Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

GenAI Chatbot for Neuro-Palliative Care - Brain Death & Recovery (BDR)

Dr. Lakshmi Devi. R[1], Dr. Savithri. V[2], Dr. Sathyamurthi Karibeeran[3]

[1]Assistant Professor, Department of Computer Applications, Women's Christian College, Chennai, India, lakshmidevir@wcc.edu.in
[2]Associate Professor, Department of Computer Science, Women's Christian College, Chennai, India, savithri@wcc.edu.in
[3]Associate Professor & HOD, Dept. of Social Work, Madras School of Social Work, Chennai, India, ksm@mssw.in

Brain death is a critical condition that marks the irreversible cessation of brain function, typically associated with significant trauma or medical emergencies. However, the accurate detection of brain death remains a challenge due to the complexity of neurological assessment and diagnostic precision. Recent advancements in Generative Artificial Intelligence (GenAI)with Large Language Models have shown promise in tackling complex medical diagnostics. This study presents an innovative approach utilizing GenAI LLM for real-time detection and recovery planning in brain death cases. By integrating neuroimaging data, electrophysiological patterns, and patient histories, GenAI applications can enhance decision-making for clinicians. Our methodology outlines a framework for detecting brain death and proposes neuro-restorative strategies to improve patient outcomes in marginal cases. Preliminary results indicate high accuracy in detection, alongside innovative recovery suggestions generated by the AI. The paper concludes by highlighting the implications of GenAI LLM in advancing critical care and neurological rehabilitation.
Keywords: Brain Death & Recovery, Neuro-restorative strategies, innovative recovery suggestions, neuro-palliative care.

1. Introduction

Brain death is defined as the irreversible loss of all cerebral and brainstem functions. It is a pivotal diagnostic in critical care, serving as the benchmark for organ donation eligibility and life support termination decisions. Traditional methods rely on neuroimaging, electrophysiology, and clinical examinations, which can sometimes result in ambiguities, particularly in borderline cases.

The emergence of Generative Artificial Intelligence (GenAI) has opened new avenues in medical diagnostics and therapeutics. GenAI's ability to process and analyze multidimensional datasets at scale offers a paradigm shift in the approach to brain death determination. By leveraging deep learning algorithms and neural network models, GenAI can identify subtle patterns within neuroimaging scans and electrophysiological data that may escape human observation.

1.1 Objectives

This study aims to:

1. Develop a GenAI-LLM based framework for brain death detection.

2. Explore the potential for recovery planning in cases where neurological restoration might be possible.

3. Evaluate the system’s accuracy and reliability through simulated and real-world datasets.

2. Review of Literature

[1]An ensembled artificial neural networks (EANN) model was used for brain death prediction. The experimental study focused on the severe head injury patients with different levels of Glasgow Coma Scale (GCS) in the neurosurgical and traumatic intensive care unit (ICU) of National Taiwan University Hospital (NTUH) in Taipei. Two prediction models were developed with equipment in ICU including the physiological signal monitor, pressure model, data acquisition card and portal computer. (Quan Liu,2011).[2]A machine learning-based logistic regression modeling was created based on intracranial pressure (ICP), mean arterial pressure (MAP), cerebral perfusion pressure (CPP) and Glasgow Coma Scale (GCS) to predict 30-day mortality. In this study based on only three and four main variables, they discriminated between survivors and non-survivors with accuracies up to 81% and 84%. (Raj,2019).[3]This study aimed to use machine learning algorithms of artificial intelligence (AI) to develop predictive models for Traumatic brain injury (TBI) patients in the emergency room triage. In this study 18,249 adult TBI patients were used in the electronic medical records of three hospitals of Chi Mei Medical Group from January 2010 to December 2019, and undertook the 12 potentially predictive feature variables for predicting mortality during hospitalization. Six machine learning algorithms including logistical regression (LR) random forest (RF), support vector machines (SVM), LightGBM, XGBoost, and multilayer perceptron (MLP) were used to build the predictive model. The results showed that all six predictive models had high AUC from 0.851 to 0.925 (Tu,2022).[4]Machine learning models were developed to predict stroke prognosis with the highest accuracy and to identify heterogeneous treatment effects of warfarin and human albumin in stroke patients. This study showed that the use of the ML method helps predict death after a stroke and this study achieved the highest AUC of 0.9217. (Zhu,2023).[5]A Machine learning model for TBI outcome prediction, was developed with comparison of nine algorithms: ridge regression, LASSO regression, random forest, gradient

boosting, extra trees, decision tree, Gaussian naïve Bayes, multinomial naïve Bayes, and support vector machine. Fourteen feasible parameters were introduced in the ML models, including age, Glasgow coma scale, systolic blood pressure, abnormal pupillary response, major extracranial injury, computed tomography findings, and routinely collected laboratory values (glucose, C-reactive protein, and fibrin/fibrinogen degradation products). Data from 232 TBI patients were used. The bootstrap method was used for validation. Random forest demonstrated the best performance for in-hospital poor outcome prediction and ridge regression for in-hospital mortality prediction with 91.7% accuracy and 88.6% accuracy, and 0.875 AUC, respectively. (Kazuya,2020).[11] The study classifies the blood smear images using CNN Models [12] The study explains the crow intelligence using AI [13] The study detects the intima media thickness of the carotid artery which used to detect the thickness of tumor.

2.1 Table - Reviews from Medical Journals

Year	Author	Model	Outcome
2022	Gajra A, Zettler ME, Miller KA, et al[6]	Augmented intelligence-cancer patient	Identifying patients at high or medium risk for short-term mortality
2021	Murphree DH, Wilson PM, Asai SW, et al[7].	Predictive modeling and healthcare informatics	A machine learning model has been successfully integrated into practice to refer new patients to personal care.
2023	Wilson PM, Ramar P, Philpot LM, et al.[8]	Artificial intelligence decision support tool on palliative care referral in hospitalized patients	A tool with decision support integrated into palliative care practice and leveraging AI/ML among hospitalized patients and reductions in hospitalizations.
2018	Walshe C, Todd C, Caress A, Chew-Graham C[9]	A literature Review	Review recent literature to identify whether such variability remains.
2016	Rosenwax L, Spilsbury K, McNamara BA, Semmens JB[10]	Specialist palliative care tool initiated in the last year of life	Life limiting conditions HIV/AIDS initiated

3. Methodology:

1. Data Collection & Implementation Steps

Input Data Set

- o Neuroimaging Data (MRI, CT, PET)
- o Electrophysiological Data (EEG, Evoked Potentials)
- o Patient Medical Histories

Actions:

- o Aggregate data from hospitals, critical care units, and anonymized repositories.
- o Preprocess the data:

▪ Standardize formats.

▪ Clean noise from EEG signals.

▪ Impute missing data using AI models.

Output:

○ A clean, unified dataset ready for AI model training.

2. GenAI Model Development

● Input:

○ Preprocessed multi-modal datasets.

● Actions:

○ Design a multi-modal transformer model to integrate neuroimaging and electrophysiological data.

○ Train the model on labeled datasets:

▪ Brain death confirmed cases.

▪ Non-brain-death critical cases.

▪ Healthy control samples.

○ Evaluate performance using metrics (sensitivity, specificity, F1-score).

● Output:

○ Trained GenAI model capable of detecting brain death

3. Brain Death Detection

● Input:

○ Patient-specific neuroimaging, EEG, and clinical data.

● Actions:

○ Input the data into the trained GenAI model.

○ Perform feature extraction:

▪ Assess cerebral blood flow, brainstem reflex activity, and cortical patterns.

○ Classify the state:

▪ Confirmed Brain Death.

▪ Probable Brain Death.

▪ Non-Brain Death (Critical Care Needed).

● Output:

○ Real-time diagnosis and classification results.

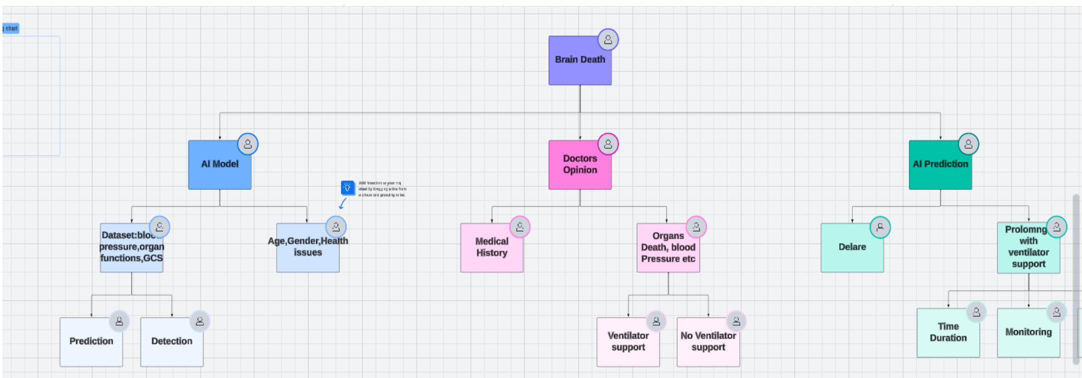
4. Recovery Potential Analysis

- Input:
  - Cases classified as "Probable Brain Death" or borderline critical.
- Actions:
  - Simulate recovery scenarios using Generative AI:
    - Model neuroplasticity.
    - Recommend interventions (e.g., hypothermia, neural stimulation, or drugs).
  - Generate a ranked list of recovery plans based on efficacy simulations.
- Output:
  - Actionable recovery strategies for clinicians.

5. Validation and Clinical Deployment

- Input:
  - AI-generated results and recovery plans.
- Actions:
  - Validate results with a multidisciplinary clinical team.
  - Cross-check AI outputs with existing standards and medical expertise.
  - Deploy GenAI system in critical care units for real-time application.
- Output:
  - AI-assisted decision-making system for brain death detection and recovery planning.
    - Probable Brain Death.
    - Non-Brain Death (Critical Care Needed).

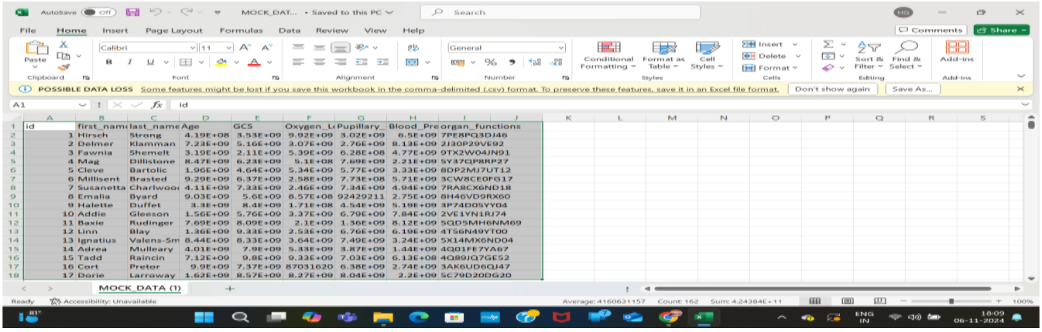
3.1 Visualization of the GenAI Workflow



3.2 Classification diagram of Detection, Diagnosis & Recover from brain death

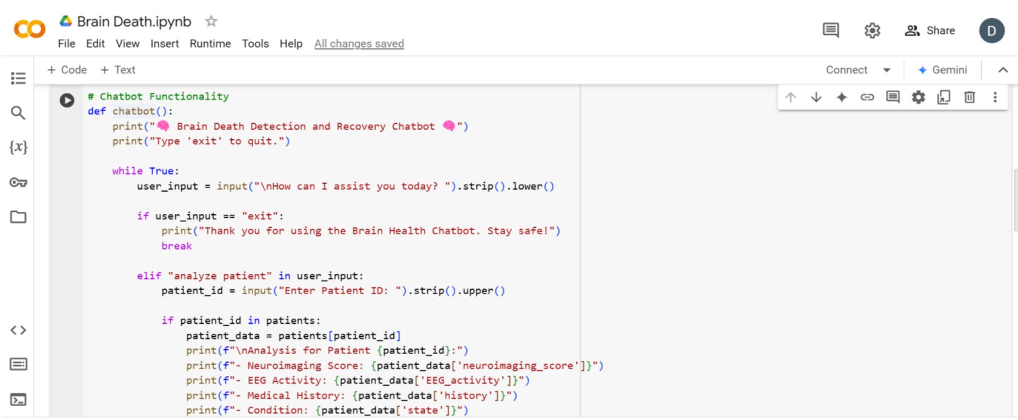
3.3 Implementation

3.3.1 Dataset

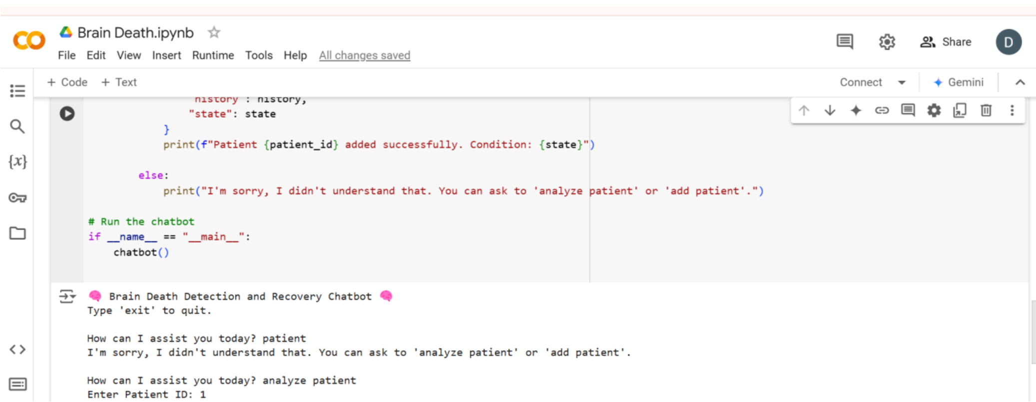


id	first_nam	last_name	Age	GCS	Oxygen_L	Pupillary_	Blood_Pre	organ_functions
1	Hirsch	Strong	4.19E+08	3.53E+09	9.92E+09	3.02E+09	6.5E+09	7PE8PQ3DJ46
2	Delmer	Klamman	7.23E+09	5.16E+09	3.07E+09	2.76E+09	8.13E+09	2J30P29VE92
3	Fawnia	Shemelt	3.19E+09	2.11E+09	5.39E+09	6.28E+08	4.77E+09	9TX2W04JN91
4	Mag	Dillistone	8.47E+09	6.23E+09	5.1E+08	7.69E+09	2.21E+09	5Y37QP8RP27
5	Cleve	Bartolic	1.96E+09	4.64E+09	5.34E+09	5.77E+09	3.33E+09	8DP2MJ7UT12
6	Millisent	Brasted	9.29E+09	6.37E+09	2.58E+09	7.73E+08	5.71E+09	3CW8CE0FG17
7	Susanetta	Charlwoo	4.11E+09	7.33E+09	2.46E+09	7.34E+09	4.94E+09	7RA8CX6ND18
8	Emalia	Byard	9.03E+09	5.6E+09	8.57E+08	92429211	2.75E+09	8H46VD9RX60
9	Halette	Duffet	3.3E+09	8.4E+09	1.71E+08	4.54E+09	5.19E+09	3P74D05YY04
10	Addie	Gleeson	1.56E+09	5.76E+09	3.37E+09	6.79E+09	7.84E+09	2VE1YN1RJ74
11	Baxie	Rudinger	7.69E+09	8.09E+09	2.1E+09	1.36E+09	8.12E+09	5QD5MH6NM69
12	Linn	Blay	1.36E+09	9.33E+09	2.53E+09	6.76E+09	6.19E+09	4TS6N49YT00
13	Ignatius	Valens-Sm	8.44E+09	8.33E+09	3.64E+09	7.49E+09	3.24E+09	5X14MX6ND04
14	Adrea	Mulleary	4.01E+09	7.9E+09	5.33E+09	3.87E+09	1.44E+09	4Q01FE7YA67
15	Tadd	Raincin	7.12E+09	9.8E+09	9.33E+09	7.03E+09	6.13E+08	4Q89JQ7GE52
16	Cort	Pretor	9.9E+09	7.37E+09	87031620	6.38E+09	2.74E+09	3AK6UD6QJ47
17	Dorie	Larroway	1.62E+09	8.57E+09	8.27E+09	8.04E+09	2.2E+09	5C79D20DG20

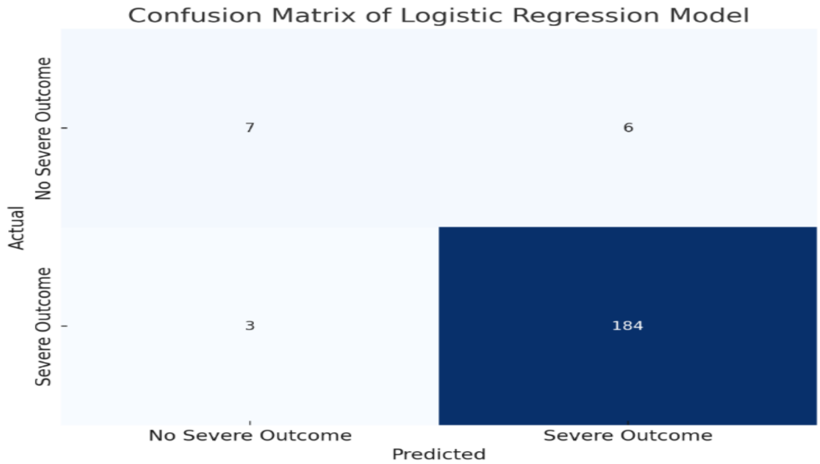
3.3.2 GenAI-LLM Chatbot Functionality



3.3.3 GenAI-LLM Chatbot Functionality - Input & Output



3.3.4 Validation



4. Conclusion:

This study demonstrates the potential of GenAI applications in transforming the landscape of brain death detection and recovery planning. By integrating complex datasets, the proposed framework offers superior diagnostic accuracy and innovative recovery insights. While the technology is still in its infancy, its implications for critical care are profound, particularly in improving decision-making and patient outcomes. By this proposed system the potential for recovery planning helps neurologists to decide with alternate solutions. This model evaluates the system's accuracy and reliability through simulated and real world datasets. Future research should focus on clinical trials and the ethical considerations of deploying GenAI in life-critical scenarios.

References

[1] Quan Liu , Xingran Cui , Maysam F. Abbod , Sheng-Jean Huang , Yin-Yi Han , Jiann-Shing Shieh , Brain death prediction based on ensembled artificial neural networks in neurosurgical intensive care units, Journal of the Taiwan Institute of Chemical Engineers, 42 (2011) 97–107.

[2] Raj, R., Luostarinen, T., Pursiainen, E. et al. Machine learning-based dynamic mortality prediction after traumatic brain injury. Sci Rep 9, 17672 (2019).

[3] Tu, K.-C., Eric Nyam, T.-T.,Wang, C.-C., Chen, N.-C., Chen, K.-T.,Chen,C.-J., Liu, C.-F., Kuo, J.-R. A,Computer-Assisted System for Early Mortality Risk Prediction in Patients with Traumatic Brain Injury Using Artificial Intelligence Algorithms in Emergency Room Triage. Brain Sci. 2022, 12, 612.

[4]Zhu E, Chen Z, Ai P, Wang J, Zhu M, Xu Z, Liu J and Ai Z (2023) Analyzing and predicting the risk of death in stroke patients using machine learning. Front. Neurol. 14:1096153. doi: 10.3389/fneur.2023.1096153.

[5]Kazuya Matsuo., Hideo Aihara., Tomoaki Nakai., Akitsugu Morishita., Yoshiki Tohma., Eiji Kohmura,Machine Learning to Predict In-hospital Morbidity and Mortality after Traumatic Brain Injury,Journal of Neurotrauma 2020 37:1, 202-210.

[6] Gajra A, Zettler ME, Miller KA, et al. Impact of augmented intelligence on utilization of palliative

care services in a real-world oncology setting. JCO Oncol Pract. 2022;18(1):e80-e88. [PMC free article] [PubMed]

[7] Murphree DH, Wilson PM, Asai SW, et al. Improving the delivery of palliative care through predictive modeling and healthcare informatics. J Am Med Inform Assoc. 2021;28(6):1065-1073. [PMC free article] [PubMed]

[8] Wilson PM, Ramar P, Philpot LM, et al. Effect of an artificial intelligence decision support tool on palliative care referral in hospitalized patients: a randomized clinical trial. J Pain Symptom Manage. 2023;66(1):24-32. [PubMed]

[9] Walshe C, Todd C, Caress A, Chew-Graham C. Patternsof access to community palliative care services: a literaturereview. J Pain Symptom Manage. 2009;37(5):884-912. [

[10]Rosenwax L, Spilsbury K, McNamara BA, Semmens JB. A retrospective population based cohort study of access to specialist palliative care in the last year of life: who is still missing out a decade on? BMC Palliat Care. 2016;15:46. [PMC free article] [PubMed].

[11] R.Lakshmi Devi, Savithri.V, Arulmathi, Diagnosis of B-ALL and classification of Blood Smear Images using Ensemble CNN models infused on Fuzzy Rank,Afr.J.Bio.Sc.6(14)(2024)

[12] Savithri, V., Hariharan, G., Anuradha, G.,Blockchain Technology in Estimating Crow Intelligence Using Artificial Intelligence, Hybridization of Blockchain and Cloud Computing: Overcoming Security Issues in IoT, 2023, pp.13– 24.

[13] Suja, T.L., Savithri, V. Backtracking algorithm for virtual cluster migration in cloud computing, Indian Journal of Science and Technology, 2015, 8(15). [15] Savithri, V., Purushothaman, S., Detections of intima-media thickness in b-mode carotid artery images using segmentation methods,Advances in Intelligent Systems and Computing, 2014, 216, pp. 471–482.