FEDERATED LEARNING FOR DECENTRALIZED AI DEVELOPMENT

TITLE: FEDERATED LEARNING FOR DECENTRALIZED AI DEVELOPMENT

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II. EXECUTIVE SUMMARY

This report outlines the project titled "Federated Learning for Decentralized AI Development," which aims to address significant challenges in healthcare, particularly in the prediction of heart attacks. The core objective of this project is to leverage federated learning, a cutting-edge technique in machine learning, to create a predictive model that can operate across multiple healthcare institutions while preserving patient data privacy.

The project is motivated by the need to balance data privacy with the desire to build robust, accurate models that benefit from diverse datasets. Federated learning allows multiple hospitals to collaboratively train a model without the need to centralize sensitive patient data, ensuring compliance with strict privacy regulations such as HIPAA.

Key objectives of the project include:

- Developing a secure and effective AI model for heart attack prediction.
- Facilitating collaboration among healthcare institutions without compromising data privacy.
- Enhancing the accuracy and generalization of predictive models through diverse data sources.

The anticipated benefits of this project are multi-faceted, impacting both the technical and healthcare domains. These include improved data privacy and security, better model performance, and strengthened collaboration in healthcare research. Ultimately, the project aims to contribute to better healthcare outcomes by enabling more accurate predictions and preventive care for heart attacks.

III. INTRODUCTION TO THE PROJECT

Federated Learning Overview: Federated Learning is a decentralized machine learning technique that enables multiple organizations to collaboratively train a model without sharing their data. This approach is particularly important in fields like healthcare, where data privacy is of utmost concern. By keeping data local to each participating institution and only sharing model updates, federated learning ensures that sensitive patient information remains secure while still benefiting from collaborative data-driven insights.

HEART ATTACK PREDICTION: The specific focus of this project is on heart attack prediction. Cardiovascular diseases, including heart attacks, are leading causes of death worldwide. Accurate prediction of heart attacks can significantly improve patient outcomes by enabling timely intervention. However, developing predictive models requires access to large, diverse datasets, which poses a challenge due to privacy concerns. Federated learning addresses this challenge by allowing hospitals to contribute to model training without sharing patient data.

GOALS AND OBJECTIVES:

- **Primary Goal**: To develop a federated learning framework that can accurately predict heart attacks across decentralized hospital networks.
- **Specific Objectives**:
    1. Create a federated learning infrastructure that allows for secure, privacy-preserving model training across multiple hospitals.
    2. Develop and validate a predictive model for heart attacks using data from diverse populations.
    3. Ensure the developed model complies with relevant data protection laws and regulations.
    4. Foster collaboration among healthcare institutions to enhance research and development in predictive analytics.

IV. BENEFITS

ENHANCED DATA PRIVACY AND SECURITY: Federated learning ensures that sensitive patient data never leaves the hospital, thereby minimizing the risk of data breaches. This method aligns with strict privacy regulations like HIPAA, making it a suitable choice for healthcare applications.

IMPROVED MODEL ACCURACY AND GENERALIZATION: By training the model on data from multiple hospitals, the model benefits from a wider variety of patient profiles, leading to better generalization and accuracy in predicting heart attacks. This diversity in data helps in creating a more robust model that performs well across different demographic groups.

COMPLIANCE WITH DATA PROTECTION REGULATIONS: The federated learning approach is designed to comply with data protection laws, ensuring that all data processing activities adhere to legal requirements. This compliance is crucial in healthcare, where patient data is highly sensitive.

FACILITATION OF COLLABORATIVE RESEARCH: This project fosters collaboration between hospitals and research institutions by allowing them to contribute to a shared goal without compromising data privacy. Such collaboration can lead to significant advancements in medical research and the development of new treatments and preventive measures.

BETTER HEALTHCARE OUTCOMES: The ultimate benefit of this project is improved healthcare outcomes. By enabling more accurate and timely predictions of heart attacks, healthcare providers can offer better preventive care and treatment, ultimately saving lives.

V. REQUIREMENTS

FUNCTIONAL REQUIREMENTS:

MODEL DISTRIBUTION: The system must be able to distribute the initial model from the central server to connected hospital nodes.

LOCAL TRAINING: Each hospital node should be capable of training the model locally on its own dataset.

MODEL AGGREGATION: The central server must aggregate model updates received from hospital nodes to create a global model.

DATA PRIVACY: Ensure that sensitive patient data remains secure and decentralized throughout the training process.

MODEL UPDATING: Hospital nodes should be able to send updated model parameters to the central server after local training.

ITERATION CONTROL: Implement mechanisms to control the number of trainings iterations and ensure convergence of the global model.

MONITORING AND LOGGING: Incorporate logging and monitoring functionalities to track model training progress and detect any anomalies.

NON-FUNCTIONAL REQUIREMENTS:

SECURITY: Implement robust security measures to prevent unauthorized access to patient data and ensure data integrity during transmission.

SCALABILITY: The system should be scalable to accommodate a growing number of hospital nodes and handle large volumes of data.

PERFORMANCE: Ensure efficient model training and aggregation processes to minimize latency and maximize system responsiveness.

COMPATIBILITY: The system should be compatible with existing hospital infrastructure and comply with relevant healthcare standards and regulations.

USABILITY: Provide a user-friendly interface for hospital administrators to manage the federated learning process and monitor system performance.

RELIABILITY: Ensure high availability and fault tolerance to prevent disruptions in model training and aggregation.

Ethical Considerations: Adhere to ethical guidelines and principles to ensure fair and responsible use of patient data and AI technologies in healthcare.

HARDWARE REQUIREMENTS:

- **HIGH-PERFORMANCE GPUS**: To efficiently train the AI models locally at each hospital, high-performance GPUs are required. These GPUs will be essential for handling the computational load of model training.

SOFTWARE REQUIREMENTS:

- **PROGRAMMING LANGUAGES AND FRAMEWORKS**: Python will be the primary programming language, with TensorFlow being used for model development. Docker will be employed to containerize the application, ensuring consistency across different environments.
- **FEDERATED LEARNING FRAMEWORKS**: Specific frameworks and libraries designed for federated learning, such as TensorFlow Federated, will be used to implement the federated learning process.

DATA REQUIREMENTS:

- **TYPE OF DATA**: The project will require access to anonymized medical records, including patient history, ECG readings, and other relevant health metrics. Data will be sourced from participating hospitals.
- **DATA PRIVACY**: All data must be anonymized to protect patient identity, and stringent data handling procedures must be followed to comply with privacy laws.

SECURITY REQUIREMENTS:

- **ENCRYPTION**: Advanced encryption methods will be used to protect data both in transit and at rest. This includes encrypting all communications between hospitals and the central server as well as encrypting local datasets.
- **ACCESS CONTROL**: Strict access control mechanisms will be implemented to ensure that only authorized personnel have access to sensitive data and system components.

PERSONNEL REQUIREMENTS:

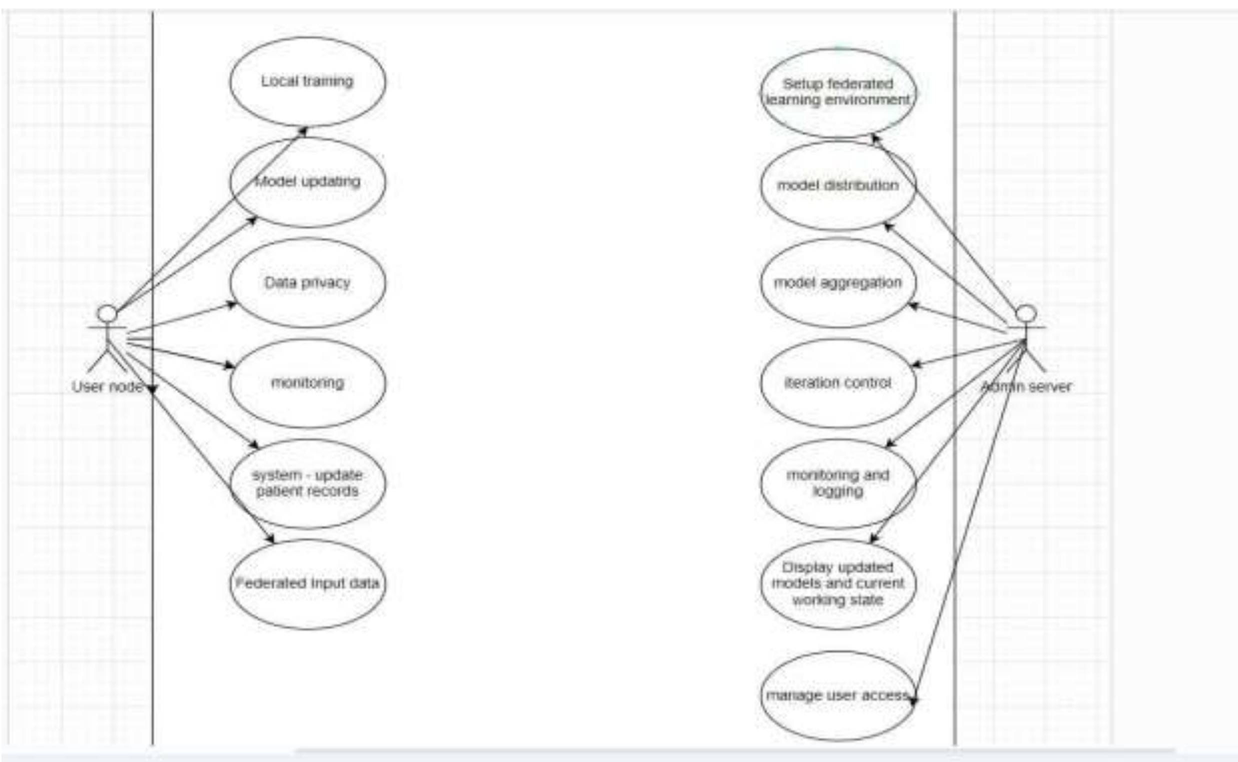
- **DATA SCIENTISTS**: Experts in machine learning and data science will be needed to develop and refine the predictive models.

- **SOFTWARE ENGINEERS**: Skilled software engineers will be responsible for building the federated learning infrastructure and ensuring its scalability and reliability.
- **HEALTHCARE EXPERTS(OPTIONAL)**: Domain experts in cardiology and healthcare will provide the necessary context and ensure that the model is clinically relevant.

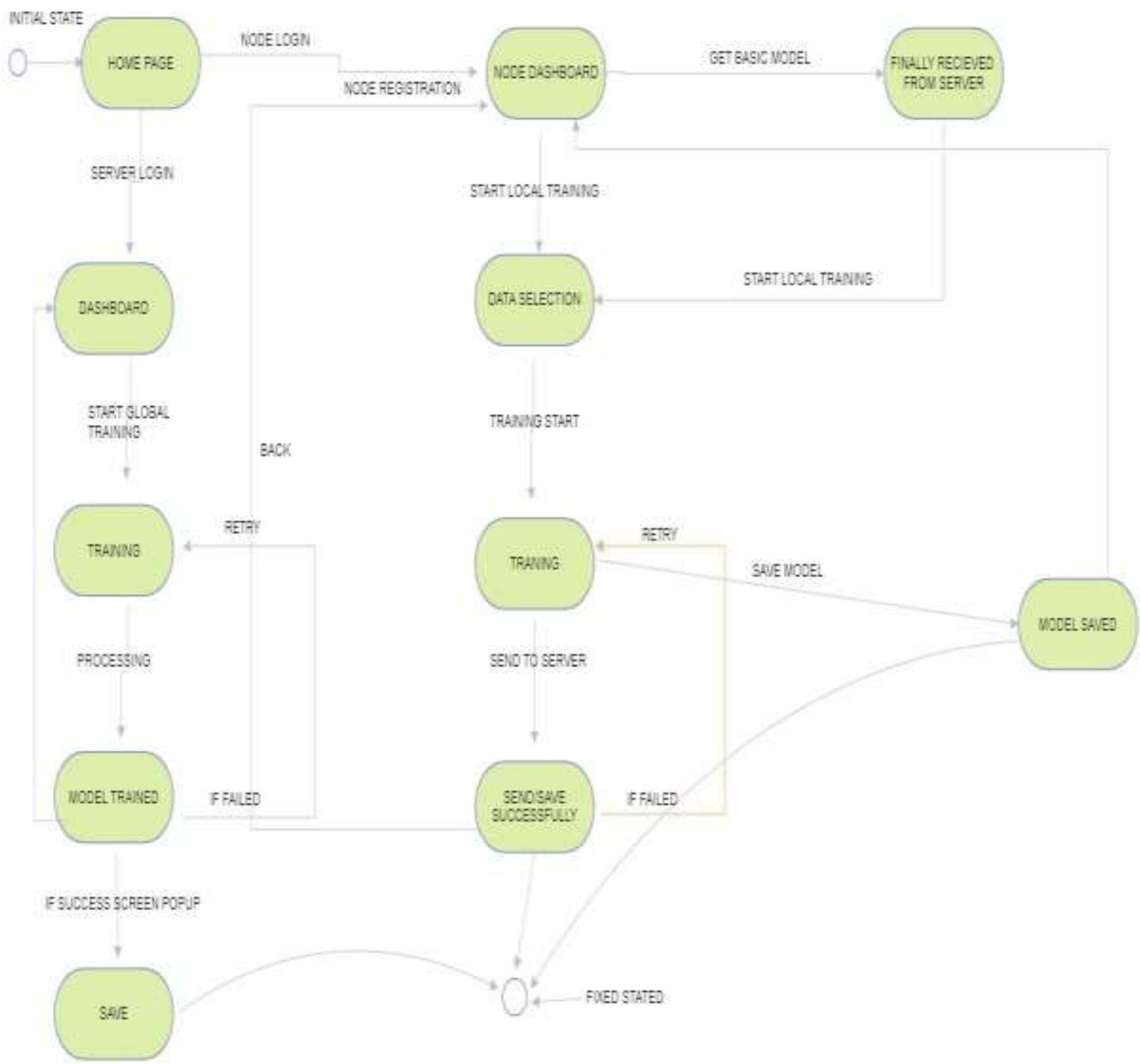
VI. ARTIFACTS CREATED

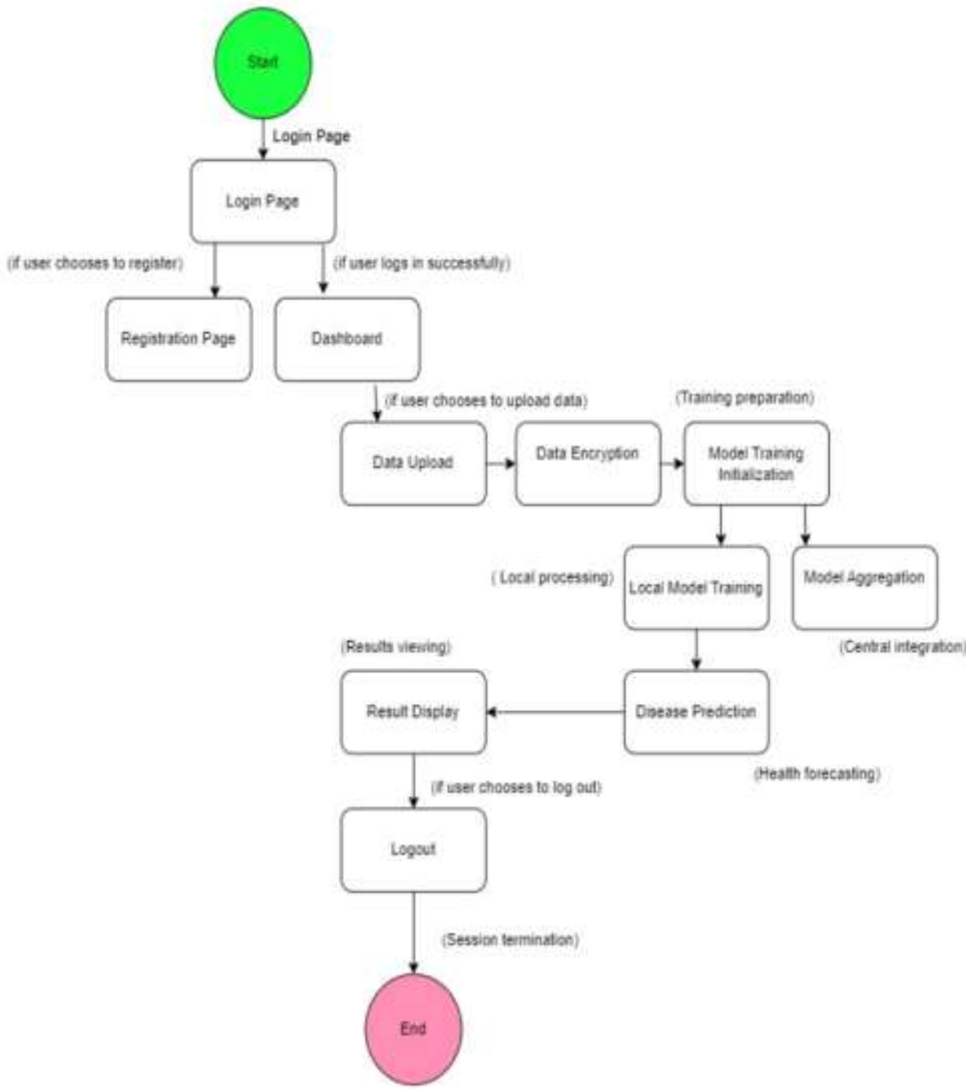
USE CASE DIAGRAM:

A Use Case Diagram will be created to depict the interactions between users (actors) and the federated learning system. This diagram will outline the various functionalities the system offers and how different stakeholders engage with these functions. Key actors may include Data Scientists, Healthcare Providers, System Administrators, and the Central Server. The use cases will encompass activities such as initiating local model training, submitting model updates, aggregating models, monitoring system performance, and managing security protocols. This diagram will provide a clear visualization of the system's capabilities and the roles of different users within the federated learning framework.

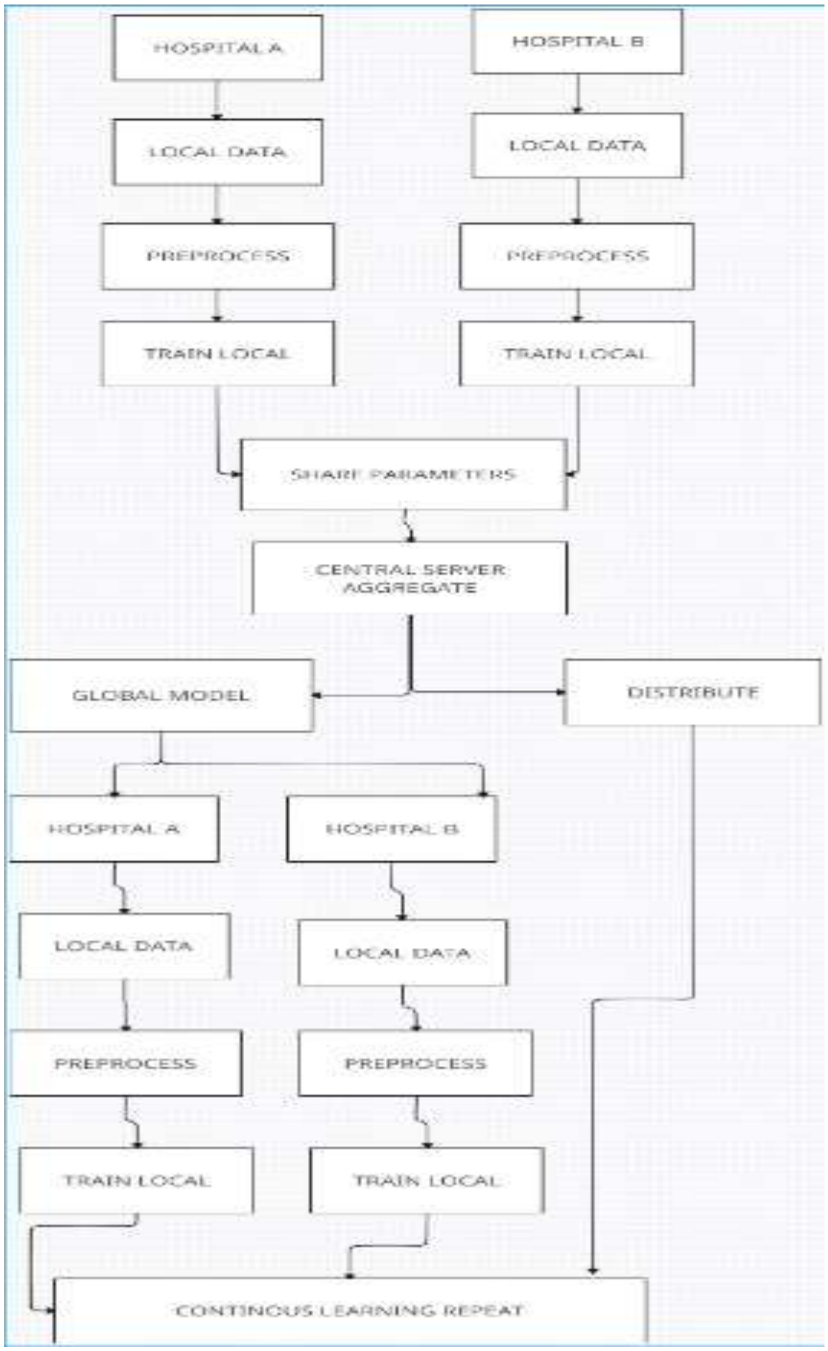


STATE DIAGRAM: A state diagram will depict the various states of the system during the federated learning process. This will help in understanding the system's behavior and in identifying potential issues.




Start
Login Page
Login Page
(if user chooses to register)
(if user logs in successfully)
Registration Page
Dashboard
(if user chooses to upload data)
(Training preparation)
Data Upload
Data Encryption
Model Training Initialization
(Local processing)
Local Model Training
Model Aggregation
(Central integration)
(Results viewing)
Result Display
Disease Prediction
(Health forecasting)
(if user chooses to log out)
Logout
(Session termination)
End

FEDERATED LEARNING WORKFLOW: A detailed flowchart will be created to show the steps involved in the federated learning process, from model initialization to final prediction. This workflow will be tailored to the specific needs of heart attack prediction.



VII. PROJECT IMPLEMENTATION METHOD

RESEARCH: The project will begin with an extensive research phase, where the team will review existing literature on heart attack prediction and federated learning. The goal is to identify gaps in current research and develop a framework that addresses these gaps.

DATA COLLECTION: Data collection will involve gathering and preprocessing anonymized medical records from participating hospitals. This data will be used to train and validate the federated learning models. The data must be carefully managed to ensure compliance with privacy regulations.

MODEL DEVELOPMENT: The model development phase will involve building and training the federated learning model. The model will be trained locally at each hospital using their respective datasets, and the model updates will be aggregated to create a global model. Techniques such as differential privacy and secure multiparty computation may be employed to further enhance data security.

TESTING: The model will be rigorously tested to ensure that it meets the required standards for accuracy and reliability. Testing will involve running the model on unseen data to evaluate its performance in predicting heart attacks. Any issues identified during testing will be addressed before the model is deployed.

PROTOTYPE: A working prototype of the federated learning system will be developed and demonstrated. This prototype will showcase the entire process, from data collection to final prediction, and will serve as a proof of concept for stakeholders. The prototype will be presented to gather feedback and make necessary adjustments before full-scale implementation.

WORKING DEMO:

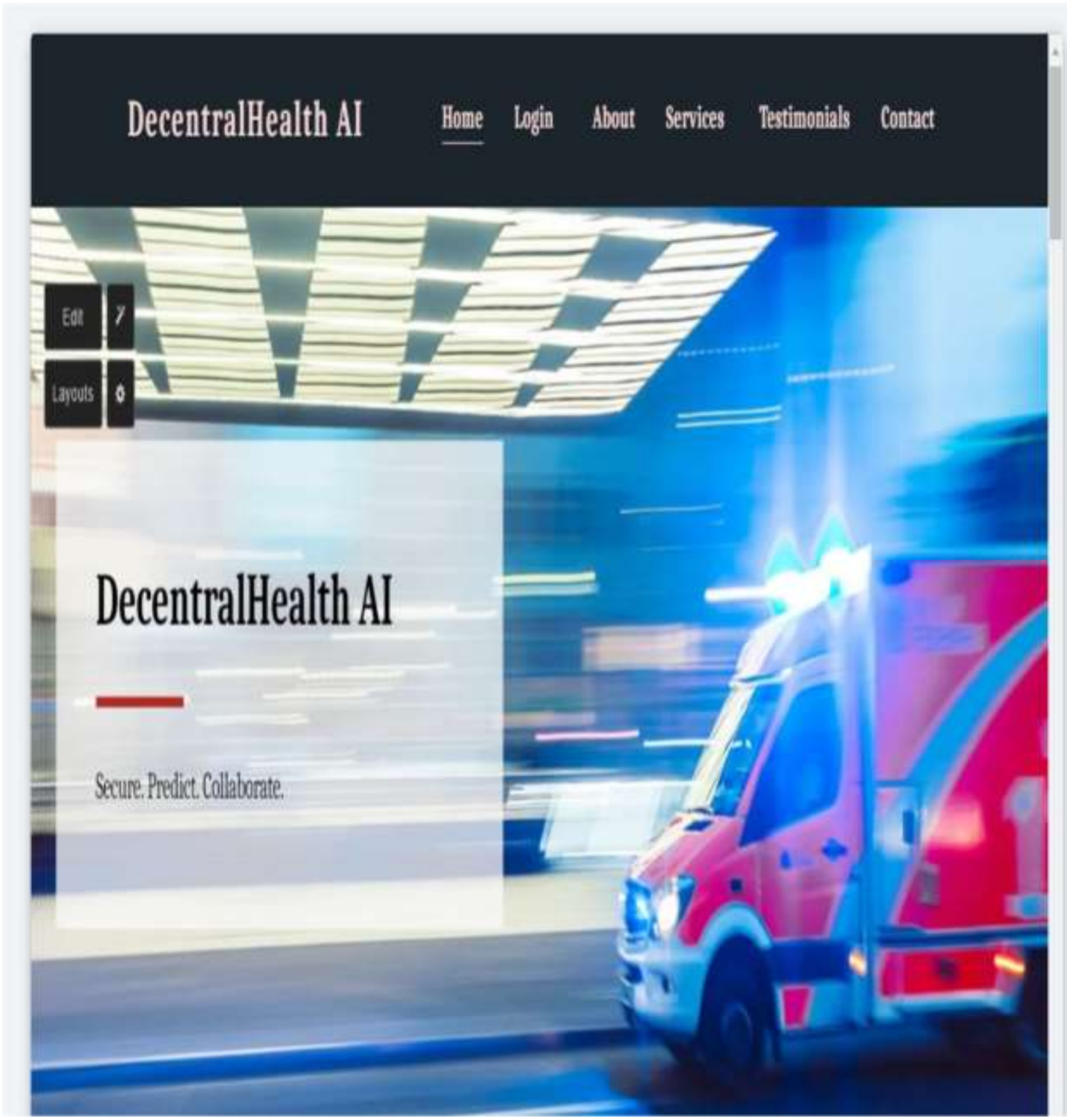
At this stage of our project, we have successfully collected a comprehensive dataset focused on heart attack prediction. We have created separate nodes (clients) and a central server node to simulate the federated learning environment. The data has been divided among these nodes to reflect the decentralized nature of our approach. The next steps include cleaning and preprocessing the data to ensure it is ready for local model training on each node. Following this, we will proceed with the aggregation of the trained models on the server node to build a more robust global model.

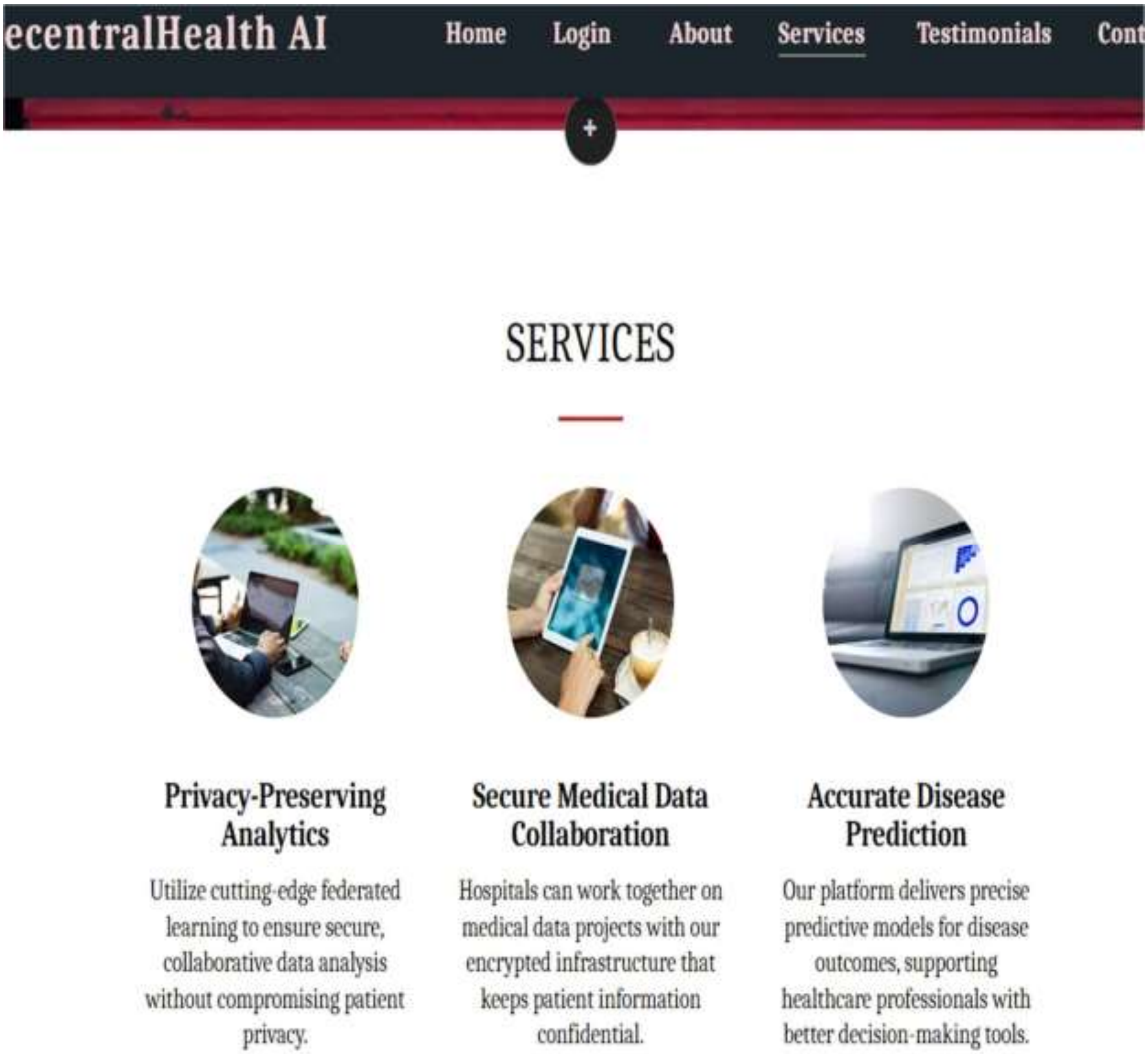
RKV2333	77	Female	194	149/83	77	1	0	1	0	1	0.7336	Unhealthy	1	[illegible]
TLA1423	65	Female	178	134/100	48	0	1	1	0	0	0.8412	Healthy	1	[illegible]
NCU4581	46	Female	155	116/85	105	1	0	1	0	1	18.415	Unhealthy	0	[illegible]
XOA9385	83	Male	240	165/79	69	1	0	1	1	1	0.948	Healthy	0	[illegible]
SLJ3300	27	Male	237	102/69	65	1	1	1	1	0	3.7587	Unhealthy	1	[illegible]
ONLS969	31	Female	333	168/107	106	1	0	0	0	0	15.733	Healthy	1	0
CFU1297	82	Male	216	160/67	109	1	1	1	1	1	15.584	Average	0	0
ATI9164	28	Male	276	92/71	65	1	0	1	1	1	13.115	Healthy	1	1
HGB5652	90	Male	224	164/65	98	1	0	1	0	1	3.5609	Average	1	0
SIQ8677	39	Male	326	155/104	47	1	0	1	0	0	12.816	Average	1	0
OGV4421	40	Male	198	104/98	59	1	1	1	0	1	15.131	Average	1	0
LD55768	86	Male	301	159/76	51	1	0	1	0	0	1.9397	Average	1	1
PLR8209	56	Male	314	152/94	51	0	1	1	0	1	11.586	Average	0	1
YLL9363	19	Male	227	108/78	81	1	1	1	0	1	14.686	Unhealthy	0	1
ITN4331	72	Female	304	168/90	57	0	0	1	1	1	8.8117	Average	0	0
ERP9347	80	Male	334	105/108	110	0	0	1	0	0	9.3414	Healthy	0	0
UFC0697	53	Female	301	146/94	47	1	1	1	1	0	2.5434	Unhealthy	1	1
JFL6450	21	Male	213	109/65	97	1	0	1	0	1	5.0403	Average	0	0
JKY9288	90	Female	254	166/89	102	1	0	1	1	0	9.8219	Unhealthy	0	0
AAX1328	28	Male	237	163/61	73	1	0	1	1	0	13.579	Unhealthy	1	1
XHX1600	69	Female	230	117/76	107	0	0	1	1	1	7.7533	Healthy	1	0
SDW5368	73	Female	248	106/60	70	1	1	1	0	1	3.2044	Healthy	0	1
GAN8948	66	Male	316	159/70	58	1	0	1	1	0	10.758	Healthy	0	1
AND5753	75	Male	277	145/92	87	1	1	1	0	1	4.0768	Average	0	0
WMN284	30	Male	388	170/106	41	1	1	1	0	1	1.2022	Healthy	0	1
LXD8525	22	Female	206	134/94	104	0	1	0	0	1	6.4348	Unhealthy	0	0
OMR5899	88	Male	384	113/80	67	1	0	1	0	0	16.18	Healthy	0	1
ZLM2405	90	Female	205	163/102	93	1	1	1	0	0	5.7811	Unhealthy	1	1
ACQ6112	79	Male	261	149/100	65	0	1	1	1	1	3.8678	Unhealthy	0	1
KMA0239	63	Female	308	125/76	96	1	1	1	0	1	13.278	Unhealthy	1	1
HHA8617	27	Male	246	100/67	71	1	1	1	0	1	8.0123	Healthy	0	0
PZM6937	18	Male	396	110/101	45	0	0	1	0	1	14.875	Healthy	1	1
ELD0719	60	Male	338	149/69	96	1	1	1	0	0	18.845	Healthy	1	1
PHK4364	34	Female	382	135/63	63	1	0	0	0	1	10.03	Average	1	1
NXR3682	60	Male	291	137/67	72	1	0	1	1	1	16.886	Unhealthy	1	1
UQC2723	37	Male	163	178/78	53	1	1	1	1	0	18.053	Average	0	1
CFZ8373	71	Male	129	116/73	107	1	1	1	0	1	15.797	Average	0	0
RNA0445	88	Female	168	110/72	48	1	1	1	0	0	4.1438	Healthy	0	0
YKA1578	89	Male	247	100/88	79	1	0	1	1	1	8.1012	Healthy	1	1
EIM7657	33	Male	218	121/72	98	0	1	1	1	1	16.111	Average	1	1
YWD5623	40	Female	237	174/102	49	1	0	0	0	0	15.035	Healthy	1	1
EAI3641	29	Female	388	177/94	53	1	0	0	0	1	2.7806	Unhealthy	1	0
EUK0592	89	Female	227	126/108	79	1	1	1	0	0	2.3041	Healthy	0	1
DXT5853	37	Male	171	120/101	88	1	1	1	0	1	11.395	Unhealthy	1	0
AZR0892	82	Male	378	118/105	96	1	1	1	0	0	1.9912	Healthy	1	0
YTL7126	86	Female	124	142/88	96	1	0	1	0	0	14.006	Healthy	0	1
GNL2507	71	Female	279	128/105	56	1	1	1	1	1	12.167	Unhealthy	1	0
PKU2212	32	Male	338	143/75	85	1	0	1	0	1	6.2095	Average	1	0
NRR1900	49	Male	253	103/78	49	0	0	1	0	1	10.797	Average	1	0
XAQ9706	34	Female	245	116/102	87	0	0	0	1	0	15.189	Healthy	0	1
IFZ1439	63	Female	226	132/76	94	0	0	1	1	1	3.6483	Average	1	0
UIP9627	23	Male	248	169/92	88	0	1	1	1	1	18.981	Average	1	1
BNA7793	74	Female	281	113/79	58	0	0	1	0	1	7.258	Average	0	0
VWX9664	33	Male	123	99/71	101	0	0	1	1	0	12.741	Average	0	1
CYT4743	59	Male	174	96/93	85	1	0	1	1	1	3.9097	Healthy	1	1
AGH6728	52	Female	231	145/82	66	1	0	1	0	1	1.536	Healthy	1	0
PUS3059	62	Female	234	173/62	61	1	0	1	0	0	13.826	Average	1	0
RCE5059	64	Male	224	179/62	59	1	1	1	1	0	10.709	Healthy	1	0
KTU2333	80	Male	268	100/69	102	1	1	1	1	0	8.9291	Average	1	1
FON8872	32	Male	253	153/77	57	1	0	1	1	1	19.413	Healthy	0	1
LTS6151	82	Male	396	156/74	60	0	1	1	0	1	19.297	Unhealthy	1	1
WER6567	45	Male	133	162/82	76	1	0	1	1	0	2.7543	Average	1	1
YIM3019	28	Male	209	98/109	81	1	0	1	1	0	4.0259	Healthy	1	0
GMX4668	61	Male	306	165/89	64	1	0	1	0	0	15.764	Healthy	1	0
TRR4979	36	Male	133	150/73	87	0	1	1	0	0	14.705	Average	1	1
LDJ4682	30	Female	186	163/102	82	1	0	0	1	0	1.0593	Healthy	1	1
SHL1488	54	Male	293	134/90	67	1	1	1	1	0	12.042	Average	0	0
LJI9585	70	Male	161	133/60	74	1	1	1	1	0	1.6195	Average	1	0
QGJ6378	76	Male	243	157/110	42	0	1	1	0	1	19.817	Unhealthy	1	1
EIH9699	41	Male	398	96/106	56	1	0	1	1	0	8.8087	Healthy	0	0
XHY0495	44	Male	380	173/82	75	1	0	1	1	0	15.644	Average	0	0
JEK2629	27	Female	297	96/92	75	0	1	0	0	1	2.8826	Average	1	0
IPU0926	45	Male	247	162/71	82	1	0	1	1	0	6.7894	Average	0	1
ZBC0359	76	Male	133	91/83	93	0	0	1	1	1	16.154	Average	0	1
FNE9444	27	Female	195	148/89	69	0	1	0	1	1	6.0867	Healthy	0	1
FYX5444	62	Male	239	145/98	86	0	1	1	0	0	16.785	Unhealthy	1	1
PID6523	69	Female	149	180/108	81	1	1	1	1	1	3.8621	Healthy	0	1
JFH5824	42	Female	320	98/67	110	1	0	1	1	0	7.278	Healthy	0	1
MGR9885	42	Female	246	154/81	100	1	1	1	1	1	16.235	Healthy	1	1
PBX8054	67	Male	208	172/64	99	1	0	1	1	0	8.9635	Unhealthy	0	1

VTW9069	88	Male	297	112/81	102	1	1	1	0	1	15.388	Unhealthy	0	1
DCY3282	73	Male	122	114/88	97	1	1	1	0	1	14.56	Average	0	0
DXB2434	69	Male	379	173/75	40	1	1	1	1	1	4.1846	Average	1	0
COP0566	38	Male	166	120/74	56	1	0	1	1	0	8.9179	Healthy	0	1
XBI0592	50	Female	303	120/100	104	1	0	1	0	1	4.9436	Average	1	1
RQX1211	60	Male	145	160/98	71	1	0	1	0	1	1.8926	Healthy	1	0
MBI0008	66	Male	340	180/101	69	1	0	1	1	0	9.1054	Unhealthy	1	1
RVN4963	45	Male	294	130/84	66	0	0	1	1	1	13.694	Healthy	0	0
LBY7992	50	Male	359	175/60	97	0	1	1	0	1	8.3544	Healthy	1	0
RDI3071	84	Male	202	173/109	81	1	1	1	0	1	10.996	Unhealthy	1	0
NCU1956	36	Male	133	161/90	97	1	0	1	1	1	3.618	Healthy	1	0
MSW420	90	Male	159	140/95	52	0	0	1	0	1	10.71	Healthy	0	1
TTO9115	48	Male	271	148/105	105	0	1	1	0	1	13.592	Unhealthy	1	0
JDP9221	40	Male	273	160/76	96	0	0	1	1	1	17.632	Average	1	1
FFF6730	79	Female	328	113/78	74	0	0	1	0	1	16.896	Unhealthy	0	0
DWN2141	63	Male	154	99/81	102	1	0	1	1	0	7.9497	Unhealthy	1	1
SLE3369	27	Female	135	120/77	49	1	1	0	0	1	16.91	Healthy	0	0
NXO4034	25	Male	197	178/72	45	0	1	1	0	1	18.849	Unhealthy	1	1
ENK3334	27	Male	321	111/91	50	1	0	1	1	0	0.7594	Unhealthy	1	1
XRL5497	86	Male	375	99/85	46	1	1	1	0	0	3.4669	Healthy	0	1
DDG3686	42	Male	360	103/107	44	1	0	1	1	1	8.5039	Healthy	0	0
FLG2019	52	Female	360	94/60	106	1	0	1	1	0	11.308	Unhealthy	0	0
IUJ5442	27	Female	263	127/109	83	0	1	0	0	0	2.0967	Unhealthy	0	0
BSV5917	29	Female	201	134/60	86	0	0	0	1	1	3.9732	Average	1	0
SCZ5893	67	Male	347	115/92	65	1	0	1	1	1	13.871	Healthy	1	0
GNK9443	29	Male	129	124/93	86	0	1	1	1	1	12.107	Unhealthy	1	1
UYU5044	30	Female	135	104/96	101	0	0	0	0	1	5.7327	Unhealthy	1	1
TTM1692	47	Male	229	144/108	65	1	0	1	1	0	5.3672	Healthy	1	0
DUX2118	86	Female	251	101/90	96	0	1	1	0	1	7.4895	Unhealthy	1	1
SQE3213	44	Male	121	115/109	51	1	0	1	1	1	16.659	Healthy	0	0
XBP3543	50	Male	190	149/73	43	1	1	1	0	0	0.618	Unhealthy	0	0
ENZ9640	33	Male	185	120/63	79	0	1	1	1	0	16.16	Healthy	0	1
QWD312	51	Male	197	106/106	79	1	1	1	1	0	14.124	Unhealthy	0	0
UBJ2564	70	Female	279	102/76	86	0	0	1	1	1	2.5906	Healthy	1	1
RRG8947	85	Male	336	114/92	73	1	1	1	0	1	17.754	Average	0	1
DRT6328	31	Female	192	124/93	90	1	0	0	0	1	3.6048	Unhealthy	1	0
BFE4900	56	Male	180	173/108	94	1	1	1	1	1	7.2721	Unhealthy	1	0
KCY9500	36	Male	203	173/109	101	1	1	1	0	0	14.206	Average	1	0
JJX0859	70	Male	368	168/91	78	0	0	1	0	0	2.1644	Healthy	1	1
IKY4481	67	Male	222	159/79	105	1	1	1	1	0	0.5169	Average	1	1
YOD3294	31	Male	243	100/80	92	1	1	1	1	1	2.4036	Unhealthy	0	1
OHD3889	24	Male	218	118/76	68	0	1	1	1	1	6.319	Average	0	1
BDG2694	54	Female	120	103/83	54	1	1	1	0	0	15.037	Unhealthy	1	0
LTU0801	70	Female	279	152/90	52	1	1	1	1	1	9.6606	Average	0	1
OFU9592	74	Male	285	151/85	109	1	1	1	0	1	5.5754	Unhealthy	0	1
WAR7163	72	Male	377	144/98	61	1	1	1	1	0	17.44	Unhealthy	1	1
TFH5628	55	Male	369	109/95	64	1	0	1	0	0	1.4022	Unhealthy	1	0
BBJ3290	42	Male	311	92/61	82	1	0	1	0	1	1.7732	Average	0	0
YTR1728	90	Female	139	179/93	85	0	1	1	1	1	1.7131	Average	1	0
AYY8711	26	Male	266	120/69	46	1	0	1	0	1	18.188	Unhealthy	0	0
TQT8266	53	Male	133	161/108	110	1	1	1	1	0	4.8697	Average	1	0
KTR4778	63	Male	153	131/76	86	1	1	1	1	1	18.596	Average	0	0
GVI1884	46	Male	120	107/65	50	1	0	1	1	1	4.9477	Average	0	0
SOM8522	57	Female	220	132/109	94	1	1	1	0	0	13.658	Average	1	1
NHX8643	31	Female	339	131/97	42	1	0	0	1	0	12.37	Healthy	0	0
BNF7145	74	Male	329	149/73	96	1	0	1	1	1	14.089	Unhealthy	1	0
BOK4939	63	Female	203	177/99	55	1	0	1	0	1	17.329	Unhealthy	0	1
DNY3115	46	Male	333	130/94	63	1	1	1	0	0	18.109	Unhealthy	1	1
SOH9843	22	Male	398	174/93	82	1	1	1	0	0	18.422	Average	0	1
ICO9779	53	Female	124	110/105	93	0	0	1	0	0	1.0175	Unhealthy	0	1
GDC1817	90	Male	183	116/98	69	1	0	1	0	0	19.714	Average	0	1
DHP4080	55	Male	163	139/107	63	0	0	1	1	0	11.475	Healthy	1	1

Here, we have divided dataset into 2. We'll assign each dataset to each node. And then will start cleaning, preprocessing, training and further processes.

OUR CONCEPTUAL SYSTEM WILL BE LIKE THAT

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Accurate Disease Prediction
Our platform delivers precise predictive models for disease outcomes, supporting healthcare professionals with better decision-making tools.

CONCLUSION

In summary, our project has the potential to revolutionize the healthcare sector by enabling secure and private collaboration between institutions through federated learning. As we continue to develop and refine our system, we aim to scale the project both in terms of the number of diseases it can predict and the number of nodes involved. This will not only enhance the predictive capabilities of our models but also broaden the scope of collaborative healthcare research, ultimately leading to better patient outcomes. Future work will focus on expanding the infrastructure to accommodate more data sources and diseases, as well as improving the accuracy and generalization of our predictive models.