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Huntington's Disease Detection and Severity Grading using Federated Learning and Agentic AI

Final Year Project Proposal

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Session 2022-2026

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Contents

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Abstract:

12 Huntington's Disease (HD) is a rare, hereditary neurodegenerative illness induced by the abnormally expanded CAG (cytosine-adenine-guanine) repeat in the HTT ((Huntington protein) gene, leading to gradual loss of motion, mental, and behavioral capabilities. Although early and precise diagnosis is so very important in reducing the advancement of a disease, the available diagnosis procedures are centralized, expensive, and create severe privacy issues due to the highly-sensitive nature of medical information. Conventional artificial intelligence (AI) approaches have shown promise in identifying neurodegenerative diseases by the use of clinical data and MRI (Magnetic Resonance Imaging) findings; however, most are based on centralized learning structures that restrict the diversity of the information and breach the privacy of patients.

It offers a Federated and Agentic Artificial Intelligence framework for privacy-preserving severity grading and Huntington's Disease detection in an effort to mitigate these challenges. The system combines Transformer-based models in the clinical and symptom information interpretation and Convolutional Neural Networks (CNNs) in the distributed analysis of MRI brain imaging. Federated Learning (FL) makes that possible. Various hospitals cooperate in the local models' training without sharing raw information, thereby upholding healthcare privacy regulations. Through the quality's automatic monitoring in the data, maximization of client engagement, and balancing of distributed node training, agentic artificial intelligence boosts flexibility more.

The suggested method tries to reach the maximum accuracy of diagnosis while maintaining the confidentiality of patients and promoting institutional cooperation beyond borders. The suggested research is designed numerically to show better performance of the model accuracy, F1-score, Area Under the Curve (AUC) than the conventional centralized schemes. It seeks to build, in the long term, a flexible, robust, and dynamic learning platform that facilitates the early diagnosis of HD and lays the foundation for subsequent AI-driven medical research in neurodegenerative diseases.

1.Introduction

1 HD is an inherited neurodegenerative disorder caused by expansion of CAG repeats in the HTT gene. Profound impairment of movement, behavior, and cognition ensues as a result of increasing brain damage to parts of the brain that are concerned with movement and thinking. HD strikes 5 to 10 individuals per 100,000 individuals worldwide [1], but because symptomatology is so multifaceted, diagnosis typically is not made until massive brain damage has already transpired. Early diagnosis and grading of severity, thus, are of paramount significance in order to allow on-time intervention and prevent disease progression. Nevertheless, privacy concerns, expenses, as well as restricted data exchange among healthcare organizations remain to restrain application of the available diagnostic methods, such as genetic testing, neuroimaging, and clinical assessment [2], [3]. Recent research has demonstrated how AI and ML methods can be used to improve the diagnosis and monitoring of neurodegenerative conditions. For instance, CNN-based approaches have been found to detect Alzheimer's and Parkinson's disease from MRI scans [1] has established that deep learning is applicable for the identification of structural brain changes associated with HD. However, such studies usually make use of centralized databases, making it highly private and erroneous to integrate clinical records in different institutions.

Also, the central models are not efficient for all categories of patients since the sources of data are limited and the same for all the patients.

As a means to address the issue of divergence among user and model, scholars have begun exploring FL, as described as a learning technique that allows institutions to jointly train models without exchanging raw data. FL has also been applied successfully in diabetes and heart disease diagnosis and in medical image tasks such as tumor classification [2] Even in the face of all these advancements, little research has leveraged FL to investigate neurodegenerative disorders such as Huntington's, for which patient data privacy, data aggregation of various data types, and inter-hospital cooperation are all very critical. Also, the majority of currently existing FL frameworks do not have flexibility or dynamic decision-making support and hence primarily do not offer the same kind of service to clients.

At the same time, Agentic Artificial Intelligence (Agentic AI) has come into play as a method of increasing model intelligence and autonomy [5], [6]. According to research, agent-based systems enable distributed agents to track the quality of data, coordinate communication, and make decisions taking into account the training environment. Scientists are able to develop adaptive, self-tuning systems that improve learning efficiency and equity in distributed settings by combining Agentic AI with FL.

This research improves on these foundations by proposing a privacy-conserving, multimodal, and adaptable scheme for the detection and severity evaluation of Huntington's Disease. It employs CNNs in analyzing MRIs and Transformer models to interpret clinical symptoms. It is constructed in a FL setting involving multiple frameworks. Agentic AI modules oversee the process of training in a manner whereby there is sound data quality, the models are current, and the sites are able to communicate with one another. The research in progress attempts to fill a required research gap by proposing an intelligent, decentralized, and privacy-aware model of learning appropriate for neurodegenerative disease detection and assessment.

2.Success Criteria

- Maintain data privacy while achieving high accuracy and dependability in identifying and classifying the severity of HD.
- Preserve patient data confidentiality with Federated Learning.
- Use CNN and Transformer Fusion Model for multimodal learning.
- Provide adaptive and equitable model updates using Agentic AI.
- Validate with multimodal datasets having MRI and clinical data.
- Finish model deployment, testing, and documentation within the timeframe.

3. Related Work

Reviewing previous research on AI, FL, and Agentic systems is essential for developing a reliable and privacy-preserving diagnostic system for HD. The studies available breakthrough in HD detection and neurodegenerative disease modeling. but also demonstrate fatal weaknesses in scalability, data privacy, and adaptability of the model. This section describes related previous work with a focus on their performance, weaknesses, and more. the knowledge gap that will drive this study.

3.1 Related Research-Based Work

13.1.1 Federated Learning Methods for Medical AI

FL has become a prominent paradigm for decentralized model training with strict data privacy. In medicine, FL allows hospitals and research institutions to enhance AI models together without exchanging patient-sensitive information an essential requirement for compliance with HIPAA (Health Insurance Portability and Accountability Act) and GDPR (General Data Protection Regulation).

For example, FLWCO (Federated Learning with Weighted Conglomeration Optimization) model suggested by [2] utilized Weighted Conglomeration Optimization to use collaborative learning and recorded 97.27% accuracy in predicting heart and diabetes disease with privacy preservation. This model has not been evaluated on neurodegenerative diseases like HD, which involve multimodal data such as MRI, symptoms, genetics and high adaptability across sites in non-IID data.

In the same vein, the survey [3] on FL for Rare Disease Detection highlighted that FL has great potential for privacy-preserving learning but noted a deficit in implementation in rare neurological diseases such as HD. The two highlight that existing FL frameworks deal with all clients alike, paying no need to diversity in demographic or institutional information, a limitation that compromises personalization and model fairness.

13.1.2 AI-Based HD Detection and Neurodegenerative Modeling

AI techniques, specifically deep learning algorithms, have been applied successfully in the detection of neurodegenerative disease [4] introduced a CNN-based HD detection model from MRI images with over 99% success in discriminating between HD and controls. The model is, however, operating on a single centralized dataset, does not handle multimodal integration e.g., symptoms or clinical data, and does not handle data privacy issues.

Similarly, as highlighted in [5] , researchers utilized the Enroll-HD dataset, using machine learning algorithms such as Light Gradient Boosting (LGBM) for prediction of age at onset and GRU (Gated Recurrent Unit) networks for determining driving ability, with a maximum AUC = 0.929 performance. Though one of the largest HD-associated datasets, it is centralized and thus under privacy and data-sharing limitations.

Furthermore, the author of [5] also presented a comprehensive narrative review issued a narrative review of AI and ML methods for HD diagnosis that incorporated developments in biomarkers, imaging, and algorithmic methods. Despite this, their findings reiterate that nearly all studies employ centralized architectures with no federated or adaptive AI mechanisms. In the same way, as discussed in [1], applications of AI in neurodegenerative conditions like Alzheimer's, Parkinson's, and HD and noted that while ML can identify patterns from MRI and EEG (electroencephalography) data, most models are built from small homogeneous sets and are not federated or adaptive collaboration.

13.1.3 Agentic AI and Intelligent Decision Systems

Agentic AI surpasses standard machine learning in enabling autonomy, flexibility, and reasoning in distributed learning. Agents can monitor training performance, ensure the quality of data, and adaptively adjust learning weights among clients.

Even though work such as [2] has proven agent-like optimization in FL via adaptive weight adjustment reaching the goal of accuracy and convergence improvement by 5–8%, their models were only applied with structured healthcare data such as diabetic and heart prediction. So far, no work such as [3]or [5] has combined Agentic AI with FL for neurodegenerative data, where multimodal and sensitive data are of utmost concern.

Additionally, studies like [4] and [6] focus on optimizing HD detection accuracy using CNNs and LGBMs but exclude adaptive or agent-based learning processes. [7] conducted a decennial bibliometric analysis of HD biomarkers with a focus on multimodal data fusion but no work has been done on proposing dynamic, self-managing FL systems for HD

3.2 Comparative Analysis and Gap Analysis

Work / Application	Gap / Purpose	Area	Strengths	Limitations	Reference
FLWCO: Privacy-Preserving Diabetes & Heart Disease Prediction (2025)	Lacked privacy in centralized models	Healthcare (Chronic Diseases)	High accuracy (97.27%); secure FL-based learning	Uses structured Kaggle data only	(Dash *et al.*, 2025)
Advances in HD Biomarkers: 10-Year Review (2025)	No ML/FL testing; descriptive only	HD Biomarker Research	Identifies key genetic & digital biomarkers	No experiments; lacks ML validation	(Aqel et al., 2025)
Deep Learning Detection of HD via CNN (2025	Centralized MRI-only model; lacks FL privacy	MRI-based HD Detection	High accuracy; automated feature extraction	Not generalizable ; small dataset	*K. Sangeetha et al., IJRPR*, 2025
Computational Matrix Benchmarking (2025)	Not applied to HD or healthcare	Algorithmic Computation	Improves matrix computatio	No biomedical relevance	Masschheleina et al., 2025

			n efficiency		
Huntington's Disease Case Report (2024)	Single patient; lacks AI/FL approach	Clinical HD Imaging	Detailed imaging & ratios (FH/CC, CC/IT)	Single case only	(Sharma et al., 2024)
FL for Rare Disease Detection: A Survey (2023)	Lacks HD-specific implementation	Federated Learning (Rare Diseases)	Reviews FL privacy methods for rare data	No HD application; theoretical focus	Wang & Ma, 2023
AI & ML for Huntington's Disease: A Narrative Review (2023)	Few studies use FL or Agentic AI; poor multimodal integration	Neurodegenerative Diseases	Review of 54 HD studies with multimodal data (MRI, EEG, omics)	Limited datasets; few clinical validations	L. M. Abu Zohair et al. (2025)
Machine Learning on Enroll-HD Dataset (2023)	No FL or Agentic adaptation	HD Prognosis Prediction	Uses large Enroll-HD dataset; GRU & LGBM models	Dataset dependency; limited external validation	Ouwerkerk et al., 2023
AI in Neurodegenerative Diseases (Including HD) (2021)	No privacy-preserving or adaptive AI methods	Disease Diagnosis	Identifies biomarkers & accuracy trends	No FL or multimodal fusion	A.M. Tăuţan et al. (2021)

Tab. 1. Comparative Analysis and Gap AnalysiS

3.3 Research Gap

Year	Algorithm / Model Used	Accuracy / Result	Dataset / Domain	Reference
2025	Random Forest, XGBoost, MLP, Gradient Boost, AdaBoost, Federated Learning with Weighted	97.27% (FLWCO)	Diabetes & Heart Disease Prediction (Privacy-Preserving FL)	(Dash *et al.*, 2025)

	Conglomeration Optimization (FLWCO)			
2025	Bibliometric R Package (v4.3.1), *No ML Model*	*Not Applicable*	Huntington's Disease Biomarker Research (Molecular, Imaging, Fluid, Digital Biomarkers)	(Aqel et al., 2025)
2025	AgentBench-2 Framework (Planner–Executor Architecture)	*Not Applicable*	Agentic AI Benchmarking (General Agent Capabilities)	Masscheleina et al., 2025
2025	CNN (RPN + Transfer Learning)	>90% Classification Accuracy	MRI scans (Normal vs HD; Severity Grading)	*K. Sangeetha et al., IJRPR*, 2025
2024	FH/CC Ratio, CC/IT Ratio, MRI Volumetric, DTI Quantitative Models	*Not Applicable*	Huntington's Disease (Single Case Study – MRI, CT, Genetic Testing)	(Sharma et al., 2024)
2023	Decision Trees, Random Forests, SVM, KNN, CNN, LSTM	*Not Reported*	Huntington's Disease (Narrative Review – multimodal data)	L. M. Abu Zohair et al. (2025)
2023	LGBM (Light Gradient Boosting Machine) – Age at Onset (AAO) GRU (Gated Recurrent Unit) – Driving Capability	R^2 = 0.60–0.63 (AAO); AUC = 0.929 (Driving)	Enroll-HD Dataset (11,397 participants after filtering)	*J. Ouwerkerk et al.*, 2023
2023	Survey of Federated Learning for Rare Diseases	*Not Applicable*	Federated Learning (Rare Disease Diagnosis conceptual analysis)	*J. Wang & F. Ma*, 2023
2021	SVM, Random Forest, CNN, LSTM, ANN	76%–90%	Huntington's Disease (MRI, EEG, Gait Data)	A.M. Tăuţan et al. (2021)

Tab.2. Research Gap

3.4 Summary of Research Gaps

Based on the examined literature, the following gaps are still apparent:

1. No current FL implementation for HD is all current work either centralized or non-collaborative.
2. Absence of multimodal fusion, integrating MRI imaging, symptom, and clinical data within a privacy-preserving framework.
3. Lack of Agentic intelligence, capable of adaptively regulating training quality and managing non-IID (heterogeneous) data across clients.
4. Low scalability and generalizability of the current centralized models to actual hospital networks.

In an effort to overcome these drawbacks, this study introduces hybrid model that integrates CNNs, Transformers, FL, and Agentic AI to improve diagnostic accuracy, preserve data privacy, and support adaptive learning across decentralized healthcare settings.

4. Project Rationale

The main aim of this research is to create an intelligent and privacy-respecting mechanism for detecting and grading HD severity using FL and Agentic AI. The project designer is to develop a smart and privacy-preserving system that employs FL and Agentic AI for the purpose of detecting and grading the seriousness of HD among patients. HD is an irreversible disease that eventually leads to death by disabling its victim in three major areas, such as movement, cognition, and behavior. Its early detection plays a crucial role in improving the patient's quality of life and timely medical intervention. Besides, the early diagnosis and the biggest issue in terms of safety, the patient will be given the chance to participate in drug trials hence leading to better and more durable treatments. It can, however, take several years and enormous effort before an AI-based tool can be used in everyday clinical practice. What's more, the problem of insufficient data in the area of neurodegenerative diseases can be solved in some large part by the project. Developing a PL-based decision-making model is only possible when adequate data in different forms are available. With FL, the hospitals enter into a cooperation mode and develop a common model that not only supports but also takes the best from the individual institutions' data and resources without the need to reveal any confidential data. The traditional concept of AI application in medical practice is further transformed by the benefits of Agentic AI which adds one more dimension to the system making it wise and trained fitting across the diverse data sources. The outcome of the project is the ability to support early diagnosis, clinical decision and monitoring of patients. By doing so, a neurodegenerative disease-friendly AI will be feasible as your project will pioneer a platform that is not only safe but has a potentiality of scaling and adaptability. From the scientific point of view, this project supports the merging of technology breakthrough with health applications bridging the gap that has been created between the medical sector and machine learning research. One of the major goals of this project is to figure out different ways of integrating vocative AI, FL, as well as all the layers of an AI model to resolve complicated medical issues in ethical and protected ways. Plus, it will develop our skills in cutting-edge AI frameworks, data protection, and health analytics.

4.1 Problem Statement

HD diagnosis and severity grading currently rely on centralized data analyses that limit multi-center collaboration and compromise patient privacy. There is no integrated, privacy-preserving approach that uses federated learning together with Agentic intelligence to fuse MRI, clinical notes, and sensor data for accurate detection and stage classification. This research addresses that gap by developing a federated, agent-enabled AI framework that detects HD and assigns severity levels (Normal, Mild, Moderate, Severe) without sharing raw patient data across institutions.

4

4.2 Aims and Objective

4.2.1 Aim:

The primary goal of this research is to build a privacy-preserving and smart AI system capable of detecting HD and grading its severity Normal, Mild, Moderate, Severe employing FL and Agentic AI.

4.2.2 Objectives:

- Detect HD early with a combination of MRI scans and clinical symptom information. To protect patient privacy by implementing Federated Learning so hospitals can collaborate without sharing sensitive data.

- To employ CNN for brain image analysis and Transformer models for understanding symptoms and clinical data.

- To have Agentic AI that takes control of training, data quality and intersite communication.

- To develop a prototype system depicting AI, FL, and Agentic integration. patterns of safe and responsive healthcare applications.

4.3 Scope

The project deals with the testing of algorithms, and data modeling with privacy-preservation. It will not has real-time clinical trial but will use datasets available to verifiy it.

5. Proposed Methodology and Architecture

The researched is focused on developing and testing a privacy-preserving adaptive AI model. in identifying and quantifying HD severity. The framework consists of deep learning to comprehend data, FL to decentralized training. lacking communication of data, and Agentic intelligence to adaptive coordination and equity of learning. It is concerned with
7 the research of multimodal learning (images, clinical data and so on). distributed AI has the potential to improve the quality of the diagnosis by retaining privacy of the information.

5.1 Framework Overview

Method Used	Purpose / Expected Outcome
MRI, Clinical, and Symptom Data	Create a varied and multimodal dataset of HD related information.
Cleaning, Normalization, Feature Extraction	Standardize and prepare data for model training.
CNN	Detect HD related brain atrophy and spatial patterns.
Transformer-based Model	Understand relationships in text-based medical and symptom data.
CNN+ Transformer Fusion	Combine visual and textual characteristics for accurate diagnosis.
Distributed Model Training	Enable hospitals to collaboratively train models while maintaining data privacy.
Adaptive Model Management	Dynamically monitor training quality and balance client contributions.
ML Classifier + Metrics (Accuracy, F1, AUC (Area Under the Curve)	Detect HD and severity levels; compare results with traditional centralized models.

Tab. 3. Framework Overview

5.2 Research Workflow

1.Data Collection:

Various clinical information, symptom information and MRI brain scans are collected. hospital centers. This gives a wide and representative data set and patient. anonymity and ownership of the data are maintained on site.

2.Data Preprocessing:

The collected data will be cleansed, normalized, anonymized and feature-extracted to nuke inconsistencies and train. Compliance with law of privacy of healthcare data. This approach is also used to ensure such standards as HIPAA and GDPR are met.

3.Local Model Training:

The local deep learning model will be trained on each site and will consist of CNN to train MRI image. processing and Transformer models of symptom and clinical data. This will enable each site to make contributions to the model learning without disseminating raw data in other places.

4. Federated Learning:

The model parameters will be safely transferred to a central server after being trained locally. aggregation. The FL strategy integrates all these updates to develop a worldwide model that considers. benefit of any location without endangering personal information.

5.Agentic AI Integration:

The training process will be monitored by the agents working smartly providing the high-quality data and good balanced inputs of all the clients. The agents will modify the weights of training on the fly, identify biases, and make the federated model more adaptable. Since the model was not previously tested prior to this study, the model cannot be compared to other relevant models.

6.Model Comparison and Evaluation:

The model has not been experimented on before this study and so it cannot be compared with the other relevant models. The developed federated model will be compared with centralized and traditional deep learning models with regards to such evaluation parameters as accuracy, precision, recall, and AUC. This justifies the performance, stability and privacy benefits achieved in the application of the proposed system.

7.Final Prediction and Severity Grading:

The resulting trained global model will predict the presence or absence of HD, and classify the severity of it into four stages namely Normal, Mild, Moderate and Severe providing a robust, privacy-respecting, system of clinical outcome diagnosis.

5.3 Conceptual Flowchart

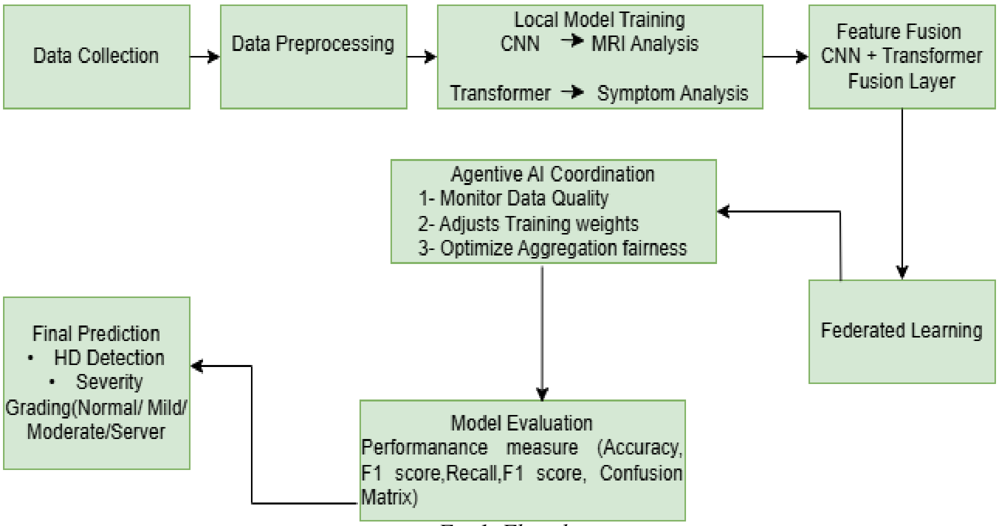


Fig.1. Flowchart

5.4 Key Highlights

❖ Assures the privacy of data as updates to the model are shared along with patient data. in the source.

❖ Compliant with privacy regulations (e.g. HIPAA and GDPR).

❖ Agentic Intelligence in adaptive and equitable training of models in institutions.

❖ Dynamically changing learning according to quality of data and client performance.

❖ Enables multimodal learning via MRI image convergence and clinical and symptom data.

❖ Accuracy and generalization involving CNN and Transformer merge.

❖ Compares the existing Federal and centralized models.

- Shows accuracy, flexibility and privacy enhancement.
- Scaled, modular design of multi-hospital cooperation.
- Secure and effective implementation in dispensable health network.

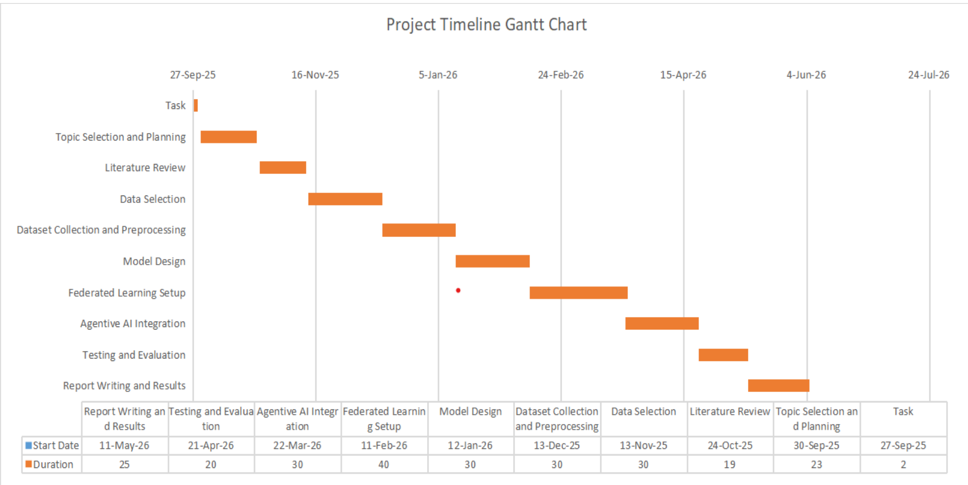
6. Work Division

11

Task / Activity	Responsible Members	Start Date	End Date	Duration (Days)
Topic Selection and Planning	Umama Qayum, Hifsa Shahid, Mahnoor Riaz	27-Sep-25	30-Sep-25	23
Literature Review	Umama Qayum, Hifsa Shahid, Mahnoor Riaz	1-Oct-25	25-Oct-25	19
Data Selection	Umama Qayum, Hifsa Shahid, Mahnoor Riaz	26-Oct-25	15-Nov-25	30
Dataset Collection and Preprocessing	Umama Qayum, Hifsa Shahid, Mahnoor Riaz	16-Nov-25	10-Jan-26	30
Model Design (CNN + Transformer)	Umama Qayum, Hifsa Shahid, Mahnoor Riaz	11-Jan-26	5-Mar-26	30
FL Setup	Umama Qayum, Hifsa Shahid, Mahnoor Riaz	6-Mar-26	10-Apr-26	40
Agentic AI Integration	Umama Qayum, Hifsa Shahid, Mahnoor Riaz	11-Apr-26	25-May-26	30
Testing and Evaluation	Umama Qayum, Hifsa Shahid, Mahnoor Riaz	26-May-26	20-Jun-26	20
Report Writing and Results Compilation	Umama Qayum, Hifsa Shahid, Mahnoor Riaz	21-Jun-26	10-Jul-26	25
Final Presentation and Defense	Umama Qayum, Hifsa Shahid, Mahnoor Riaz	11-Jul-26	31-Jul-26	20

Tab.4. Work Division

7. Gantt Chart



Tab.5. Gannt Chart

8. Tools and Technologies

In this study, we will use a combination of general tools and computer resources appropriate designing and experimenting with artificial intelligence healthcare systems. The aim is to build a privacy aware and adaptive framework for detecting and grading Huntington's Disease using modern learning approaches.

Category	**Description / Purpose**
Programming Language	A versatile programming language will be used for preparing datasets, building models, and running experimental evaluations.
Learning Frameworks	Machine and deep learning environments will support the training and testing of algorithms applied to both image and clinical data.
FL Platform	A distributed training setup will allow multiple medical centers to collaborate in model building without exchanging sensitive information.
Libraries and Utilities	Standard analytical and visualization tools will assist in data cleaning, transformation, feature generation, and performance assessment.
Privacy and Security Components	Techniques for preserving privacy will be embedded to protect all patient information during model training and communication.
Development Environment	A combination of local and cloud-based workspaces will be used to conduct experiments, compare results, and refine the proposed system.

Tab.5. Tools and Technologies

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