AI in Palliative Care Decision-Making in Brain Death

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Abstract—Predicting the recovery or death of a brain-dead patient using AI presents both ethical and medical challenges. Brain death is a state in which a person has irreversibly lost all brain function, including the brainstem, and is legally considered dead in many countries. Once brain death is diagnosed, there is no chance of recovery. However, the body can sometimes remain on life support, with the heart continuing to beat for a period of time. To uphold the value of human life, our application offers a second opinion to assist families and medical professionals in making informed decisions about a patient's condition before concluding whether recovery is possible after a diagnosis of brain death.

Keywords-Human Values, Brain Death, Decision Making, EANN Model

I. Introduction

The current scenario for declaring death in cases of brain death is increasing and still it's becoming a challenge for doctors to decide or declare death. To overcome this issue, we have proposed a study with Artificial Neural Networks which is biologically based on the human brain to diagnose a patient's condition before conferring death. The same can be helpful to the doctors to decide whether there are any future symptoms to survive or to confer death.

Generalizability: Ensure the model performs well across different hospitals and patient populations.

Interpretability: Provide transparent reasoning behind the AI predictions to support clinician decisions.

Importance of this Topic:

This proposed system outlines the steps to develop an ANN system that could assist in predicting the outcomes for brain-dead patients. The focus always remains on enhancing clinical decision-making rather than replacing it. Our study helps to predict the hypothesis conclusion whether the patient will be able to survive later or not.

II. Literature Review

[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).

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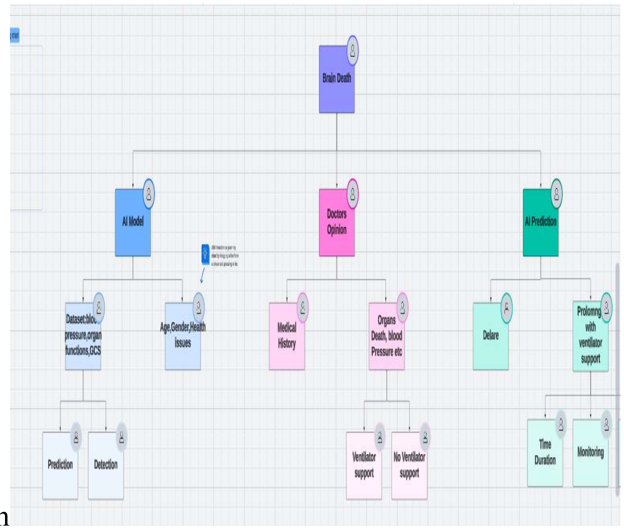
III. Methodology



The work flow of the Proposed System

Brain Death Evaluation Questionnaire:

1. Patient's History

   Name

   Age

   Gender

   Date of Brain Death Diagnosis

   Cause of Brain Death

2. Patient's Medical History

   Prior Medical Conditions

   Duration of Life Support Before Diagnosis

   Investigation Conducted

3. Family and Caregiver Considerations

   Relationship to the Patient

   Understanding of the brain death

   Concerns or questions regarding diagnosis

   Support System Available

4. Decision Making Process

What information would be more useful to you in making decisions related to patients care

Are they cultural or religious beliefs that influence your decision about life support?

What are their wishes for the patient's end-of-life care?

5. Second Opinion

   Would they require the second opinion regarding the brain death diagnosis?

   If yes, What specific information they require from the second opinion.

6. Additional Comments

   If anything else to be gathered regarding the patient's condition.

   Objective:

- This proposed study with Artificial Neural Networks which is biologically based on the human brain helps to

- diagnose apatient's condition before conferring death.
- This ANN model helps the doctors to predict whether the patient will recover in future or to declare death.
- Predict how long a brain-dead patient can be maintained on life support or the viability of their organs for transplantation.

  Ethical Framework:

- Work with healthcare professionals, ethicists, and legal experts to ensure that AI is only used as a tool for clinical support and for making end-of-life decisions. All patient data must be anonymized and handled under strict privacy regulations (e.g., HIPAA, GDPR).

Data Collection and Preprocessing

Type of Data: To Collect data from brain-dead patients, focusing on:

Vital signs (heart rate, blood pressure, respiratory metrics) Organ function metrics (liver enzymes, kidney function, oxygen saturation) Imaging data (e.g., MRI, CT scans) Laboratory biomarkers (e.g., blood chemistry, electrolytes)

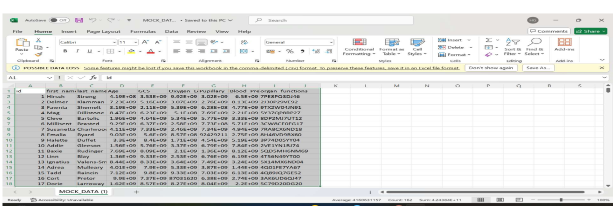
Year	Author	Model	Outcome
2022	Gajra A, Zettler ME, Miller KA, et al[6]	Augmented intelligence-cancer patient	Identifying patients at high or medium risk for short-term

			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

Preprocessing:

Clean the data, handling missing values and outliers.Normalize physiological signals for consistency.Anonymize and categorize data to ensure patient privacy.

Dataset



AI Model Selection

Time-Series Analysis Models:

LSTM (Long Short-Term Memory): Suitable for predicting physiological changes over time based on past vital sign data. GRU (Gated Recurrent Unit): Another recurrent neural network (RNN) that can predict time until systemic organ failure or cardiac arrest.

Survival Analysis Models:

Cox Proportional Hazards Model: Can be used to estimate survival time (how long the body will sustain life) after brain death. Deep Learning-based Survival Models: For more complex, multi-variable data from imaging and lab results.

Organ Viability Prediction:

Used Convolutional Neural Networks (CNNs) to analyze imaging data and predict the viability of organs such as the heart, lungs, liver, and kidneys.

IV IMPLEMENTATION

Improved Diagnostic Accuracy, Standardization of Protocols, Predictive Insights,Patient Management Optimization,Ethical Implications:Through this innovative approach, we aspire to set a precedent for the adoption of artificial intelligence in critical medical decision-making, potentially pioneering a new standard for assessing brain death in clinical practice.

Relevance of the proposed study:

The proposed study on predicting the recovery or death of brain-dead patients using AI presents significant relevance in various domains, including medical ethics, healthcare decision-making, technology in medicine, and familial support. Here are several key points to highlight its relevance:

Clarification of Medical Definitions- The study addresses the complex definition of brain death, an area that can lead to confusion among patients' families and healthcare providers. By utilizing AI to provide a second opinion, the study contributes to a clearer understanding of brain death and the irreversible nature of such a diagnosis. Supporting Informed Decision-Making-Families often face immense emotional turmoil when making decisions about the care of a brain-dead loved one. Providing an AI-driven second opinion can offer additional perspectives, helping them make more informed choices based on data and analysis rather than solely on emotional responses. Ethical Considerations- The study raises important ethical questions about life support and the prolongation of biological functions in brain-dead patients. By exploring how AI can assist in determining the likelihood of recovery versus death, the research may prompt discussions on the ethical implications of continuing life support in these situations, balancing hope and medical reality. Advancements in Medical Technology-The integration of AI into medical decision-making reflects current trends in healthcare technology. This study positions itself at the intersection of medicine and technology, showcasing how AI can augment traditional clinical practices and improve patient outcomes. Potential for Improved End-of-Life Care- By providing insights into the potential for recovery or the certainty of death, the study may improve the quality of end-of-life care. This can lead to more compassionate approaches tailored to the values and wishes of patients and families. Interdisciplinary Collaboration- The study may promote collaboration among clinicians, ethicists, data scientists, and technologists, fostering interdisciplinary dialogue and innovation in how we approach complex medical decisions.

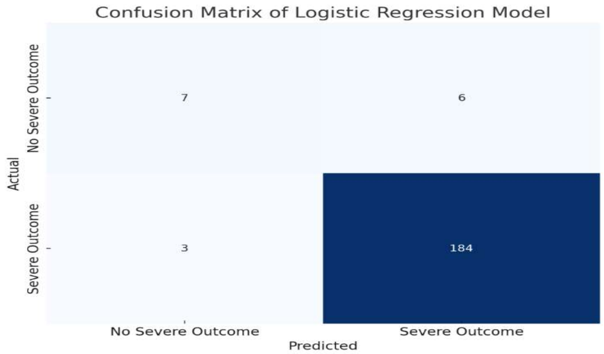
Future Research Directions-Should the study yield promising results, it may inspire further research into AI applications for other complex medical diagnoses and prognoses, paving the way for broader advancements in predictive healthcare technologies. Enhancing Trust in AI- By rigorously evaluating the effectiveness of AI in this sensitive area, the study can contribute to building trust among healthcare providers and patients in AI-driven decision-making tools. Public Awareness and Education- The outcomes of this study may serve to educate the public and healthcare professionals on the nuances of brain death, enhancing overall awareness and understanding of this critical topic.

In summary, the proposed study is highly relevant as it navigates the intersection of medical ethics, technology, and compassionate care, addressing a pressing need for clarity and support in complex decision-making regarding brain-dead patients.

Snippet of AI Model

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

# Load dataset (replace 'your_dataset.csv' with your actual file)
# The dataset should contain columns like GCS, pupillary response, age, etc., and a binary
outcome variable
# Assuming 'Outcome' column is binary (0 = no severe outcome, 1 = severe outcome)
X = data[['GCS', 'Pupillary_Response', 'Age', 'Blood_Pressure', 'Oxygen_Level']]
y = data['Outcome']

# Split dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize logistic regression model
model = LogisticRegression()

# Train the model
model.fit(X_train, y_train)

# Predict on test data
y_pred = model.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
```

```
conf_matrix = confusion_matrix(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy}")
print("Confusion Matrix:\n", conf_matrix)
print("Classification Report:\n", report)
```



The logistic regression model achieved an accuracy of 95.5% on the test set. The confusion matrix shows the distribution of correct and incorrect predictions, with a high precision and recall for the class representing severe outcomes. This result demonstrates that the model is generally effective at identifying patients at risk, though it has a lower recall for patients not at risk.

V CONCLUSION

The current scenario for declaring death in cases of brain death is increasing and still it's becoming a challenge for doctors to decide or declare death. To overcome this issue, we have proposed a study with Artificial Neural Networks which is biologically based on the human brain to diagnose a patient's condition before conferring death. The same can be helpful to the doctors to decide whether there are any future symptoms to survive or to confer death. Our Proposed System helps to consider human values.

Currently, artificial neural networks (ANN) are not routinely employed in clinical settings to assist in the determination of brain death. In this proposed study, we implement advanced ANN architectures, complemented by robust mathematical and statistical techniques, to enhance the accuracy and reliability of predicting brain death. By training our models on a comprehensive dataset encompassing a diverse population of patients, we aim to identify key physiological and neurological indicators that contribute to the determination of brain death.

Through the integration of machine learning algorithms with established clinical criteria, our approach seeks to minimize human error and provide an objective framework for decision-making. The model will leverage inputs such as neuroimaging results, clinical examination findings, and vital signs to generate probabilistic assessments of brain death stat

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