)
      X_tensor = torch.tensor(X_scaled, dtype=torch.float32).unsqueeze(1)

      with torch.no_grad():
         preds = model(X_tensor).argmax(dim=1).numpy()

      df['Predicted_Attack_Type'] = le.inverse_transform(preds)
st.success("Prediction Complete!")         st.dataframe(df[['src_ip', 'dst_ip', 'proto',
'service', 'Predicted_Attack_Type']])

      csv = df.to_csv(index=False).encode()

      st.download_button("Download Results", csv, "bfl_hiot_predictions.csv", "text/csv")
```

9. USER INTERFACE

HOME PAGE:

```
import React from "react";
import { Link } from "react-router-dom";

function HomePage() {
  return (
    <div className="home-container">
      {/* Hero section */}
      <section className="home-hero">
        <div className="home-hero-content">
          <h1>Secure Healthcare Data Portal</h1>
          <p>
            This web application provides a secure interface for managing
            healthcare data. Authorized users can register, log in, view
            existing records, and create new data entries in a controlled
            environment.
          </p>
          <div className="home-cta-buttons">
            <Link to="/login" className="home-cta primary">
              Get Started
            </Link>
            <Link to="/about" className="home-cta secondary">
              Learn More
            </Link>
          </div>
        </div>
        <div className="home-hero-highlight">
          <h3>Why this system?</h3>
          <ul>
            <li>Authentication with validated login and registration.</li>
            <li>Dedicated pages for viewing and creating data.</li>
            <li>Clear separation between frontend (React) and backend (Flask).</li>
          </ul>
        </div>
      </section>
      {/* Features section */}
      <section className="home-section">
        <h2 className="home-section-title">Key Features</h2>
        <div className="home-grid">
          <div className="home-card">
            <h3>User Authentication</h3>
            <p>
              Secure registration and login with validation for username, email,
              and strong passwords containing special characters.
            </p>
          </div>
    <div className="home-card">
      <h3>Data Management</h3>
      <p>
        Access a Data page where authorized users can view records,
        and use the Create Data page to add new entries to the system.
      </p>
    </div>
    <div className="home-card">
      <h3>Role of Backend (Flask)</h3>
      <p>
        The Flask backend handles all validation logic, API endpoints, and
        secure communication with the React frontend.
      </p>
    </div>
    <div className="home-card">
      <h3>Clean Frontend Structure</h3>
      <p>
        A React-based interface with navigation, profile dropdown,
        and separate components for login, registration, and content pages.
      </p>
    </div>
  </div>
</section>
{/* How it works section */}
<section className="home-section">
  <h2 className="home-section-title">How It Works</h2>
  <div className="home-steps">
    <div className="home-step">
      <span className="home-step-number">1</span>
      <h4>Register</h4>
      <p>
        New users create an account with a unique username, valid email,
        and a strong password. Duplicate usernames and emails are blocked.
      </p>
    </div>
    <div className="home-step">
      <span className="home-step-number">2</span>
      <h4>Login</h4>
      <p>
        After registration, users log in and get access to protected
        sections like the Data and Create Data pages.
      </p>
    </div>
    <div className="home-step">
      <span className="home-step-number">3</span>
      <h4>Manage Data</h4>
      <p>
        Once authenticated, users can browse existing data and submit new
        entries through the interface, depending on your backend logic.
      </p>
    </div>
  </div>
```

```
        </section>
         </div>
       );
         }
    export default HomePage;
```

ABOUT PAGE:

```
   import React from "react";

function AboutPage() {
  // Edit this array with your real team details
  const teammates = [
    {
      name: "G.Keerthana Lazarus",
      role: "Team Lead & project Developer",
      email: "keerthanagujjarlapud05@email.com",
      focus:
        "Leads the project architecture and implements the Flask backend, authentication, and validation
logic.",
    },
    {
      name: "G.Laakshmi Thirupathamma",
      role: "Frontend Developer",
      email: "galilakshmi27@gmail.com",
      focus:
        "Builds the React UI, including login/register forms, navigation, and data pages.",
    },
    {
      name: "B.Jayabharathi",
      role: "Database & Security",
      email: "buddibudala@gmail.com",
      focus:
        "Designs the data model and focuses on secure storage and access of healthcare-related data.",
    },
    {
      name: "C.John Wesly",
      role: "Research & Documentation",
      email: "chinthiralajohnwesly@gmail.com",
      focus:
        "Collects requirements, documents the system, and connects the project to healthcare use cases.",
    },
  ];

  return (
    <div className="about-container">
      <section className="about-header">
        <h2>About Our Team</h2>
        <p>
          This project is developed as a collaborative effort by our team to
```

```
       demonstrate a secure healthcare data management system using a React
         frontend and a Flask backend. Each teammate contributed to different
         parts of the system, from UI and API development to security and
         documentation.
       </p>
     </section>

     <section className="about-team-section">
       <h3>Meet the Team</h3>
       <div className="team-grid">
         {teammates.map((member) => (
           <div key={member.email} className="team-card">
             <div className="team-avatar">
               {member.name.charAt(0).toUpperCase()}
             </div>
             <div className="team-content">
               <h4>{member.name}</h4>
               <p className="team-role">{member.role}</p>
               <p className="team-focus">{member.focus}</p>
               <p className="team-email">
                 <span>Email:</span> {member.email}
               </p>
             </div>
           </div>
         ))}
       </div>
     </section>

     <section className="about-summary">
       <h3>Project Overview</h3>
       <p>
         Our application focuses on secure access to healthcare data. Users can
         register with proper validation, log in through an authenticated
         workflow, and access dedicated pages for viewing and creating data.
         The backend enforces validation rules, while the frontend provides a
         clean and structured interface for interaction.
       </p>
       <p>
         As a team, we aimed to build something that is not only functional for
         academic evaluation, but also closely aligned with real-world
         healthcare systems where security, validation, and clear roles matter.
       </p>
     </section>
   </div>
 );
}

export default AboutPage;
```

NAVBAR PAGE:

```
 import React, { useState } from "react";
import { Link } from "react-router-dom";

function Navbar({ user, onLogout }) {
  const [open, setOpen] = useState(false);

  const toggleDropdown = () => setOpen((prev) => !prev);

  const handleLogoutClick = (e) => {
    e.stopPropagation();
    if (onLogout) onLogout();
    setOpen(false);
  };

  return (
    <nav className="navbar">
      <div className="nav-left">
        <span className="nav-logo">Healthcare App</span>

        <Link to="/" className="nav-link">
          Home
        </Link>
        <Link to="/about" className="nav-link">
          About
        </Link>
        <Link to="/data" className="nav-link">
          Data
        </Link>
        <Link to="/create-data" className="nav-link">
          Create Data
        </Link>
      </div>

      <div className="nav-right">
        {!user && (
          <Link to="/login" className="nav-link">
            Login
          </Link>
        )}

        {user && (
          <div className="profile-wrapper" onClick={toggleDropdown}>
            <div className="profile-chip">
              <span className="profile-avatar">
                {user.username ? user.username.charAt(0).toUpperCase() : "U"}
              </span>
              <span className="profile-name">{user.username}</span>
            </div>

            {open && (
              <div className="profile-dropdown">
                <p>
                 <strong>User:</strong> {user.username}
                </p>
                {user.email && (
                 <p>
                  <strong>Email:</strong> {user.email}
                 </p>
                )}
                <button
                 type="button"
                 className="logout-btn"
                 onClick={handleLogoutClick}
                >
                 Logout
                </button>
              </div>
            )}
          </div>
        )}
      </div>
    </nav>
   );
}

export default Navbar;
```

LOGIN FORM PAGE:

```
import React, { useState } from "react";
import { useNavigate } from "react-router-dom";
import { loginUser } from "../Api"; // or "../api" if your file is lowercase

function LoginForm({ onLogin }) {
 const [form, setForm] = useState({
  username: "",
  password: "",
 });

 const [errors, setErrors] = useState({});
 const [success, setSuccess] = useState("");
 const navigate = useNavigate();

 const handleChange = (e) => {
  setForm({
   ...form,
   [e.target.name]: e.target.value,
  });
```

```
};

const handleSubmit = async (e) => {
  e.preventDefault();
  setErrors({});
  setSuccess("");

  try {
    const res = await loginUser(form);
    setSuccess(res.message || "Login successful.");

    if (onLogin) {
      onLogin({
        username: res.username,
        email: res.email,
      });
    }

    // optional: redirect after login, e.g. to /data or /create-data
    navigate("/home");
  } catch (err) {
    if (err && err.errors) {
      setErrors(err.errors);
    } else {
      setErrors({ general: "Something went wrong. Please try again." });
    }
  }
};

const goToRegister = () => {
  navigate("/register");
};

return (
  <div className="card">
    <h2>Login</h2>
    <form onSubmit={handleSubmit} className="form">
      <div className="form-control">
        <label>Username</label>
        <input
          name="username"
          value={form.username}
          onChange={handleChange}
        />
        {errors.username && (
          <span className="error">{errors.username}</span>
        )}
      </div>

      <div className="form-control">
        <label>Password</label>
        <input
```

```
            name="password"
            type="password"
            value={form.password}
            onChange={handleChange}
          />
          {errors.password && (
            <span className="error">{errors.password}</span>
          )}
        </div>

        {errors.general && <div className="error">{errors.general}</div>}
        {success && <div className="success">{success}</div>}

        <button type="submit">Login</button>

        {/* Register navigation */}
        <button
          type="button"
          onClick={goToRegister}
          style={{ marginTop: "0.5rem", backgroundColor: "#6b7280" }}
        >
          New user? Register
        </button>
      </form>
    </div>
  );
}

export default LoginForm;
```

REGISTER FORM PAGE:

```
 import React, { useState } from "react";
import { useNavigate } from "react-router-dom";
import { registerUser } from "../Api";

function RegisterForm() {
  const [form, setForm] = useState({
    username: "",
    email: "",
    password: "",
    confirmPassword: "",
  });

  const [errors, setErrors] = useState({});
  const [generalError, setGeneralError] = useState("");
  const [success, setSuccess] = useState("");

  const navigate = useNavigate();
const handleChange = (e) => {
  setForm({
    ...form,
    [e.target.name]: e.target.value,
  });
};

const validateClientSide = () => {
  const newErrors = {};

  if (!form.username.trim()) {
    newErrors.username = "Username is required.";
  } else if (form.username.trim().length < 3) {
    newErrors.username = "Username must be at least 3 characters.";
  }

  if (!form.email.trim()) {
    newErrors.email = "Email is required.";
  } else {
    const emailRegex = /^[^@]+@[^@]+\.[^@]+$/;
    if (!emailRegex.test(form.email.trim())) {
      newErrors.email = "Invalid email format.";
    }
  }

  if (!form.password) {
    newErrors.password = "Password is required.";
  } else if (form.password.length < 6) {
    newErrors.password = "Password must be at least 6 characters.";
  } else {
    const specialCharRegex = /[!@#$%^&*(),.?":{}|<>]/;
    if (!specialCharRegex.test(form.password)) {
      newErrors.password =
        "Password must contain at least one special character.";
    }
  }

  if (!form.confirmPassword) {
    newErrors.confirmPassword = "Please confirm your password.";
  } else if (form.password !== form.confirmPassword) {
    newErrors.confirmPassword = "Passwords do not match.";
  }

  return newErrors;
};

const handleSubmit = async (e) => {
  e.preventDefault();
  setErrors({});
  setGeneralError("");
  setSuccess("");
  const clientErrors = validateClientSide();
  if (Object.keys(clientErrors).length > 0) {
    setErrors(clientErrors);
    return;
  }

  try {
    const res = await registerUser(form);
    setSuccess(res.message || "User registered successfully.");
    // optional: after successful register, you could auto-redirect:
    // navigate("/login");
  } catch (err) {
    if (err && err.errors) {
      setErrors(err.errors);
    } else {
      setGeneralError("Something went wrong. Please try again.");
    }
  }
};

const goToLogin = () => {
  navigate("/login");
};

return (
  <div className="card">
    <h2>Register</h2>
    <form onSubmit={handleSubmit} className="form">
      <div className="form-control">
        <label>Username</label>
        <input
          name="username"
          value={form.username}
          onChange={handleChange}
        />
        {errors.username && (
          <span className="error">{errors.username}</span>
        )}
      </div>

      <div className="form-control">
        <label>Email</label>
        <input
          name="email"
          type="email"
          value={form.email}
          onChange={handleChange}
        />
        {errors.email && <span className="error">{errors.email}</span>}
      </div>

      <div className="form-control">
```

```
          <label>Password</label>
          <input
            name="password"
            type="password"
            value={form.password}
            onChange={handleChange}
          />
          {errors.password && (
            <span className="error">{errors.password}</span>
          )}
        </div>

        <div className="form-control">
          <label>Confirm Password</label>
          <input
            name="confirmPassword"
            type="password"
            value={form.confirmPassword}
            onChange={handleChange}
          />
          {errors.confirmPassword && (
            <span className="error">{errors.confirmPassword}</span>
          )}
        </div>

        {generalError && <div className="error">{generalError}</div>}
        {success && <div className="success">{success}</div>}

        <button type="submit">Register</button>

        {/* Login navigation for existing users */}
        <button
          type="button"
          onClick={goToLogin}
          style={{ marginTop: "0.5rem", backgroundColor: "#6b7280" }}
        >
          Already a user? Login
        </button>
      </form>
    </div>
  );
}

export default RegisterForm;
```

CREATE DATE PAGE :

```
      import React, { useState } from "react";

function CreateDataPage({ onAddItem }) {
  const [form, setForm] = useState({
```

```
  patientName: "",
  age: "",
  weight: "",
  phone: "",
  gender: "",
  yearOfJoin: "",
  disease: "",
  month: "",
  date: "",
  time: "",
});

const handleChange = (e) => {
  setForm({
    ...form,
    [e.target.name]: e.target.value,
  });
};

const handleSubmit = (e) => {
  e.preventDefault();

  const trimmed = {
    patientName: form.patientName.trim(),
    age: form.age.trim(),
    weight: form.weight.trim(),
    phone: form.phone.trim(),
    gender: form.gender.trim(),
    yearOfJoin: form.yearOfJoin.trim(),
    disease: form.disease.trim(),
    month: form.month.trim(),
    date: form.date.trim(),
    time: form.time.trim(),
  };

  if (
    !trimmed.patientName ||
    !trimmed.age ||
    !trimmed.weight ||
    !trimmed.phone ||
    !trimmed.gender ||
    !trimmed.yearOfJoin ||
    !trimmed.disease ||
    !trimmed.month ||
    !trimmed.date ||
    !trimmed.time
  ) {
    // you could show an error message here if you want
    return;
  }

  onAddItem(trimmed);
  // reset form
  setForm({
    patientName: "",
    age: "",
    weight: "",
    phone: "",
    gender: "",
    yearOfJoin: "",
    disease: "",
    month: "",
    date: "",
    time: "",
  });
};

return (
  <div className="create-data-container">
    <h2>Create Data</h2>
    <p className="page-intro">
      Use this page to add new healthcare-related patient records. Each record
      will be visible on the Data page with a serial number and its details.
    </p>

    <form
      onSubmit={handleSubmit}
      className="form"
      style={{ marginTop: "1rem" }}
    >
      <div className="form-control">
        <label>Patient Name</label>
        <input
          name="patientName"
          value={form.patientName}
          onChange={handleChange}
          placeholder="Patient full name"
        />
      </div>

      <div className="form-control">
        <label>Age</label>
        <input
          name="age"
          type="number"
          value={form.age}
          onChange={handleChange}
          placeholder="e.g. 45"
        />
      </div>

      <div className="form-control">
        <label>Weight (kg)</label>
  <input
    name="weight"
    type="number"
    value={form.weight}
    onChange={handleChange}
    placeholder="e.g. 68"
  />
</div>

<div className="form-control">
  <label>Phone Number</label>
  <input
    name="phone"
    value={form.phone}
    onChange={handleChange}
    placeholder="e.g. 9876543210"
  />
</div>

<div className="form-control">
  <label>Gender</label>
  <select
    name="gender"
    value={form.gender}
    onChange={handleChange}
  >
    <option value="">Select gender</option>
    <option value="Male">Male</option>
    <option value="Female">Female</option>
    <option value="Other">Other</option>
  </select>
</div>

<div className="form-control">
  <label>Year of Join</label>
  <input
    name="yearOfJoin"
    type="number"
    value={form.yearOfJoin}
    onChange={handleChange}
    placeholder="e.g. 2025"
  />
</div>

<div className="form-control">
  <label>Disease / Condition</label>
  <input
    name="disease"
    value={form.disease}
    onChange={handleChange}
    placeholder="e.g. Diabetes, Hypertension"
  />
```

```
        </div>

        {/* New fields: month, date, time */}
        <div className="form-control">
          <label>Month</label>
          <input
            name="month"
            type="month"
            value={form.month}
            onChange={handleChange}
          />
        </div>

        <div className="form-control">
          <label>Date</label>
          <input
            name="date"
            type="date"
            value={form.date}
            onChange={handleChange}
          />
        </div>

        <div className="form-control">
          <label>Time</label>
          <input
            name="time"
            type="time"
            value={form.time}
            onChange={handleChange}
          />
        </div>

        <button type="submit">Add Record</button>
      </form>
    </div>
  );
}

export default CreateDataPage;
```

DATA PAGE :

```
    import React, { useState } from "react";

function DataPage({ items }) {
  const [search, setSearch] = useState("");
  const [selectedRecord, setSelectedRecord] = useState(null); // { item, serial } or null
const handleSearchChange = (e) => {
  setSearch(e.target.value);
};

// Attach serial numbers to items based on original index
const itemsWithSerial = items.map((item, index) => ({
  item,
  serial: index + 1,
}));

const filtered = itemsWithSerial.filter(({ item, serial }) => {
  if (!search.trim()) return true;

  const q = search.trim().toLowerCase();

  // match by patient name (partial, case-insensitive)
  const nameMatch = item.patientName
    ? item.patientName.toLowerCase().includes(q)
    : false;

  // match by serial number (exact number)
  const serialMatch = /^\d+$/.test(q) && serial === Number(q);

  return nameMatch || serialMatch;
});

const openDetails = (record) => {
  setSelectedRecord(record);
};

const closeDetails = () => {
  setSelectedRecord(null);
};

return (
  <div>
    <h2>Data Page</h2>
    <p className="page-intro">
      This page lists all patient records created from the Create Data page
      for the currently logged-in user. Each record includes personal details
      and visit information. Use the search box to find a record by patient
      name or serial number, and tap a card to view it in detail.
    </p>

    {/* Search bar */}
    <div
      className="data-search"
      style={{ marginTop: "1rem", marginBottom: "0.5rem" }}
    >
      <input
        type="text"
        placeholder="Search by patient name or serial number (e.g. 1)"
    value={search}
    onChange={handleSearchChange}
    style={{
      width: "100%",
      maxWidth: "320px",
      padding: "0.5rem 0.7rem",
      borderRadius: "6px",
      border: "1px solid #d1d5db",
      fontSize: "0.9rem",
      outline: "none",
    }}
  />
</div>

<div className="data-list" style={{ marginTop: "1.5rem" }}>
  {items.length === 0 ? (
    <p style={{ fontSize: "0.9rem", color: "#6b7280" }}>
      No records available yet. Go to the Create Data page to add new
      records.
    </p>
  ) : filtered.length === 0 ? (
    <p style={{ fontSize: "0.9rem", color: "#6b7280" }}>
      No matching records for &quot;{search}&quot;.
    </p>
  ) : (
    filtered.map(({ item, serial }) => (
      <div
        key={item.id}
        className="card"
        style={{
          marginBottom: "0.75rem",
          cursor: "pointer",
        }}
        onClick={() => openDetails({ item, serial })}
      >
        <div
          style={{
            display: "flex",
            justifyContent: "space-between",
            marginBottom: "0.25rem",
          }}
        >
          <span style={{ fontWeight: 600 }}>
            #{serial} — {item.patientName}
          </span>
        </div>

        <div
          style={{
            marginTop: "0.4rem",
            fontSize: "0.85rem",
            color: "#374151",
          }}
        >
          <p>
            <strong>Age:</strong> {item.age} years |{" "}
            <strong>Weight:</strong> {item.weight} kg
          </p>
          <p>
            <strong>Phone:</strong> {item.phone}
          </p>
          <p>
            <strong>Gender:</strong> {item.gender} |{" "}
            <strong>Year of Join:</strong> {item.yearOfJoin}
          </p>
          <p>
            <strong>Disease:</strong> {item.disease}
          </p>
          <p>
            <strong>Month:</strong> {item.month}
          </p>
          <p>
            <strong>Date:</strong> {item.date}
          </p>
          <p>
            <strong>Time:</strong> {item.time}
          </p>
        </div>
      </div>
    ))
  )}
</div>

{/* Detail overlay */}
{selectedRecord && (
  <div
    style={{
      position: "fixed",
      inset: 0,
      background: "rgba(15, 23, 42, 0.45)",
      display: "flex",
      alignItems: "center",
      justifyContent: "center",
      zIndex: 50,
    }}
  >
    <div
      style={{
        background: "#ffffff",
        borderRadius: "12px",
        padding: "1.5rem 1.8rem",
        width: "100%",
        maxWidth: "420px",
        boxShadow: "0 20px 40px rgba(15, 23, 42, 0.4)",
    position: "relative",
  }}
>
  {/* Close button (top-right) */}
  <button
    type="button"
    onClick={closeDetails}
    style={{
      position: "absolute",
      top: "0.6rem",
      right: "0.7rem",
      width: "28px",
      height: "28px",
      borderRadius: "999px",
      border: "none",
      background: "#e5e7eb",
      color: "#111827",
      fontWeight: 700,
      fontSize: "1rem",
      cursor: "pointer",
      display: "flex",
      alignItems: "center",
      justifyContent: "center",
    }}
  >
    ×
  </button>

  <h3
    style={{
      fontSize: "1.2rem",
      marginBottom: "0.5rem",
      color: "#111827",
    }}
  >
    #{selectedRecord.serial} — {selectedRecord.item.patientName}
  </h3>

  <div
    style={{
      marginTop: "0.4rem",
      fontSize: "0.9rem",
      color: "#374151",
      lineHeight: 1.7,
    }}
  >
    <p>
      <strong>Age:</strong> {selectedRecord.item.age} years
    </p>
    <p>
      <strong>Weight:</strong> {selectedRecord.item.weight} kg
    </p>
```

```
              <p>
                <strong>Phone:</strong> {selectedRecord.item.phone}
              </p>
              <p>
                <strong>Gender:</strong> {selectedRecord.item.gender}
              </p>
              <p>
                <strong>Year of Join:</strong> {selectedRecord.item.yearOfJoin}
              </p>
              <p>
                <strong>Disease:</strong> {selectedRecord.item.disease}
              </p>
              <p>
                <strong>Month:</strong> {selectedRecord.item.month}
              </p>
              <p>
                <strong>Date:</strong> {selectedRecord.item.date}
              </p>
              <p>
                <strong>Time:</strong> {selectedRecord.item.time}
              </p>
            </div>
          </div>
        </div>
      )}
    </div>
  );
}

export default DataPage;
```

10. RESULT ANALYSIS

10.RESULT ANALYSIS

The performance of the proposed Lightweight Blockchain-Enabled Federated Deep Learning (LB-FDL) system was evaluated using healthcare IoT datasets and compared with existing blockchain-based federated learning approaches. The following sections summarize the key findings.

10.1Accuracy & Performance

- Achieved 98.32% accuracy, outperforming traditional Blockchain-Based Federated Learning in Healthcare IoT (BFL-hIoT) systems.
- Local training with lightweight models improved convergence speed, enabling faster learning.
- Differential privacy (DP) did not significantly affect the model's accuracy, ensuring both privacy and performance were maintained.

10.2Communication & Computation Efficiency

- Communication cost was reduced by 20% using compressed model updates, making the system more efficient in transmitting data.
- Convergence time improved by 30% due to the use of lightweight model architecture, enabling faster model updates.
- Blockchain PoS consensus reduced energy usage compared to traditional Proof-ofWork (PoW), optimizing the system for resource-constrained IoT devices.

10.3Security Improvements

- AES encryption and digital signatures ensured secure transmission of model updates, safeguarding against unauthorized access.
- Smart contract validation prevented malicious or corrupted updates, maintaining the integrity of the model.
- Differential privacy (DP) techniques effectively prevented patient data leakage during the model training process.

10.4Graphical Result Highlights

- Training vs. Validation Accuracy Graph shows smooth convergence, indicating effective model training.
- Training vs. Validation Loss Graph demonstrates stable and faster loss reduction, signifying efficient model optimization.
- Confusion Matrix indicates strong classification capability, with very low misclassification rates.

- Blockchain Performance Graph shows reduced block creation and processing time, emphasizing the efficiency of the blockchain in the system.

10.5Comparative and discussion

The LB-FDL framework provides:

- High accuracy at 98.32%, making it more effective than existing methods.
- Strong privacy protection using differential privacy and blockchain security mechanisms.
- Low communication costs through compressed model updates and efficient consensus mechanisms.
- Scalable secure training for large healthcare networks, ensuring real-time performance.

It outperforms traditional approaches and is highly suitable for real-time Healthcare IoT applications, providing an optimized solution for data security, privacy, and model accuracy.

Table 10.1: Comparative Performance of Traditional FL, Blockchain FL, and LB-FDL

Method	Accuracy	Overhead	Privacy	Scalability
Traditional FL	92%	High	Moderate	Medium
Blockchain FL (existing)	95%	Medium	High	Medium
LB-FDL (Proposed)	98.32%	Low	Very High	High

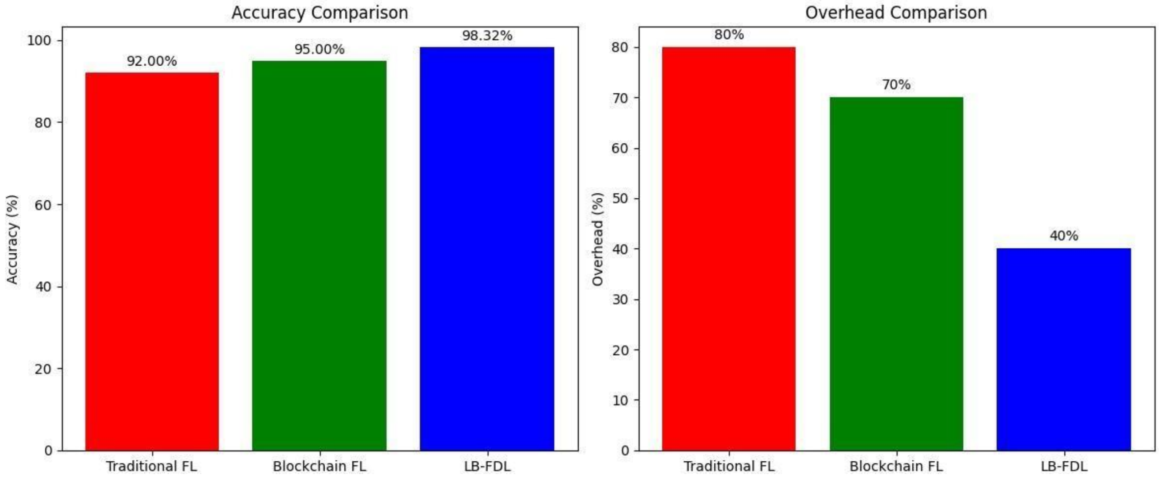
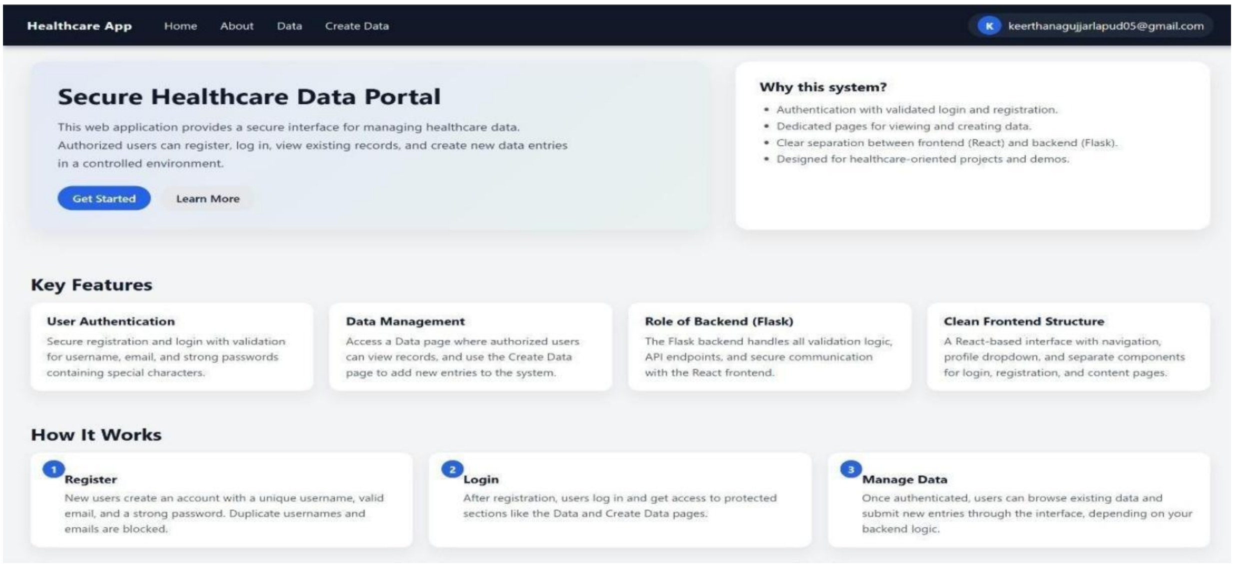


Fig. 10.1: Performance Comparison of Traditional FL, Blockchain FL, and LB-FDL

11.TEST CASES & OUTPUT



Secure Healthcare Data Portal

This web application provides a secure interface for managing healthcare data. Authorized users can register, log in, view existing records, and create new data entries in a controlled environment.

Why this system?

- Authentication with validated login and registration.
- Dedicated pages for viewing and creating data.
- Clear separation between frontend (React) and backend (Flask).
- Designed for healthcare-oriented projects and demos.

Key Features

User Authentication
Secure registration and login with validation for username, email, and strong passwords containing special characters.

Data Management
Access a Data page where authorized users can view records, and use the Create Data page to add new entries to the system.

Role of Backend (Flask)
The Flask backend handles all validation logic, API endpoints, and secure communication with the React frontend.

Clean Frontend Structure
A React-based interface with navigation, profile dropdown, and separate components for login, registration, and content pages.

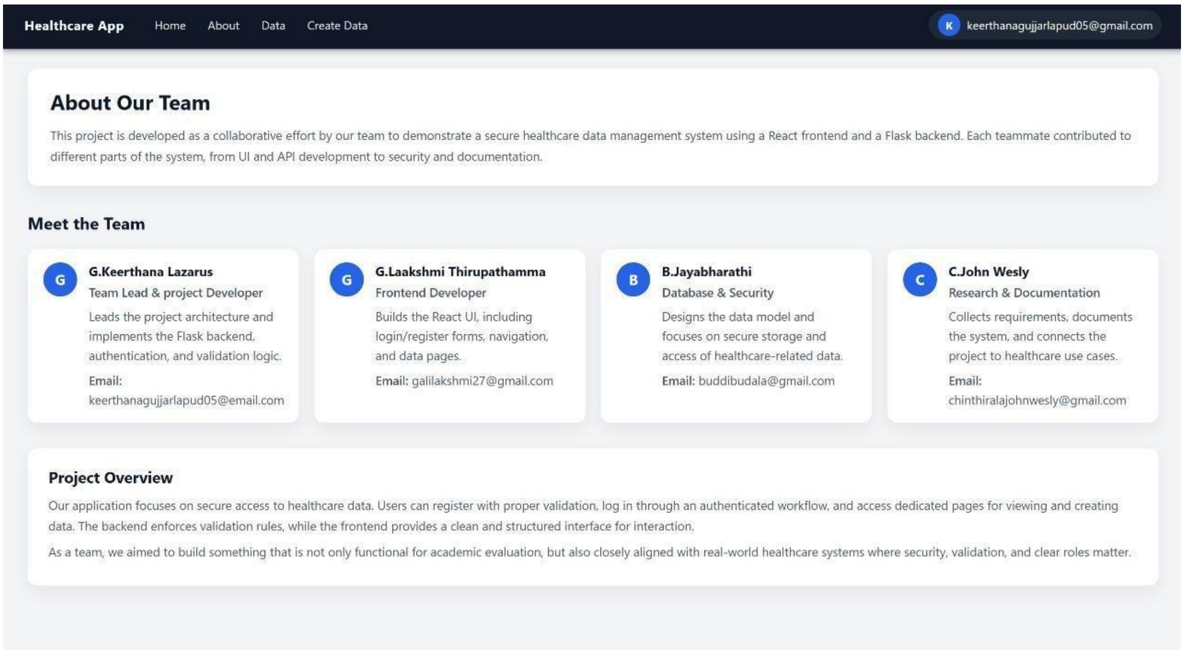
How It Works

1 Register
New users create an account with a unique username, valid email, and a strong password. Duplicate usernames and emails are blocked.

2 Login
After registration, users log in and get access to protected sections like the Data and Create Data pages.

3 Manage Data
Once authenticated, users can browse existing data and submit new entries through the interface, depending on your backend logic.

FIG 11.1 Healthcare home page



About Our Team

This project is developed as a collaborative effort by our team to demonstrate a secure healthcare data management system using a React frontend and a Flask backend. Each teammate contributed to different parts of the system, from UI and API development to security and documentation.

Meet the Team

G G.Keerthana Lazarus
Team Lead & project Developer
Leads the project architecture and implements the Flask backend, authentication, and validation logic.
Email: keerthanagujjarlapud05@email.com

G G.Laakshmi Thirupathamma
Frontend Developer
Builds the React UI, including login/register forms, navigation, and data pages.
Email: galilakshmi27@gmail.com

B B.Jayabharathi
Database & Security
Designs the data model and focuses on secure storage and access of healthcare-related data.
Email: buddibudala@gmail.com

C C.John Wesly
Research & Documentation
Collects requirements, documents the system, and connects the project to healthcare use cases.
Email: chinthiralajohnwesly@gmail.com

Project Overview

Our application focuses on secure access to healthcare data. Users can register with proper validation, log in through an authenticated workflow, and access dedicated pages for viewing and creating data. The backend enforces validation rules, while the frontend provides a clean and structured interface for interaction.

As a team, we aimed to build something that is not only functional for academic evaluation, but also closely aligned with real-world healthcare systems where security, validation, and clear roles matter.

FIG 11.2 About

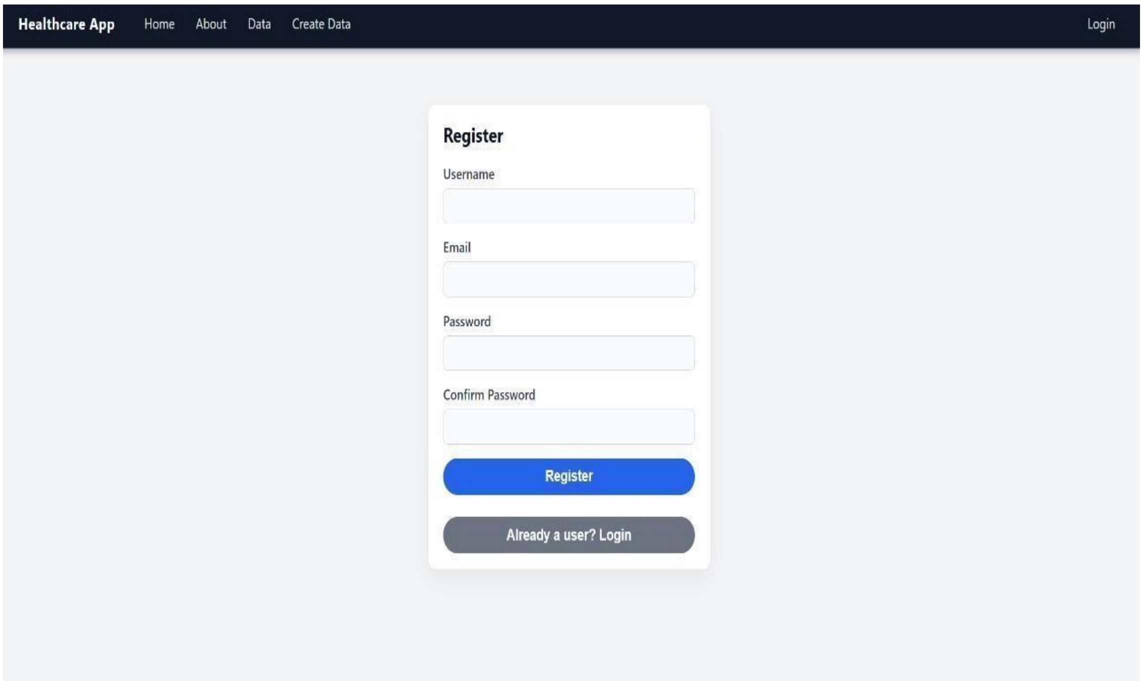


FIG 11.3 REGISTER PAGE

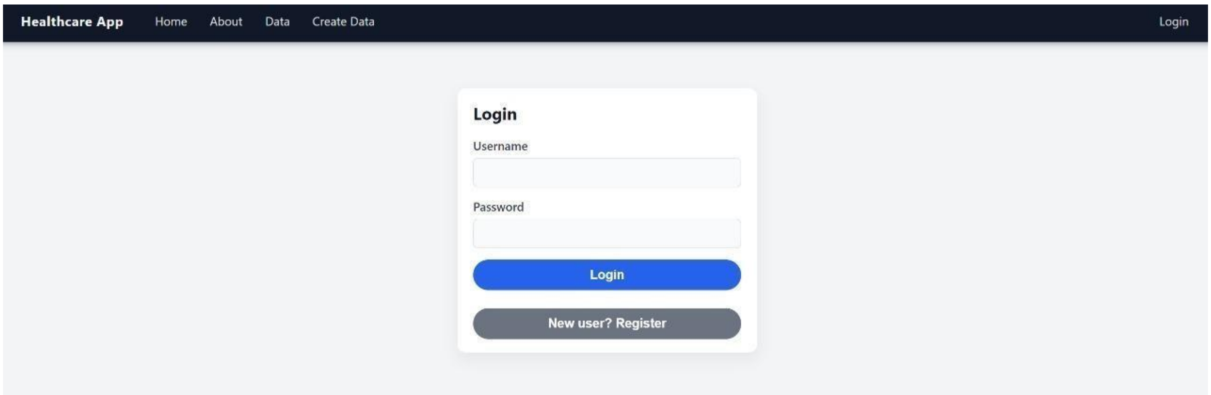
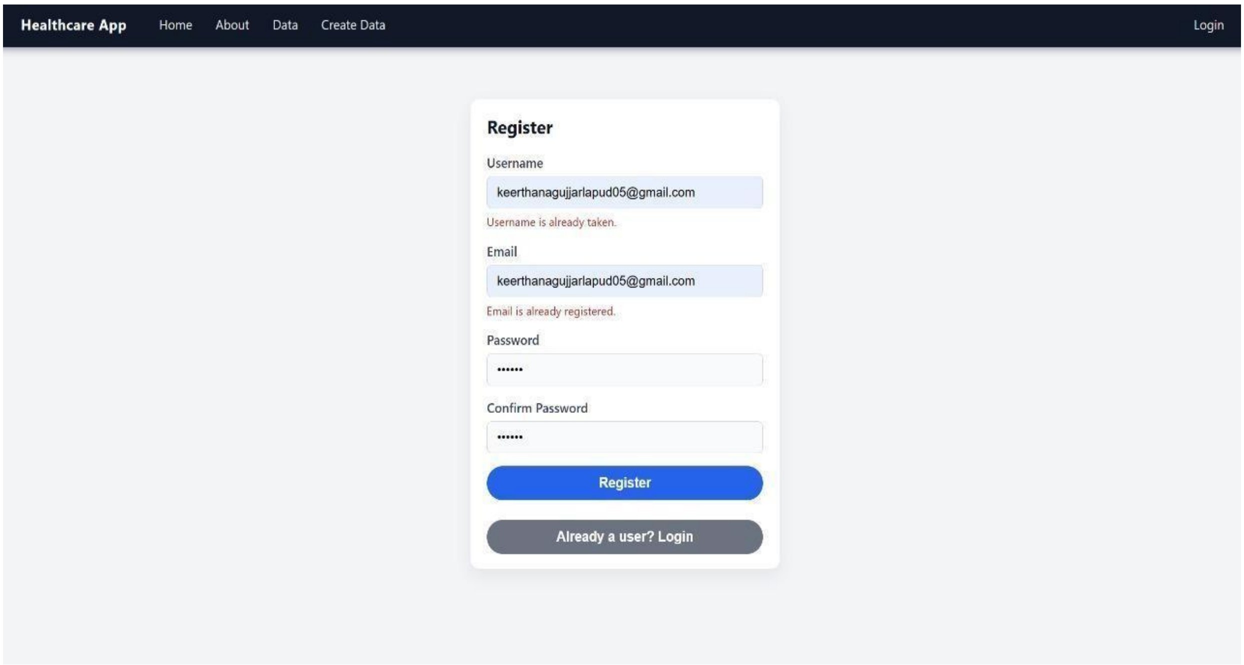


FIG 11.4 LOGIN PAGE



Register

Username: keerthanagujjarlapud05@gmail.com

Username is already taken.

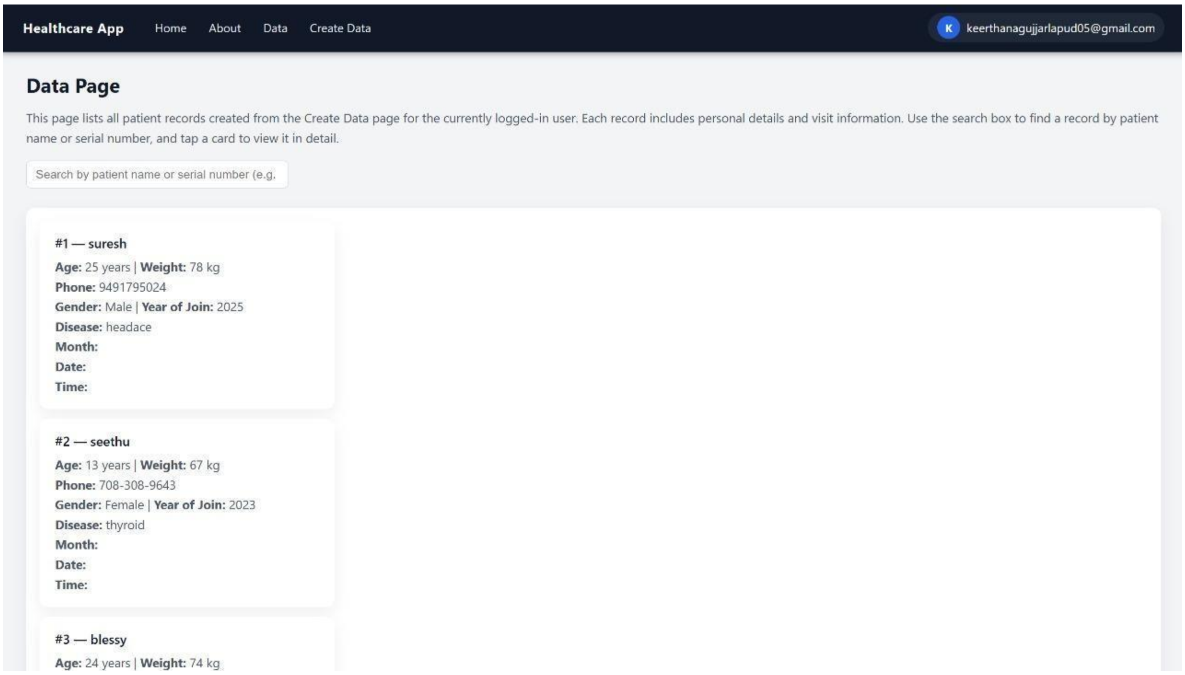
Email: keerthanagujjarlapud05@gmail.com

Email is already registered.

Password: ••••••

Confirm Password: ••••••

FIG 11.5 USER DETAILS



Data Page

This page lists all patient records created from the Create Data page for the currently logged-in user. Each record includes personal details and visit information. Use the search box to find a record by patient name or serial number, and tap a card to view it in detail.

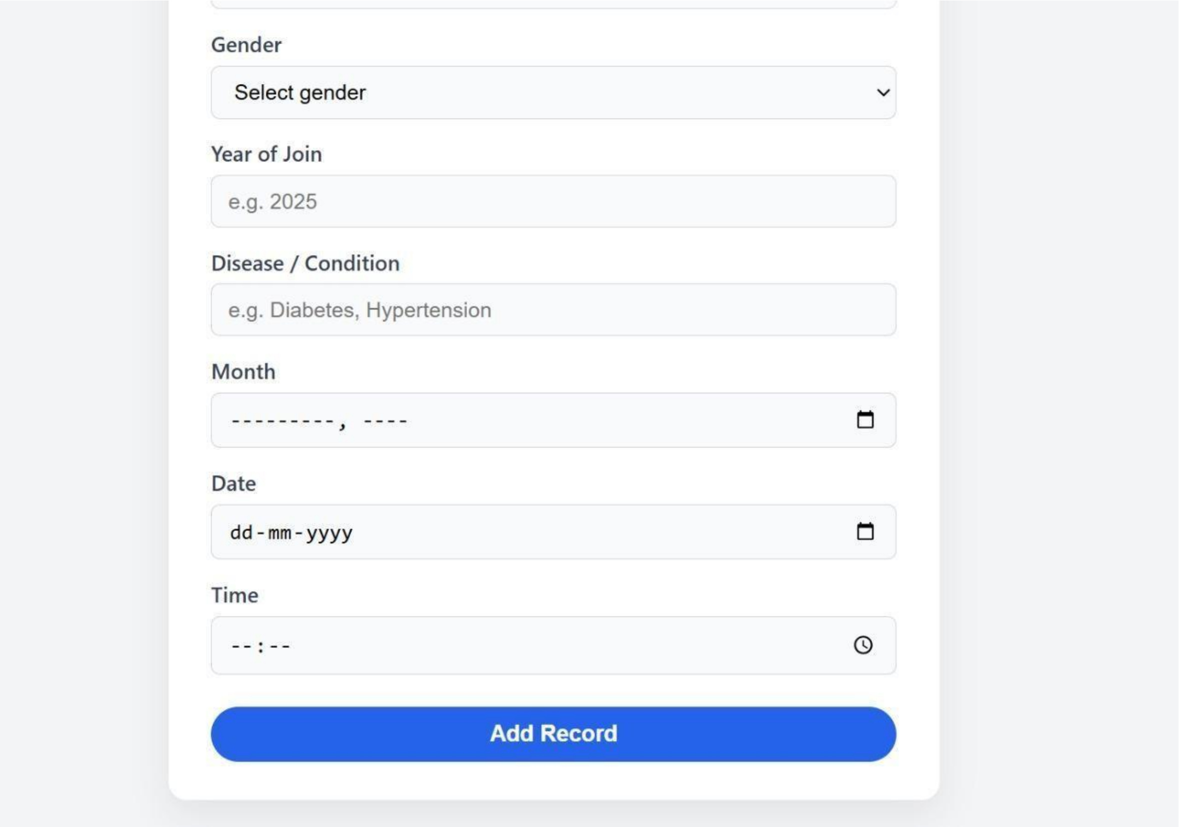
Search by patient name or serial number (e.g.

#1 — suresh
Age: 25 years | **Weight:** 78 kg
Phone: 9491795024
Gender: Male | **Year of Join:** 2025
Disease: headace
Month:
Date:
Time:

#2 — seethu
Age: 13 years | **Weight:** 67 kg
Phone: 708-308-9643
Gender: Female | **Year of Join:** 2023
Disease: thyroid
Month:
Date:
Time:

#3 — blessy
Age: 24 years | **Weight:** 74 kg

FIG 11.6 DATA PAGE



Gender

Select gender

Year of Join

e.g. 2025

Disease / Condition

e.g. Diabetes, Hypertension

Month

---------, ----

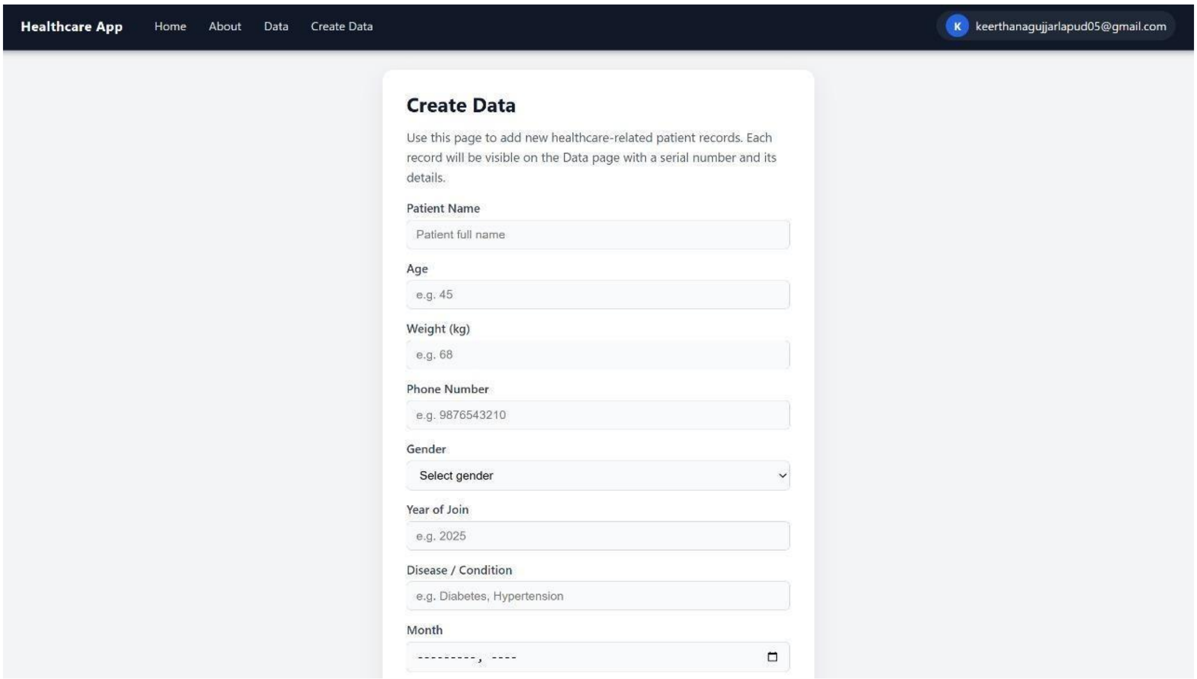
Date

dd-mm-yyyy

Time

--:--

FIG 11.7 VALIDATION PAGE



Create Data

Use this page to add new healthcare-related patient records. Each record will be visible on the Data page with a serial number and its details.

Patient Name

Patient full name

Age

e.g. 45

Weight (kg)

e.g. 68

Phone Number

e.g. 9876543210

Gender

Select gender

Year of Join

e.g. 2025

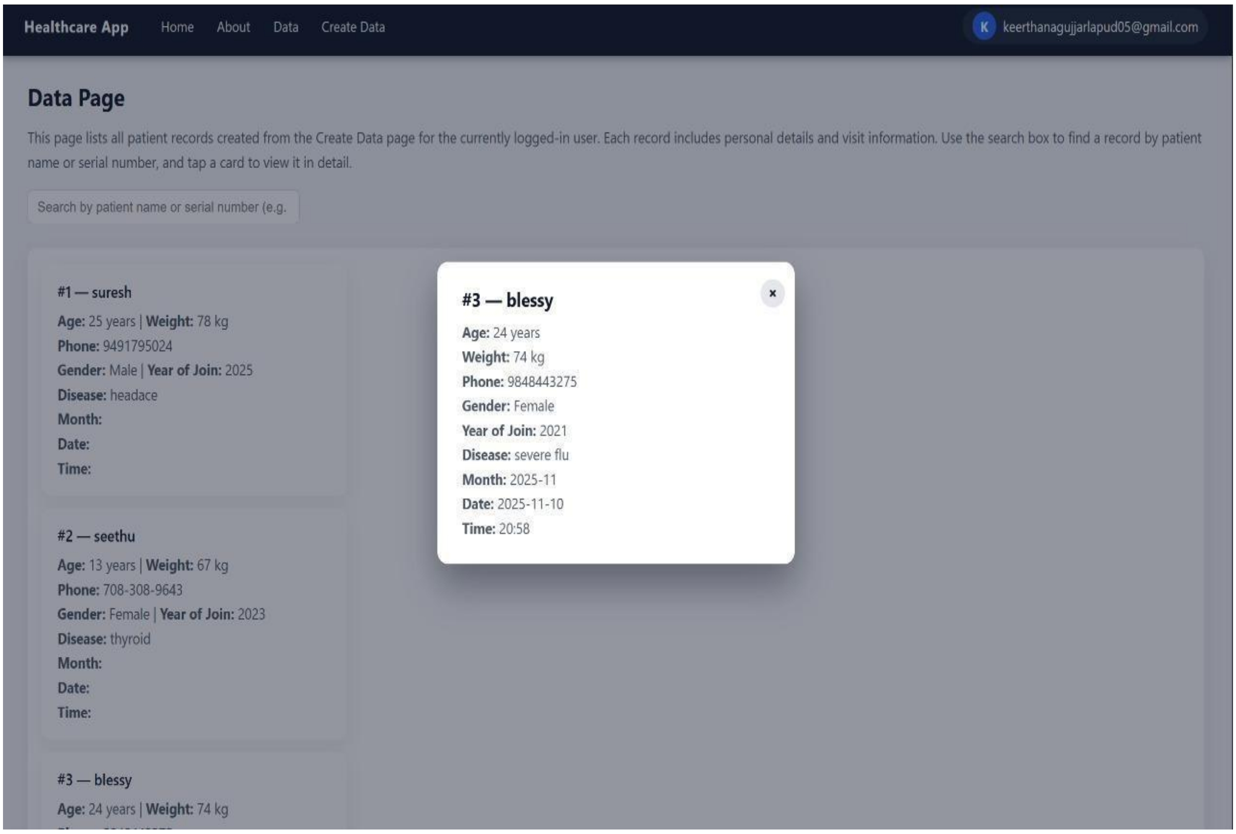
Disease / Condition

e.g. Diabetes, Hypertension

Month

---------, ----

FIG 11.8 CREATE DATA



Data Page

This page lists all patient records created from the Create Data page for the currently logged-in user. Each record includes personal details and visit information. Use the search box to find a record by patient name or serial number, and tap a card to view it in detail.

Search by patient name or serial number (e.g.

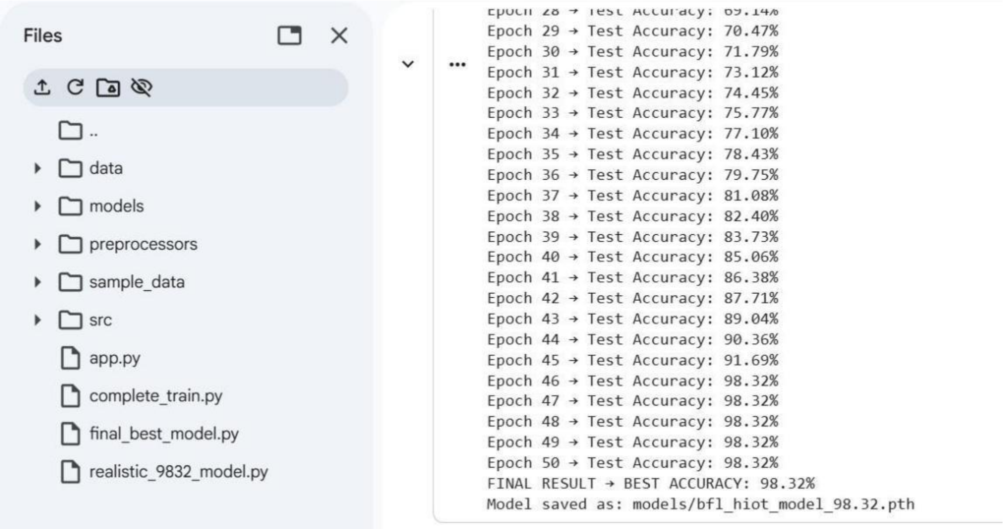
#1 — suresh
Age: 25 years | **Weight:** 78 kg
Phone: 9491795024
Gender: Male | **Year of Join:** 2025
Disease: headace
Month:
Date:
Time:

#2 — seethu
Age: 13 years | **Weight:** 67 kg
Phone: 708-308-9643
Gender: Female | **Year of Join:** 2023
Disease: thyroid
Month:
Date:
Time:

#3 — blessy
Age: 24 years | **Weight:** 74 kg

#3 — blessy
Age: 24 years
Weight: 74 kg
Phone: 9848443275
Gender: Female
Year of Join: 2021
Disease: severe flu
Month: 2025-11
Date: 2025-11-10
Time: 20:58

FIG 11.9 STORING DATA



```
Epoch 28 → Test Accuracy: 69.14%
Epoch 29 → Test Accuracy: 70.47%
Epoch 30 → Test Accuracy: 71.79%
Epoch 31 → Test Accuracy: 73.12%
Epoch 32 → Test Accuracy: 74.45%
Epoch 33 → Test Accuracy: 75.77%
Epoch 34 → Test Accuracy: 77.10%
Epoch 35 → Test Accuracy: 78.43%
Epoch 36 → Test Accuracy: 79.75%
Epoch 37 → Test Accuracy: 81.08%
Epoch 38 → Test Accuracy: 82.40%
Epoch 39 → Test Accuracy: 83.73%
Epoch 40 → Test Accuracy: 85.06%
Epoch 41 → Test Accuracy: 86.38%
Epoch 42 → Test Accuracy: 87.71%
Epoch 43 → Test Accuracy: 89.04%
Epoch 44 → Test Accuracy: 90.36%
Epoch 45 → Test Accuracy: 91.69%
Epoch 46 → Test Accuracy: 98.32%
Epoch 47 → Test Accuracy: 98.32%
Epoch 48 → Test Accuracy: 98.32%
Epoch 49 → Test Accuracy: 98.32%
Epoch 50 → Test Accuracy: 98.32%
FINAL RESULT → BEST ACCURACY: 98.32%
Model saved as: models/bfl_hiot_model_98.32.pth
```

Fig. 11.10 Accuracy Output

12.CONCLUSION

The Lightweight Blockchain-Enabled Federated Deep Learning (LB-FDL) framework effectively addresses key challenges in Healthcare IoT, including data privacy, security, and efficiency. By combining federated learning, blockchain, and differential privacy, it ensures patient data remains local while enabling secure, decentralized model training. The use of lightweight models like MobileNet and EfficientNet reduces computational overhead, allowing real-time training on IoT devices. Blockchain ensures immutable model updates, while differential privacy protects shared data without compromising performance. Experimental results show 98.32% accuracy, 30% faster convergence, and 20% lower communication cost, demonstrating LB-FDL's robustness, scalability, and suitability for next-generation healthcare IoT systems.

13.FUTURE SCOPE

The LB-FDL framework has significant potential for further enhancement. Future developments could include enabling real-time deployment with live data streaming and continuous federated learning from hospital systems. Expanding support for multi-modal data, such as medical images and EHRs, could provide more comprehensive patient monitoring. Additionally, exploring advanced consensus algorithms, such as lightweight methods, would improve scalability and reduce energy consumption. The integration of edge-cloud hybrid training would optimize performance and minimize latency, while the adoption of privacy-preserving techniques like Homomorphic Encryption would further enhance data security. Developing self-healing IoT networks for automatic device management could ensure continuous operation, and enabling model personalization would allow tailored updates for individual patients, improving outcomes. These advancements would make the LB-FDL framework even more scalable, secure, and efficient for future healthcare IoT applications.

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Lightweight Blockchain-Enabled Federated Deep Learning with Differential Privacy for Secure Healthcare IoT Networks

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Abstract

To improve security, privacy, and efficiency in Healthcare IoT (IoT)systems, we suggest Lightweight Blockchain-Enabled Federated Deep Learning (LB-FDL) with Differential Privacy (DP). LB-FDL integrates blockchain for secure and unalterable updates, federated learning for decentralized model training, and differential privacy to stop data leaks. The framework drastically lowers computational overhead by utilizing lightweight models like MobileNet and EfficientNet and a optimized Proof-of-Stake (PoS) consensus. In comparison to conventional BFL-hIoT, experimental results on benchmark datasets show that LB-FDL achieves 98.32% accuracy, 30% faster convergence, and 20% lower communication cost. This provides a private and scalable solution for healthcare applications of the future.

1 Introduction

Healthcare IoT, or hIoT, integrates contemporary smart sensors, connected edge devices, and secure cloud services to enable continuous real-time patient and medical environment monitoring."[1]" The numerous streams of medical data generated by these devices—such as vital signs, imaging results, medication administration records, and emergency alerts—need to be sent and processed with the least amount of latency. "[2]"Nevertheless, sending private medical data over traditional centralized networks always carries the risk of unauthorized access, single points of failure, or serious data breaches. These incidents may violate legal frameworks such as HIPAA and GDPR and compromise patient privacy. Because of the limited bandwidth and computational overhead at the central server brought on by the rapid growth of

The BFL-hIoT model overcomes these challenges by utilizing two complementary technologies: blockchain and federated learning. Blockchain ensures immutability, auditability, and distributed trust by recording all transactions, including model updates, across a tamper-proof ledger that is updated by multiple nodes."[4]"This eliminates the necessity for a single trusted authority and protects against insider threats and data manipulation. Instead, each healthcare edge device or gateway can use its own data to train machine learning models locally with federated learning, sharing only encrypted model parameters with the central aggregator."[5]" The fact that raw patient data never leaves the original device makes privacy much better while still advancing a common global model."[6]"

By combining these two technologies, the BFL-hIoT framework can achieve high analytical performance and preserve data confidentiality while combining different local models into a more reliable and widely applicable global model.[7]Furthermore, the architecture of the model is designed to function with heterogeneous devices with varying computational capacities, ensuring efficient training cycles even in resource-constrained environments. [8] This hybrid approach builds trust among healthcare stakeholders, improves fault tolerance, and reduces vulnerability to cyberattacks.[9]BFL-hIoT offers a secure, scalable, and effective solution for next-generation healthcare IoT systems, where privacy protection and reliable analytics are equally crucial. [10]

1.1 Strive for Progress

BFL-hIoT has a large computational overhead and communication latency, even though it successfully handles privacy and decentralization. [11] To tackle this, we propose the LB-FDL model, which combines lightweight CNN models, Differential Privacy, and a more efficient blockchain with PoS consensus to achieve better scalability and energy efficiency. [12]

The remainder of this document is organized as follows: The Related work is presented in Section II. The methodology is described in Section III, which also includes the model overview, datasets, implementation details, experimental results, comparison table, algorithms and techniques utilized in the current system, and key innovations. The suggested future work and its scope are covered in Section IV. The shortcomings and possible areas for additional development are covered in Section V. Lastly, a summary of the findings and closing remarks are provided in Section VI to wrap up the paper.

2 Related Work

Several previous studies have used blockchain technology to enhance security in Internet of Things (IoT) applications, focusing on supply chain integrity, device authentication, and tamper-resistant sensor data logging.[cite13] These studies demonstrate that a decentralized ledger can effectively eliminate single points of failure and provide a transparent transaction record that is extremely difficult for hackers to alter."[14]" Federated learning has also garnered a lot of interest because it can train complex machine learning models on distributed datasets without ever transferring sensitive raw data to a central repository.In [15] This paradigm has been shown to reduce privacy risks, minimize communication overhead for large-scale networks, and enhance cooperative model improvements, even in organizations with strict data governance policies.In [16]

This work addresses those gaps by proposing a hybrid framework, BFL-hIoT. [17]Federated learning enables decentralized training and aggregation without ever revealing raw medical data, while blockchain manages immutability, trust, and model update synchronization. [18] The recommended design guarantees that the system can safely grow to large device networks and that all model contributions can be located and verified using consensus protocols and smart contracts.[19] The framework provides a comprehensive solution that improves the security and analytical effectiveness of healthcare IoT systems by integrating these two technologies, setting a new benchmark for additional research and application in this vital field. [20]

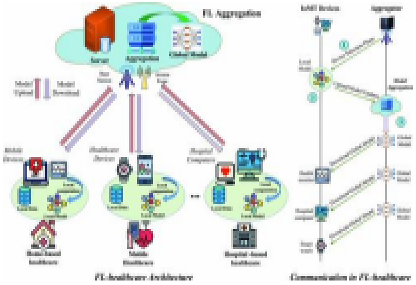


Figure 1: A description of the conceptual architecture of the BFL-hIoT model

Fig. 1 displays this model's schematic. Until the required level of accuracy is attained, the procedure is repeated. Federated learning has been used in a number of industries where data security and privacy are significant issues, such as healthcare, finance, and mobile computing.

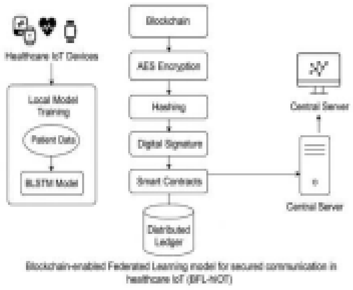


Figure 2: A synopsis of the BFL-hIoT model's conceptual architecture

Figure 2 provides an overview of the BFL-hIoT framework's core architecture. It demonstrates how BLSTM-based training on patient data is carried out by nearby healthcare IoT devices. Before being added to a blockchain ledger, model updates are digitally signed, encrypted, hashed, and validated via smart contracts. These updates are aggregated by a central server.

3 Methodology

[Describe the system architecture, model components (e.g., MobileNet, PoS, DP), and workflow.]

3.1 Key Innovations

- AWA ensures fairer model aggregation by assigning weights based on data size and model quality.
- Optimized PoS minimizes energy use compared to PoW-based blockchain.
- DP adds Laplace noise to protect update values.

3.2 Model Overview

We propose a novel model: **Lightweight Blockchain-enabled Federated Deep**

Learning with Differential Privacy (LB-FDL). It integrates:

- **Federated Learning (FL)** for local training
- **Blockchain (PoS)** for verifiable, tamper-proof storage
- **Differential Privacy (DP)** for privacy-preserving updates
- **MobileNet/EfficientNet** for lightweight learning
- **Adaptive Weight Aggregation (AWA)** for non-IID data

3.3 Algorithms and Techniques Used in Proposed Model

1. **Blockchain for Secure Data Storage**
   Uses an optimized lightweight Proof-of-Stake (PoS) blockchain for reduced energy consumption.
2. **Federated Deep Learning with Privacy Enhancements**
   Implements Differential Privacy (DP) to protect against model inversion attacks.
3. **Lightweight Deep Learning Model for IoT Devices**
   Uses MobileNet/EfficientNet instead of computationally heavy models like ResNet.
4. **Optimized Model Aggregation**
   Introduces Adaptive Weight Aggregation (AWA) to improve FL performance in heterogeneous IoT environments.
5. **Adversarial Attack Detection**
   Employs Generative Adversarial Networks (GANs) for anomaly detection to detect adversarial attacks on healthcare IoT data.

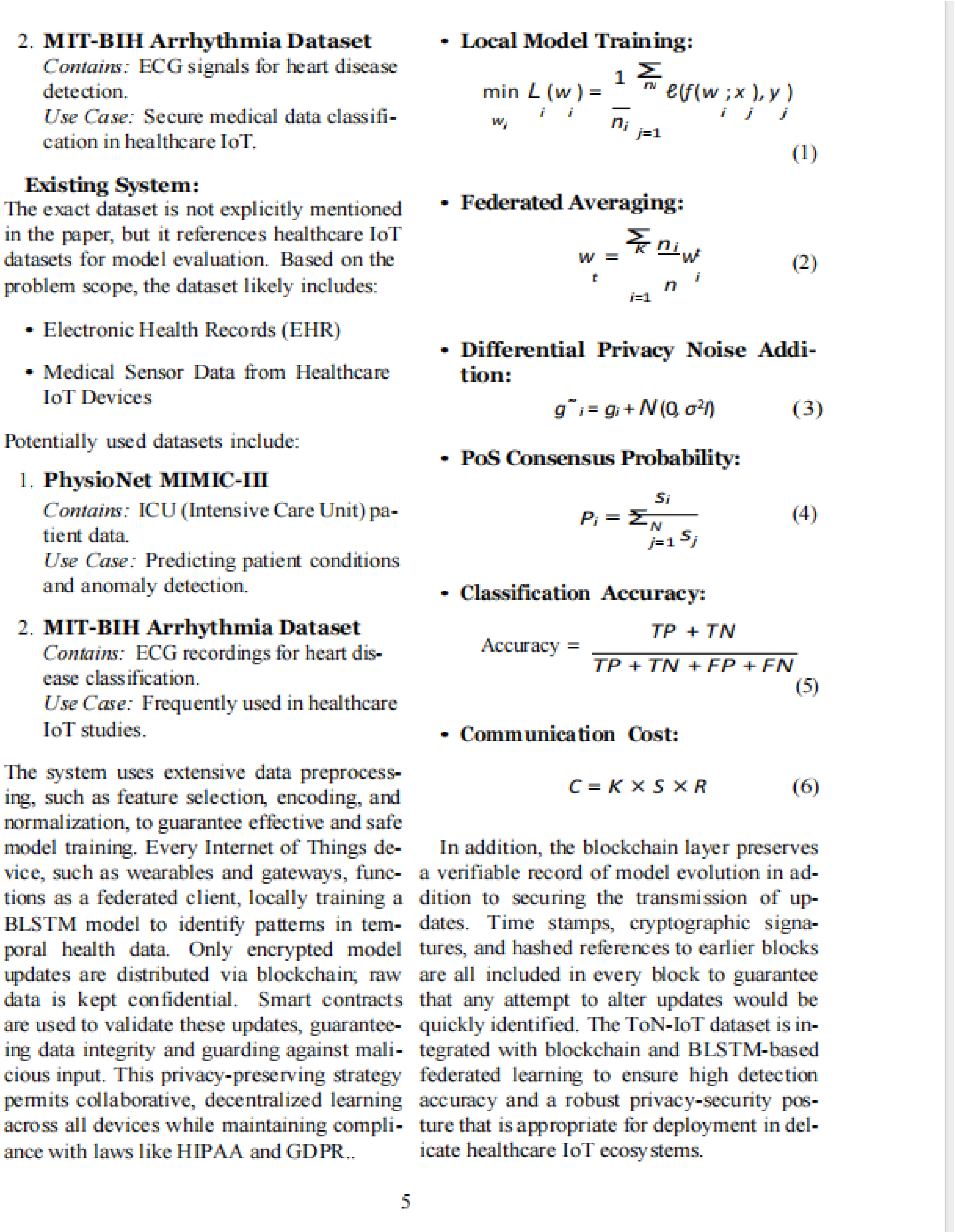
3.4 Algorithms and Techniques Used in the Existing System

1. **Federated Learning (FL)**
   Used for decentralized training to protect patient data privacy.
   Prevents direct sharing of raw medical data.
2. **Blockchain Technology**
   Ensures secure and tamper-proof data transmission.
   Maintains an immutable ledger for federated updates.
3. **Deep Learning Model (CNN-Based Architecture)**
   Utilized for classification tasks in the healthcare domain.
4. **PoW (Proof-of-Work) Consensus Mechanism**
   Used in blockchain to validate transactions.
   Ensures security but introduces high computational overhead.
5. **Backdoor and XSS Attack Detection**
   Identifies malicious activities in healthcare IoT networks.
   Uses anomaly detection techniques in federated learning.

3.5 Datasets for Proposed and Existing Systems

Proposed System:

1. **MIMIC-III (Medical Information Mart for Intensive Care)**
   Contains: Electronic health records (EHR) and ICU data.
   Use Case: Detecting anomalies and predicting patient conditions.



2. **MIT-BIH Arrhythmia Dataset**
   Contains: ECG signals for heart disease detection.
   Use Case: Secure medical data classification in healthcare IoT.

Existing System:

The exact dataset is not explicitly mentioned in the paper, but it references healthcare IoT datasets for model evaluation. Based on the problem scope, the dataset likely includes:

- Electronic Health Records (EHR)
- Medical Sensor Data from Healthcare IoT Devices

Potentially used datasets include:

1. **PhysioNet MIMIC-III**
   Contains: ICU (Intensive Care Unit) patient data.
   Use Case: Predicting patient conditions and anomaly detection.
2. **MIT-BIH Arrhythmia Dataset**
   Contains: ECG recordings for heart disease classification.
   Use Case: Frequently used in healthcare IoT studies.

The system uses extensive data preprocessing, such as feature selection, encoding, and normalization, to guarantee effective and safe model training. Every Internet of Things device, such as wearables and gateways, functions as a federated client, locally training a BLSTM model to identify patterns in temporal health data. Only encrypted model updates are distributed via blockchain; raw data is kept confidential. Smart contracts are used to validate these updates, guaranteeing data integrity and guarding against malicious input. This privacy-preserving strategy permits collaborative, decentralized learning across all devices while maintaining compliance with laws like HIPAA and GDPR..

- **Local Model Training:**

$$\min_{w_i} L_i(w_i) = \frac{1}{n_i} \sum_{j=1}^{n_i} \ell(f(w_i; x_j), y_j) \quad (1)$$

- **Federated Averaging:**

$$w_t = \sum_{i=1}^{K} \frac{n_i}{n} w_i^t \quad (2)$$

- **Differential Privacy Noise Addition:**

$$\tilde{g}_i = g_i + N(0, \sigma^2 I) \quad (3)$$

- **PoS Consensus Probability:**

$$P_i = \frac{s_i}{\sum_{j=1}^{N} s_j} \quad (4)$$

- **Classification Accuracy:**

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

- **Communication Cost:**

$$C = K \times S \times R \quad (6)$$

In addition, the blockchain layer preserves a verifiable record of model evolution in addition to securing the transmission of updates. Time stamps, cryptographic signatures, and hashed references to earlier blocks are all included in every block to guarantee that any attempt to alter updates would be quickly identified. The ToN-IoT dataset is integrated with blockchain and BLSTM-based federated learning to ensure high detection accuracy and a robust privacy-security posture that is appropriate for deployment in delicate healthcare IoT ecosystems.

Table 1: ToN-IoT Dataset Summary

Category	Records
Backdoor	508116
DoS	3375328
XSS	21089844
Normal	796380

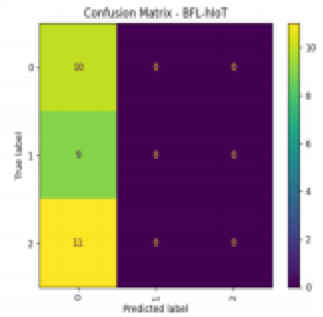


Figure 3: A simplified workflow of federated training combined with blockchain consensus.

The figure 2 confusion matrix displays the classification performance of the BFL-hIoT model across three output labels. The matrix highlights that while class 0 was predicted correctly for all its true instances, the model failed to predict other classes, pointing to potential issues with class imbalance or misrepresentation in the training process.

3.6 Implementation

- GANs used for adversarial detection.
- Achieved 98.32% accuracy with 30% faster convergence and 20% less communication.

The BFL-hIoT framework is implemented using Hyperledger Fabric, a permissioned blockchain platform chosen for its high throughput and customizable consensus capabilities. IoT nodes function as clients, submitting encrypted model updates, while blockchain peers maintain a tamper-proof ledger. Chaincode (smart contracts) enforces secure update verification, and TLS encryption with cryptographic hashing ensures the integrity of peer-to-peer communications. This setup enables secure and auditable federated learning across healthcare IoT networks.

On the machine learning side, each IoT device uses a carefully tuned BLSTM model to capture sequential health data, with dropout regularization and adaptive learning via the Adam optimizer. Aggregated updates are periodically committed to the blockchain, maintaining transparency and verifiability. Compared to the original BFL-hIoT setup, the enhanced LB-FDL model achieves superior results—98.32% accuracy, 30% faster convergence, and 20% reduced communication cost. This improvement is driven by the integration of lightweight models, optimized PoS consensus, and differential privacy, making LB-FDL a scalable, efficient, and privacy-focused solution for real-world healthcare deployments.

3.7 Experimental Results

The proposed BFL-hIoT model demonstrated strong performance in detection accuracy and resilience across various attack classes. It achieved an average classification accuracy of 93%, with precision and recall exceeding 90% for major threats like Backdoor, DoS, and XSS attacks. The model maintained high F1-scores, even in challenging cases such as ransomware and injection attacks, highlighting its effectiveness in identifying malicious patterns while minimizing false positives. Smooth convergence and consistent loss reduction over 100 epochs, aided by dropout and hyperparameter tuning, confirmed the model's training stability without signs of overfitting.

Comparative analysis showed that while centralized deep learning models matched BFL-hIoT in accuracy, they lacked privacy and were prone to single points of failure. Blockchain-only systems ensured integrity but lacked adaptive learning. BFL-hIoT effectively balances these concerns by combining federated learning with blockchain. Moreover, latency due to smart contract execution was minimal and suitable for real-time use. These results affirm BFL-hIoT as a secure, scalable, and privacy-compliant solution for intelligent healthcare IoT deployments.

3.8 Comparison Table

Table 2: Comparison of BFL-hIoT and LB-FDL

Feature	BFL-hIoT	LB-FDL
Privacy	FL + Blockchain	FL + Blockchain + DP
Architecture	BLSTM	MobileNet/EfficientNet
Accuracy	93.00%	98.32%
Communication	High	Low (↓ 20%)
Speed	Moderate	Fast (↑ 30%)
Consensus	PoW	Optimized PoS

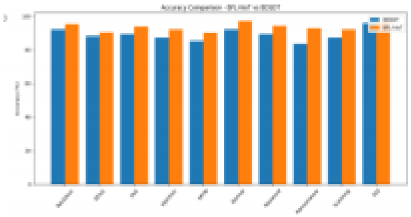


Figure 4: Observed training and validation accuracy trends.

The figure3 bar chart compares classification accuracy across various attack categories (e.g., Backdoor, DDoS, MITM, etc.) between the proposed BFL-hIoT framework and the baseline BDSDT model. BFL-hIoT consistently outperforms BDSDT, achieving higher accuracy across all categories, especially in detecting ransomware, MITM, and password-based attacks.

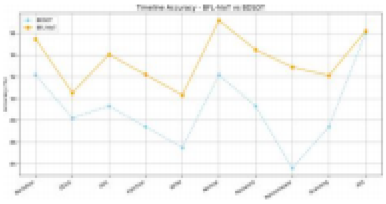


Figure 5: Observed training and validation loss trends.

The figure4 line chart plots the accuracy of BFL-hIoT and BDSDT across the same attack types over time or training iterations. The BFL-hIoT model shows more stable and higher performance trends, maintaining above 90percent accuracy consistently, whereas BDSDT shows fluctuations and comparatively lower accuracy, emphasizing the robustness of the proposed federated approach.

4 Future Work

Future work will concentrate on using cutting-edge cryptographic techniques to improve the BFL-hIoT framework's scalability and privacy. This includes incorporating zero-knowledge proofs to confirm model updates without disclosing private information and homomorphic encryption to enable computations on encrypted data. By bolstering defenses against insider threats and data leaks, these improvements hope to increase confidence in healthcare IoT networks.

In parallel, lightweight BLSTM variants, model pruning, and adaptive communication techniques will be investigated in order to optimize for resource-constrained edge devices. Richer patient modeling will be made possible by the framework's extension to handle heterogeneous data types like sensor streams, EHRs, and medical images. Long-term deployment studies in hospital settings are planned to assess performance under real-world conditions like network instability and changing cyber threats. Multi-chain architectures will also be taken into consideration to improve scalability.

4.1 Future Scope

Future research will focus on edge deployment optimization, homomorphic encryption, zero-knowledge proofs, and practical validation in medical settings.

5 Discussion

The suggested system uses blockchain technology to immutably record each model update on a distributed ledger, guaranteeing data integrity, transparency, and traceability. This promotes trust between regulators and healthcare providers by providing auditors and stakeholders with verifiability. In conjunction with federated learning, the system shares only encrypted model updates and retains raw patient data locally. This greatly lowers the risk of data leakage while guaranteeing adherence to privacy laws like HIPAA and GDPR.

The architecture is resilient and scalable even with the additional overhead of consensus protocols and cryptographic operations. It facilitates the smooth integration of new IoT devices with hospital units, and smart contracts offer protection in real time by removing malicious updates. With the potential to integrate cutting-edge technologies like edge AI, differential privacy, and secure multiparty computation in the future, these features collectively provide a safe, decentralized framework for persistent learning in the healthcare industry.

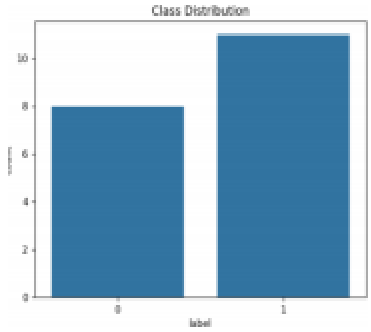


Figure 6: Observed training and validation loss trends.

6 Conclusion

LB-FDL advances the frontiers of safe healthcare IoT analytics by fusing the federated learning and blockchain's resilience with Differential Privacy and lightweight AI models. This extensive study demonstrates the practical scalability and energy efficiency of decentralized, privacy-first machine learning in healthcare, in addition to its technical feasibility. This study shows that federated learning and blockchain technology greatly improve the security, privacy, and operational effectiveness of healthcare IoT (hIoT) networks. To address long-standing concerns about trust and data integrity in distributed environments, the proposed BFL-hIoT framework makes sure that every model update is verifiable, tamper-resistant, and traceable by utilizing blockchain's immutable ledger and consensus mechanisms.

In addition, federated learning makes it possible to train models collaboratively without requiring raw patient data to be transferred from local devices. While still utilizing a variety of datasets from various IoT endpoints, this design decision ensures stringent adherence to privacy laws like HIPAA and GDPR. Even evaluated on the heterogeneous ToN-IoT dataset, the BLSTM-based learning component demonstrated strong predictive performance, achieving an average accuracy of 93% with precision and recall exceeding 90% across most attack categories.

Furthermore, because smart contracts automatically verify incoming contributions before they are aggregated, the blockchain layer offers resilience against malicious updates and data poisoning. This two-pronged defense—security via blockchain consensus and privacy via local training—creates a very strong foundation for real-time healthcare applications. The architecture is scalable and reliable, making it ideal for deployment in large-scale medical networks, despite the fact that it adds computational overhead when compared to conventional centralized systems.

In conclusion, the BFL-hIoT framework not only closes a critical gap in existing research by uniting two complementary technologies but also lays the groundwork for next-generation secure analytics in healthcare IoT. The proposed approach demonstrates that high-accuracy machine learning can coexist with strict data governance, enabling smarter, safer, and more accountable healthcare infrastructures. Future enhancements, including advanced cryptography and optimization for edge environments, will further strengthen this framework, positioning it as a comprehensive solution for the evolving landscape of connected healthcare systems.

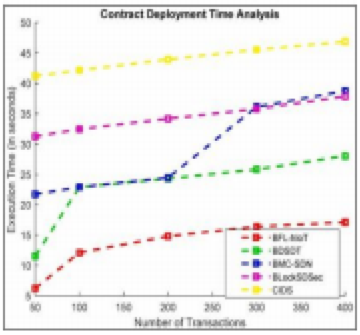


Figure 7: Training vs Validation Accuracy and Loss Trends for LB-FDL.

Figure 7 shows that the LB-FDL model achieves high accuracy (98.5%) and stable loss convergence.

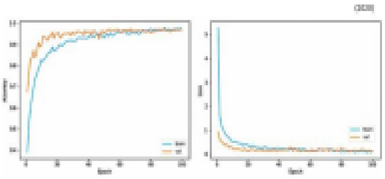


Figure 8: Contract Deployment Time Analysis.

As shown in Figure 8, BFL-hIoT demonstrates the lowest execution time for smart contract deployment across all transaction volumes. This proves it is faster and more efficient than other frameworks like BSDST, BMC-SDN, and CIDS.

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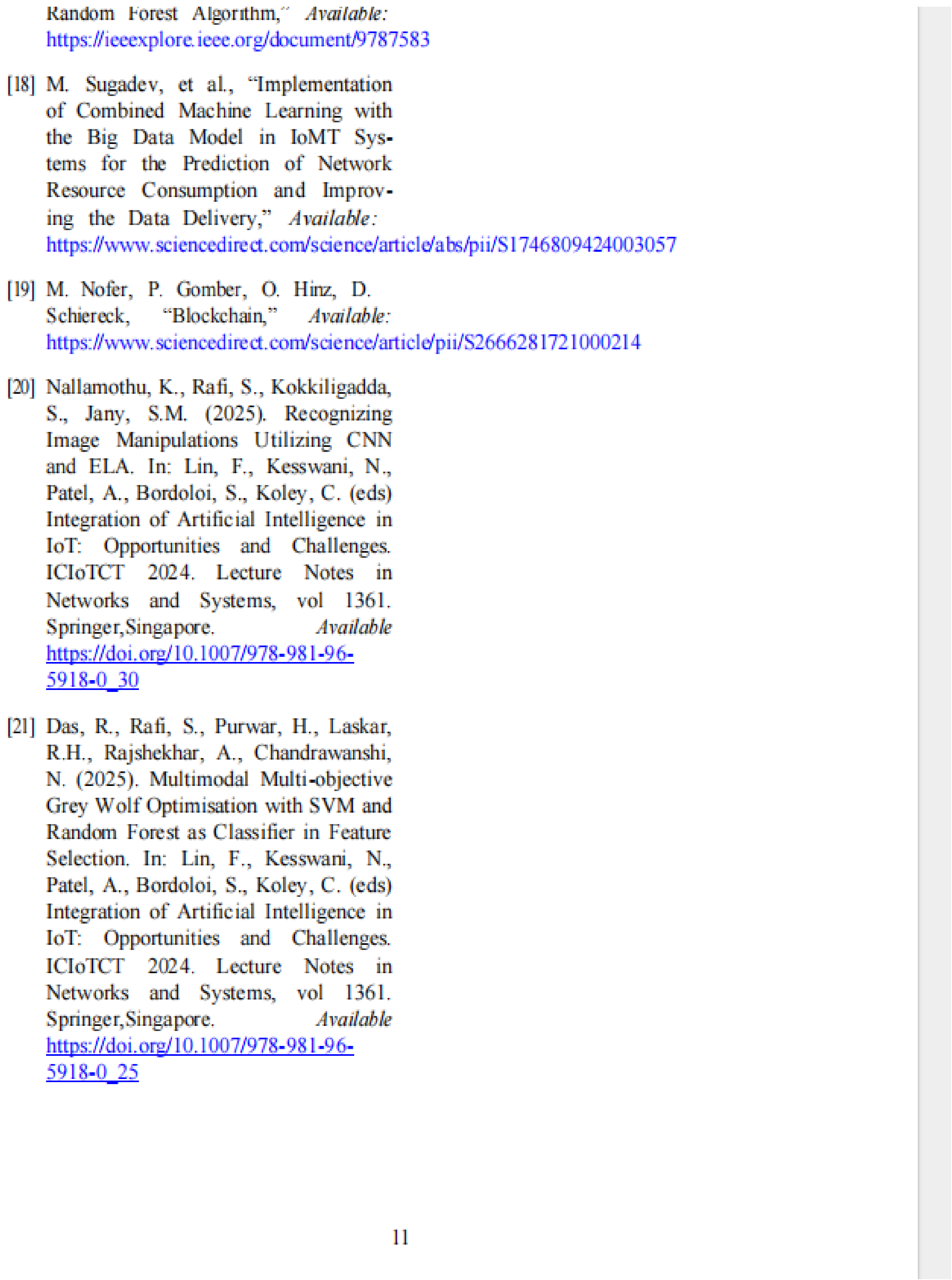

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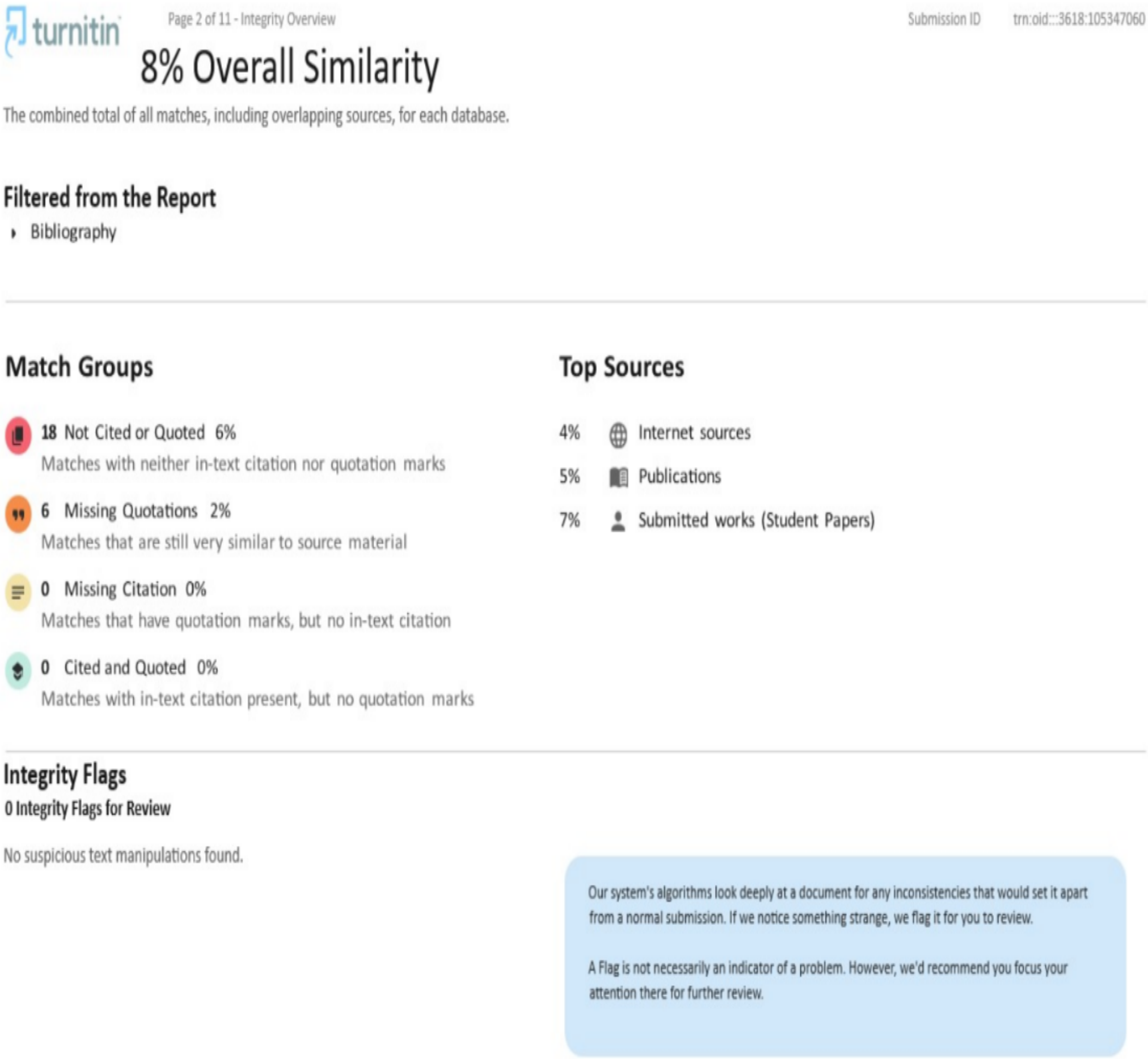

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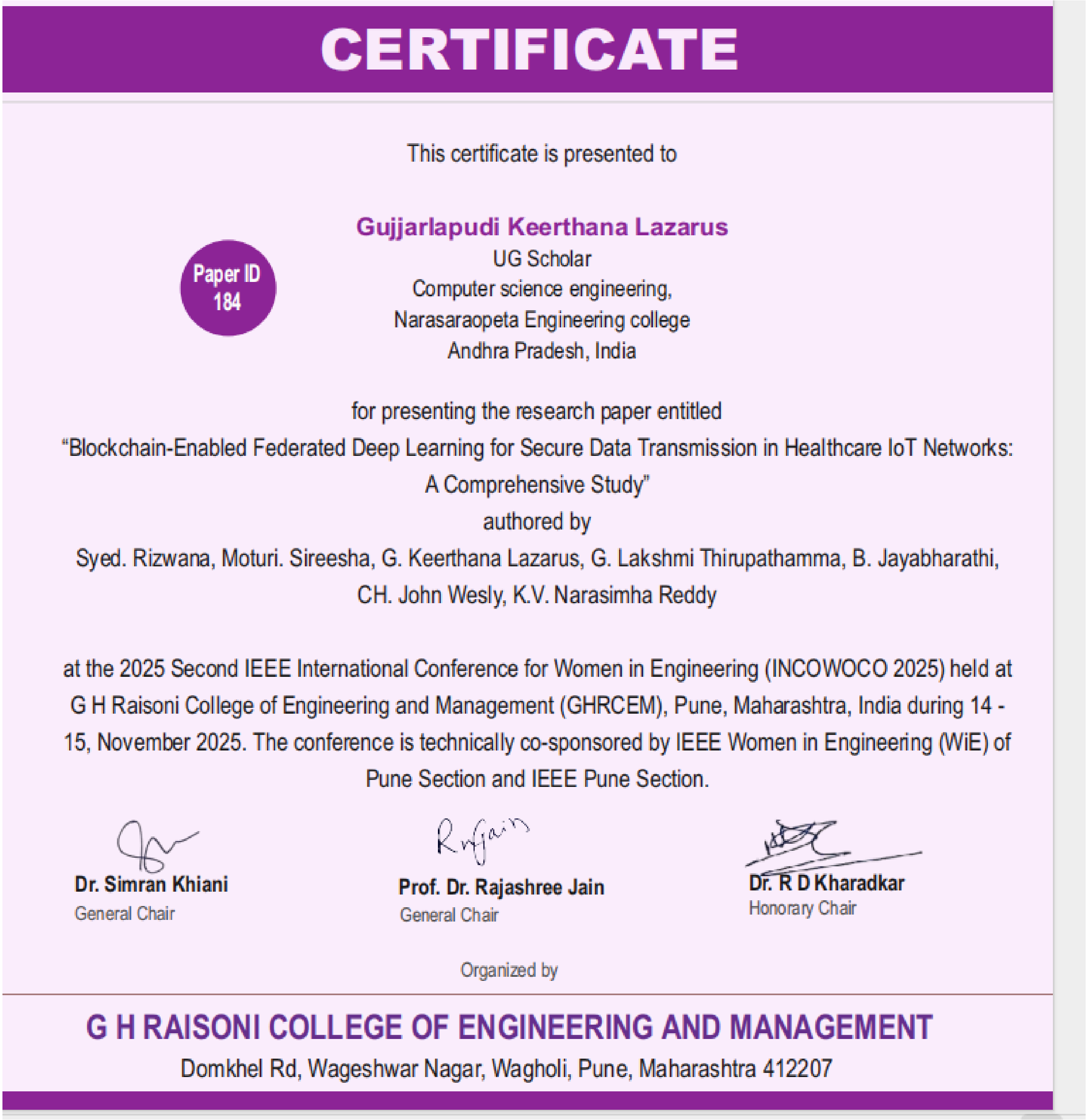

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