## 1 Brief overview of the purpose and scope of the database

### 1.1 Database design plays a crucial role in achieving project goals for several reasons:

**Data Organization:** Proper database design ensures that data is organized logically, making it easier to store, retrieve, and manage. This organization improves efficiency and reduces the likelihood of errors.

**Data Integrity:** A well-designed database enforces data integrity Constraints, such as unique keys and foreign key relationships, to maintain data accuracy and consistency.

**Performance:** Effective database design can significantly impact performance. By optimizing table structures, indexing, and query execution plans, we can improve query performance and overall system responsiveness.

**Scalability:** A well-designed database can accommodate future growth and scalability requirements. Properly normalized tables and scalable architecture choices can support increasing data volumes and user loads.

**Security:** Database design plays a crucial role in ensuring data security. Proper access controls, encryption, and other security measures can be implemented more effectively with a well-designed database.

**Adaptability:** A well-designed database can adapt to changing business requirements more easily. By anticipating potential future needs, such as new data attributes or relationships, we can design a database that is more flexible and adaptable.

Overall, database design is essential for achieving project goals as it lays the foundation for a reliable, efficient, and secure data management system. In the following I prepared a data status description.

### 1.2 Requirements Analysis

The table outlines the data to be stored in a database for electroconvulsive therapy (ECT) patients. It includes anonymized patient information such as age, gender, and contact details, as well as their medical history including diagnosis and medications like anesthesia. Treatment information encompasses dates of ECT sessions, parameters like electrode placement and stimulus intensity, anesthesia used, and the patient's response to treatment. The database also includes EEG signal records, with details on the EEG data files, their conversion to UTF-8 text files, and information on the date and time of recordings, electrode placement, and EEG machine settings such as sampling rate and filter settings. Side effects are not declared in this dataset.

|  |  |
| --- | --- |
| Category | Data Description |
| Patient Information |  |
| Name | Anonymized |
| Age | Declared |
| Gender | Not declared |
| Address | Not declared |
| Contact information | Not declared |
| Medical History | Not declared |
| Diagnosis information | Not declared |
| Medications | declared |
| Treatment Information | declared |
| Dates of ECT sessions | declared |
| ECT parameters | (e.g., electrode placement, stimulus intensity) |
| Anesthesia used | declared |
| Response to treatment | declared |
| Side effects | Not declared |
| EEG Signal Records | declared |
| EEG data files | Originally generated by ECT machine, Converted by the original software to txt file (UTF-8 unicode) |
| Date and time of EEG recordings | Declared |
| Electrode placement information | declared |
| EEG machine settings | (e.g., sampling rate, filter settings) |

Designing and implementing an SQLite database for Electroconvulsive Therapy (ECT) data involves integrating three types of files (text, dat, xlsx) into a cohesive structure. The text files contain EEG signal records, while the dat files represent raw ECT machine output, each corresponding to a converted txt file. Each txt file includes a 6-digit patient ID in its name, and there is a clinical data file (xlsx) for each txt file with the following columns depicted in Table1:

Table 1: Clinical data file's columns description

|  |  |
| --- | --- |
| Column | Description |
| Site | The electrode location skull location where the Electroconvulsive therapy (ECT) treatment is administered. |
| Ti vs Tt | Indicates whether the corresponding ECT pule is a titration pulse or therapeutic pulse. |
| Phase | The phase of the ECT treatment process, which could refer to the preparation, administration, or recovery phases. |
| % Charge | The percentage of the electric charge delivered during the ECT treatment session. |
| Durée clinique | The total duration of the clinical treatment process, including pre-treatment assessment, ECT sessions, and follow-up. |
| Durée EEG | The duration of the EEG recording or monitoring during the ECT procedure. |
| Anesthésiant | The type of anesthetic used during the ECT procedure to induce unconsciousness and muscle relaxation. |
| Qualité clinique | The overall clinical quality of the ECT treatment, including adherence to best practices and patient outcomes. |
| Qualité EEG | The quality (post suppression index) of the EEG signals recorded |
| Adranergie | The level of adrenergic activity in the patient, which may be relevant for monitoring physiological responses. |
| Qualité Aplatissement | The degree of flattening or normalization of EEG signals after the ECT treatment, indicating brain activity changes. |
| Patho | The specific psychiatric or neurological condition for which ECT is being administered. |
| Age | The age of the patient undergoing ECT treatment. |
| Sex | The gender or sex of the patient undergoing ECT treatment. |

Based on the above description provided, here is a proposed design for an SQLite database structure for Electroconvulsive Therapy (ECT) data: *Table 2*

Table 2: The proposed Data Catalog

|  |  |  |  |
| --- | --- | --- | --- |
| Data Catalog | | | |
| Table Name | **Column Name** | **Data Type** | **Description** |
| Patients | PatientID | INTEGER | Unique identifier for each patient (derived from the 6-digit patient ID in the file name). |
| EEGRecords | EEGRecordID | INTEGER | Unique identifier for each EEG record. |
| EEGRecords | PatientID | INTEGER | References the **PatientID** in the Patients table. |
| EEGRecords | EEGData | BLOB | Binary Large Object storing EEG signal records. |
| EEGRecords | FilePath | TEXT | Path to the original text file containing EEG signal records. |
| ECTMachineOutput | ECTOutputID | INTEGER | Unique identifier for each ECT machine output. |
| ECTMachineOutput | PatientID | INTEGER | References the **PatientID** in the Patients table. |
| ECTMachineOutput | OutputData | BLOB | Binary Large Object storing raw ECT machine output (DAT files). |
|  | FilePath | TEXT | Path to the original DAT file. |
| ClinicalData | ClinicalDataID | INTEGER | Unique identifier for each clinical data entry. |
| ClinicalData | PatientID | INTEGER | References the **PatientID** in the Patients table. |
| ClinicalData | Site | TEXT | The electrode location on the skull where ECT is administered. |
| ClinicalData | TiVsTt | TEXT | Indicates whether the corresponding ECT pulse is a titration pulse or therapeutic pulse. |
| ClinicalData | Phase | TEXT | The phase of the ECT treatment process. |
| ClinicalData | %Charge | REAL | The percentage of electric charge delivered during the ECT treatment session. |
| ClinicalData | DureeClinique | INTEGER | The total duration of the clinical treatment process. |
| ClinicalData | DureeEEG | INTEGER | The duration of EEG recording or monitoring during the ECT procedure. |
| ClinicalData | Anesthesiant | TEXT | The type of anesthetic used during the ECT procedure. |
| ClinicalData | QualiteClinique | TEXT | The overall clinical quality of the ECT treatment. |
| ClinicalData | QualiteEEG | TEXT | The quality of EEG signals recorded. |
| ClinicalData | Adranergie | TEXT | The level of adrenergic activity in the patient. |
| ClinicalData | QualiteAplatissement | TEXT | The degree of flattening or normalization of EEG signals after ECT treatment. |
| ClinicalData | Patho | TEXT | The specific psychiatric or neurological condition for which ECT is administered. |
| ClinicalData | Age | INTEGER | The age of the patient undergoing ECT treatment. |
| ClinicalData | Sex | TEXT | The gender or sex of the patient undergoing ECT treatment. |

This structure allows us to store and relate the different types of data associated with Electroconvulsive Therapy (ECT) in a cohesive manner. We can adjust the datatypes and constraints as needed based on our specific requirements and the capabilities of SQLite[[1]](#footnote-1).

To prepare for the Extraction, Transformation, and Loading (ETL) process, we will enhance the txt and xlsx files by inserting the patient ID and date columns. This enhancement will facilitate secure table joins and ensure that the data is organized effectively for analysis and retrieval.

### 1.3 Database implementation

Before going to the database implementation let's find out why SQLite is a good choice for this project:

SQLite is a lightweight, server less, self-contained, and open-source relational database management system (RDBMS) that is embedded into the end program. It is known for its simplicity, reliability, and ease of use, making it a popular choice for applications that require a local database.

Comparison between Serverless and Server Databases

**1. Deployment and Setup:** Serverless Databases: Easier to deploy as they do not require a separate server setup. Developers can simply include the database library in their application. Server Databases: Require a separate server setup and configuration, which can be more complex and time-consuming.

**2. Scalability: Serverless Databases:** Typically, easier to scale horizontally by adding more instances or partitions, as they are designed to handle variable workloads.

Server Databases: Scaling requires careful planning and often involves vertical scaling (upgrading server hardware)

**3. Cost: Serverless Databases:** Often more cost-effective for small to medium workloads, as users only pay for the resources they consume. Server Databases: Can be more expensive, especially for smaller applications, as they require dedicated server resources regardless of usage.

**4. Performance: Serverless Databases:** May have slightly higher latency compared to server databases due to the lack of dedicated server resources. Server Databases: Can offer better performance, especially for complex queries and high-volume transactions, as they have dedicated hardware.

**5. Management and Maintenance:** Serverless Databases: Easier to manage as there is no need to perform server maintenance tasks such as patching, updates, and backups. Server Databases: Require regular maintenance tasks to ensure optimal performance, including security updates, backups, and monitoring.

**6. Security: Serverless Databases:** Security is handled by the database provider, which can be both a pro and a con depending on the provider's security practices. Server Databases: Security is the responsibility of the organization, requiring careful management of access controls, encryption, and other security measures.

**7. Flexibility and Customization:** Serverless Databases: Limited in terms of customization and configuration options, as they are designed to be simple and easy to use. Server Databases: Offer more flexibility and customization options, allowing users to configure the database to meet specific requirements.

**8. Reliability and Availability:** Serverless Databases: Reliability and availability are generally high, as they are managed by the provider and often include built-in redundancy and failover mechanisms. Server Databases: Reliability and availability depend on the server setup and configuration, with the potential for downtime due to hardware failures or maintenance. In conclusion, the choice between server less and server databases depends on the specific requirements of the application. Serverless databases are often a good choice for small to medium applications with variable workloads and limited resources, while server databases are more suitable for large-scale applications that require high performance, scalability, and customization options.

### 1.3.1 Database code description

!pip install pandas sqlalchemy openpyxl  
!pip install XlsxWriter

import re  
import os  
import pandas as pd  
import chardet  
from sqlalchemy import create\_engine  
  
  
def get\_id(input\_string):  
 # Extract all sequences of digits  
 digits = re.findall(r'\d+', input\_string)  
 return digits  
##########################  
  
"""Overview  
This snippet is a Python function designed to extract all sequences of digits from a given input string. It utilizes the re module for regular expression matching to find sequences of digits (\d+) in the input string. The extracted digits are then returned as a list.  
  
Code Description  
re: This module provides support for regular expressions.  
os: This module provides a portable way of using operating system-dependent functionality.  
chardet: This module is used for character encoding detection in Python.  
create\_engine from sqlalchemy: This function creates a new Engine instance for Sqlite.  
Function Definition: The get\_id function is defined with one parameter, input\_string, representing the input string from which digits are to be extracted.  
Regular Expression: The re.findall method is used to find all sequences of digits (\d+) in the input\_string."""

**#TXT extractor**  
  
def find\_txt\_files(path):  
 txt\_files\_dict = {}  
   
 def recursive\_search(current\_path):  
 for item in os.listdir(current\_path):  
 item\_path = os.path.join(current\_path, item)  
 if os.path.isfile(item\_path) and item.endswith(".txt"):  
 txt\_files\_dict[item] = item\_path  
 elif os.path.isdir(item\_path):  
 recursive\_search(item\_path)  
   
 recursive\_search(path)  
 return txt\_files\_dict  
  
path = "/Users/hany/Downloads/ECTDATA"  
result\_txt = find\_txt\_files(path)  
  
########################################################  
"""Overview  
This snippet defines a function find\_txt\_files that recursively searches a specified directory (path) for all .txt files and returns a dictionary containing the filenames as keys and their full paths as values. The function utilizes a nested recursive function recursive\_search to traverse the directory structure.  
  
Code Description  
Function Definition: The find\_txt\_files function takes a single parameter path, representing the directory path to be searched for .txt files.  
Nested Function: The recursive\_search function is defined inside find\_txt\_files to handle the recursive traversal of directories.  
Dictionary Initialization: A dictionary txt\_files\_dict is initialized to store the filenames and their paths.  
Recursive Search: The recursive\_search function iterates over each item in the specified directory (current\_path), checking if it is a file with a .txt extension or a subdirectory.  
File Check: If the item is a file and has a .txt extension, its filename and full path are added to txt\_files\_dict.  
Directory Check: If the item is a directory, the recursive\_search function is called recursively to search the subdirectory.  
Return Value: The function returns txt\_files\_dict, which contains the filenames and full paths of all .txt files found in the specified directory and its subdirectories.  
  
"""

**#XLSX extractor**  
  
def find\_xlsx\_files(path):  
 xlsx\_files\_dict = {}  
   
 def recursive\_search(current\_path):  
 for item in os.listdir(current\_path):  
 item\_path = os.path.join(current\_path, item)  
 if os.path.isfile(item\_path) and item.endswith(".xlsx"):  
 xlsx\_files\_dict[item] = item\_path  
 elif os.path.isdir(item\_path):  
 recursive\_search(item\_path)  
   
 recursive\_search(path)  
 return xlsx\_files\_dict

def get\_txt\_ids(file\_name):  
 F = file\_name.split('.')  
 f= F[-1].split()[0]  
 F[-1] = f   
 return F[0].split(',')  
  
###############################  
"""Overview  
This defines a function get\_txt\_ids that extracts IDs from a given file name. It assumes that the file name is in the format 'date,word$.ext', where IDs are separated by commas and the extension .ext is present.  
Code Description  
Function Definition: The get\_txt\_ids function takes a single parameter file\_name, representing the name of the file from which IDs are to be extracted.  
Splitting the File Name: The file\_name is split using the dot (.) separator to separate the extension from the rest of the name. The last element of the split result (F[-1]) is further split using whitespace to extract the first word (f), assuming it represents the file extension. This word is then reassigned to replace the last element of the split result (F[-1]).  
Extracting IDs: The function returns the first element of the split result (F[0]), which is split using commas (,) to extract the IDs. This assumes that the IDs are comma-separated within the file name.  
"""

from tqdm import tqdm  
L = list(result\_txt.values())  
names = list(result\_txt.keys())  
with open(L[0], 'rb') as f:  
 result = chardet.detect(f.read())  
  
c = -1  
engine = create\_engine('sqlite:///ECT1.db', echo=False)  
for item in tqdm(L):  
 c+=1  
 try:  
 df = pd.read\_csv(item, encoding=result['encoding'], delim\_whitespace=True, skiprows= 5, on\_bad\_lines='skip')  
 ID = get\_txt\_ids(list(result\_txt.keys())[c])  
 df.insert(0, 'patient\_id', ID[0])  
 df.insert(1, 'Date', ID[1])  
 df.insert(2, 'Site', ID[2])  
 df.columns = df.columns.str.replace(' ', '\_')  
 table\_name = 'Patient\_EEG' + "{}".format(ID[0])  
 df.to\_sql(table\_name, engine, if\_exists='append', index=False)  
  
  
 except:  
 pass  
   
engine.dispose()  
  
####################################  
"""Overview  
This snippet demonstrates a process for reading and processing multiple CSV files, each representing EEG data for a patient, and storing the data into an SQLite database. The code utilizes the tqdm library for progress tracking, chardet for character encoding detection, pandas for data manipulation, and sqlalchemy for database management.  
  
Code Description  
Data Preparation: The code initializes two lists L and names with the values and keys from the result\_txt dictionary, respectively. These lists are used to iterate over the file paths (L) and file names (names).  
  
Character Encoding Detection: The code uses the chardet.detect method to detect the character encoding of the first file (L[0]) in order to correctly read the CSV files.  
  
SQLite Database Initialization: An SQLite database engine is created using create\_engine from sqlalchemy. The engine is configured to create or connect to a database file named ECT1.db.  
  
CSV Processing Loop: The code iterates over each file path (item) in L, reads the CSV file using pd.read\_csv, and processes the data.  
  
The read\_csv method is used to read the CSV file with specified parameters, including the detected encoding, skipping the first 5 rows, and skipping lines with bad formatting.  
The get\_txt\_ids function is used to extract patient IDs, dates, and site information from the file name.  
The extracted information is inserted into the DataFrame as new columns.  
The column names are standardized by replacing spaces with underscores.  
A table name (table\_name) is generated based on the patient ID for storing the DataFrame into the SQLite database using to\_sql.  
Exception Handling: The code includes a try-except block to handle any exceptions that may occur during the processing of CSV files. If an exception occurs, it is caught and the loop continues to the next file.  
  
Database Disposal: Finally, the database engine is disposed of using engine.dispose() to release any resources.  
  
"""

**# Sample SQL query**  
sql\_query = """  
SELECT name FROM sqlite\_master WHERE type='table';  
"""  
  
# Execute the query  
with engine.connect() as connection:  
 result = connection.execute(text(sql\_query))  
  
 # Fetch the results  
 for row in result:  
 print(row)

('Patient\_EEG353456',)  
('Patient\_EEG354886',)  
('Patient\_EEG526847',)  
('Patient\_EEG525847',)  
('Patient\_EEG234300',)  
('Patient\_EEG234400',)  
('Patient\_EEG465293',)  
('Patient\_EEG369690',)  
('Patient\_EEG203961',)  
('Patient\_EEG685561',)  
('Patient\_EEG658561',)  
('Patient\_EEG348655',)  
('Patient\_EEG191007',)  
('Patient\_EEG494811',)  
('Patient\_EEG218132',)  
('Patient\_EEG325733',)  
('Patient\_EEG537723',)  
('Patient\_EEG377765',)  
('Patient\_EEG37765',)  
('Patient\_EEG2343300',)  
('Patient\_EEG201575',)  
('Patient\_EEG640178',)  
('Patient\_EEG227193',)  
('Patient\_EEG388304',)  
('Patient\_EEG674119',)  
('Patient\_EEG491130',)  
('Patient\_EEG755767',)  
('Patient\_EEG419494',)  
('Patient\_EEG301672',)  
('Patient\_EEG245446',)  
('Patient\_EEG374227',)  
('Patient\_EEG296707',)  
('Patient\_EEG226238',)  
('Patient\_EEG218957',)  
('Patient\_EEG334217',)  
('Patient\_EEG420874',)  
('Patient\_EEG342303',)  
('Patient\_EEG241039',)  
('Patient\_EEG393834',)  
('Patient\_EEG615502',)  
('Patient\_EEG221197',)  
('Patient\_EEG363269',)  
('Patient\_EEG289577',)  
('Patient\_EEG312976',)  
('Patient\_EEG270225',)  
('Patient\_EEG170894',)  
('Patient\_EEG215488',)  
('Patient\_EEG135866',)  
('Patient\_EEG399426',)  
('Patient\_EEG212619',)  
('Patient\_EEG212629',)  
('Patient\_EEG514538',)  
('Patient\_EEG258322',)  
('Patient\_EEG440246',)

path = "/Users/hany/Downloads/ECTDATA"  
result\_xlsx = find\_xlsx\_files(path)

Xlsx\_path = []  
for key, value in result\_xlsx.items():  
 try:  
 if len(get\_id(key)[-1]) == 6:  
 Xlsx\_path.append(value)  
 except:   
 pass

files = Xlsx\_path  
  
for file\_name in files:  
 # Read the Excel file  
 df = pd.read\_excel(file\_name)  
   
 # Add a new column filled with the file name without the extension  
 df.insert(0, 'patient\_id', get\_id(file\_name)[-1])  
   
 # Write the updated DataFrame back to the Excel file  
 df.to\_excel('/Users/hany/Downloads/ECTDATA/Id\_fixed/{}.xlsx'.format(get\_id(file\_name)[-1]), index=False)  
##############################  
"""Overview  
This snippet iterates over a list of Excel file paths (files), reads each Excel file using pandas, adds a new column to the DataFrame filled with the file name without the extension, and then writes the updated DataFrame back to the Excel file with the new column added. The function get\_id is used to extract the patient ID from the file name.  
  
Code Description  
File Iteration: The code iterates over each file path (file\_name) in the files list.  
  
Excel File Reading: For each file, the code reads the Excel file into a DataFrame (df) using pd.read\_excel.  
  
New Column Addition: A new column named 'patient\_id' is inserted at the beginning of the DataFrame, filled with the patient ID extracted from the file name using get\_id(file\_name)[-1]. This assumes that the get\_id function returns a list of IDs and the patient ID is the last element in the list.  
  
Excel File Writing: The updated DataFrame is written back to the Excel file, with the new column added, using df.to\_excel. The file is saved to a new location (/Users/hany/Downloads/ECTDATA/Id\_fixed/) with the file name based on the extracted patient ID.  
  
"""

Xlsx\_id = find\_xlsx\_files('/Users/hany/Downloads/ECTDATA/Id\_fixed')

F = list(Xlsx\_id.values())  
  
for fi in F:  
 print(get\_id(fi)[0])

F = list(Xlsx\_id.values())  
# Replace 'sqlite:///example.db' with your database connection string  
engine = create\_engine('sqlite:///ECT1.db', echo=False)  
  
# Loop through each Excel file  
i = 0  
for file\_name in F:  
 i += 1  
 # Read the Excel file into a DataFrame  
 df = pd.read\_excel(file\_name)  
  
 # Replace spaces in column names with underscores  
 df.columns = df.columns.str.replace(' ', '\_')  
  
 # Remove the extension from the file name for the table name  
 table\_name = 'Clinical\_' + "{}".format(get\_id(file\_name)[0])  
 # table\_name = table\_name.replace('.xlsx', '')  
  
 # Save the DataFrame to a SQL table  
 df.to\_sql(table\_name, engine, if\_exists='append', index=False)  
  
# Close the database connection  
engine.dispose()  
**"""Overview  
This snippet reads Excel files into Pandas DataFrames, processes the data, and saves the DataFrames into an SQLite database. It iterates over a list of Excel file paths (F), reads each file, replaces spaces in column names with underscores, and saves the DataFrame into an SQLite table named based on the file name.  
  
Code Description  
Data Preparation: The code initializes a list F with the values from the Xlsx\_id dictionary, assuming it contains the file paths of Excel files to be processed.  
  
SQLite Database Initialization: An SQLite database engine is created using create\_engine from sqlalchemy. The engine is configured to create or connect to a database file named ECT1.db.  
  
Excel Processing Loop: The code iterates over each file path (file\_name) in F and processes the Excel file.  
  
The Excel file is read into a DataFrame (df) using pd.read\_excel.  
Column names in the DataFrame are standardized by replacing spaces with underscores using df.columns.str.replace.  
A table name (table\_name) is generated based on the file name, assuming that the get\_id function returns a list of IDs and the table name is constructed from the first element of the ID list.  
The DataFrame is saved into the SQLite database as a table using df.to\_sql.  
Database Disposal: Finally, the database engine is disposed of using engine.dispose() to release any resources.  
  
"""**

from sqlalchemy import text  
engine = create\_engine('sqlite:///ECT1.db')  
  
# Sample SQL query  
sql\_query = """  
SELECT name FROM sqlite\_master WHERE type='table';  
"""  
  
# Execute the query  
with engine.connect() as connection:  
 result = connection.execute(text(sql\_query))  
  
 # Fetch the results  
 for row in result:  
 print(row[0])

Patient\_EEG353456  
Patient\_EEG354886  
Patient\_EEG526847  
Patient\_EEG525847  
Patient\_EEG234300  
Patient\_EEG234400  
Patient\_EEG465293  
Patient\_EEG369690  
Patient\_EEG203961  
Patient\_EEG685561  
Patient\_EEG658561  
Patient\_EEG348655  
Patient\_EEG191007  
Patient\_EEG494811  
Patient\_EEG218132  
Patient\_EEG325733  
Patient\_EEG537723  
Patient\_EEG377765  
Patient\_EEG37765  
Patient\_EEG2343300  
Patient\_EEG201575  
Patient\_EEG640178  
Patient\_EEG227193  
Patient\_EEG388304  
Patient\_EEG674119  
Patient\_EEG491130  
Patient\_EEG755767  
Patient\_EEG419494  
Patient\_EEG301672  
Patient\_EEG245446  
Patient\_EEG374227  
Patient\_EEG296707  
Patient\_EEG226238  
Patient\_EEG218957  
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Patient\_EEG420874  
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Patient\_EEG393834  
Patient\_EEG615502  
Patient\_EEG221197  
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Patient\_EEG215488  
Patient\_EEG135866  
Patient\_EEG399426  
Patient\_EEG212619  
Patient\_EEG212629  
Patient\_EEG514538  
Patient\_EEG258322  
Patient\_EEG440246  
Clinical\_1  
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Clinical\_674119  
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Clinical\_537723  
Clinical\_615502  
Clinical\_419494  
Clinical\_289577  
Clinical\_526847  
Clinical\_494811  
Clinical\_755767  
Clinical\_218132  
Clinical\_342203  
Clinical\_191007  
Clinical\_334217  
Clinical\_245446  
Clinical\_348655  
Clinical\_420874  
Clinical\_241039  
Clinical\_640178  
Clinical\_201575  
Clinical\_685561  
Clinical\_393834  
Clinical\_377765  
Clinical\_369690  
Clinical\_388304  
Clinical\_312976  
Clinical\_226238  
Clinical\_270225  
Clinical\_221197  
Clinical\_465293  
Clinical\_215488  
Clinical\_218957  
Clinical\_227193  
Clinical\_234300  
Clinical\_399426  
Clinical\_363269  
Clinical\_170894  
Clinical\_203961  
Clinical\_342303  
Clinical\_374227  
Clinical\_440246  
Clinical\_296707  
Clinical\_354886  
Clinical\_135866  
Clinical\_514538  
Clinical\_353456  
Clinical\_301672  
Clinical\_212629  
Clinical\_258322

# Replace 'sqlite:///ECT.db' with the correct path to your SQLite database  
engine = create\_engine('sqlite:///ECT1.db')  
  
# Execute a query to select data from a table  
query = "SELECT \* FROM Clinical\_14;"  
df = pd.read\_sql\_query(query, engine)  
  
# Display the DataFrame  
print(df)  
  
# Close the database connection  
engine.dispose()

patient\_id Date Ti\_vs\_Tt Site Phase %\_Charge Durée\_clinique\_ \  
0 334217 30-07-2021 Ti Uni Index 5 -   
1 334217 02-08-2021 Tt Uni Index 30 8   
2 334217 29-11-2021 Tt Uni Index 30 23   
3 334217 13-12-2021 Tt Uni Index 30 45   
4 334217 01-08-2022 Ti Uni Index 15 26   
5 334217 03-08-2022 Tt Uni Index 60 23   
6 334217 05-08-2022 Tt Uni Index 60 19   
7 334217 08-08-2022 Tt Uni Index 65 12   
8 334217 10-08-2022 Tt Uni Index 70 38   
9 334217 12-08-2022 Tt Uni Index 70 18   
10 334217 30-09-2022 Tt Uni Entretien 70 26   
11 334217 07-10-2022 Tt Uni Entretien 70 46   
  
 Durée\_EEG Anesthésiant Qualité\_clinique ... Age Sexe Charge\_(Mc) \  
0 270 Propofol - ... 34.0 M NaN   
1 30 Propofol +++ ... NaN None NaN   
2 27 Propofol +++ ... NaN None NaN   
3 62 Propofol +++ ... NaN None NaN   
4 26 Propofol +++ ... NaN None NaN   
5 27 Propofol +++ ... NaN None NaN   
6 24 Propofol +++ ... NaN None NaN   
7 24 Propofol +++ ... NaN None NaN   
8 50 Propofol +++ ... NaN None NaN   
9 22 Propofol +++ ... NaN None NaN   
10 67 Propofol +++ ... NaN None NaN   
11 105 Propofol +++ ... NaN None 325.7   
  
 EEG\_Endpoint Average\_Seizure\_Energy\_Index Post-Ictal\_Suppression\_Index \  
0 NaN NaN NaN   
1 NaN NaN NaN   
2 NaN NaN NaN   
3 NaN NaN NaN   
4 NaN NaN NaN   
5 NaN NaN NaN   
6 NaN NaN NaN   
7 NaN NaN NaN   
8 NaN NaN NaN   
9 NaN NaN NaN   
10 NaN NaN NaN   
11 105.0 11377.6 83.1   
  
 Maximum\_Sustain\_Power Time\_to\_Peak\_Power Maximum\_Sustain\_Coherence \  
0 NaN NaN NaN   
1 NaN NaN NaN   
2 NaN NaN NaN   
3 NaN NaN NaN   
4 NaN NaN NaN   
5 NaN NaN NaN   
6 NaN NaN NaN   
7 NaN NaN NaN   
8 NaN NaN NaN   
9 NaN NaN NaN   
10 NaN NaN NaN   
11 25995.8 35.0 99.2   
  
 Time\_to\_Peak\_Coherence   
0 NaN   
1 NaN   
2 NaN   
3 NaN   
4 NaN   
5 NaN   
6 NaN   
7 NaN   
8 NaN   
9 NaN   
10 NaN   
11 20.0   
  
[12 rows x 25 columns]

engine = create\_engine('sqlite:///ECT1.db')  
query = "SELECT \* FROM Clinical\_334217 C join Patient\_EEG334217 P ON C.patient\_id = P.patient\_id"  
df = pd.read\_sql\_query(query, engine)  
print(df)  
  
engine.dispose()

patient\_id Date Ti\_vs\_Tt Site Phase %\_Charge \  
0 334217 01-08-2022 Ti Uni Index 15   
1 334217 02-08-2021 Tt Uni Index 30   
2 334217 03-08-2022 Tt Uni Index 60   
3 334217 05-08-2022 Tt Uni Index 60   
4 334217 07-10-2022 Tt Uni Entretien 70   
... ... ... ... ... ... ...   
442603 334217 12-08-2022 Tt Uni Index 70   
442604 334217 13-12-2021 Tt Uni Index 30   
442605 334217 29-11-2021 Tt Uni Index 30   
442606 334217 30-07-2021 Ti Uni Index 5   
442607 334217 30-09-2022 Tt Uni Entretien 70   
  
 Durée\_clinique\_ Durée\_EEG Anesthésiant Qualité\_clinique ... \  
0 26 26 Propofol +++ ...   
1 8 30 Propofol +++ ...   
2 23 27 Propofol +++ ...   
3 19 24 Propofol +++ ...   
4 46 105 Propofol +++ ...   
... ... ... ... ... ...   
442603 18 22 Propofol +++ ...   
442604 45 62 Propofol +++ ...   
442605 23 27 Propofol +++ ...   
442606 - 270 Propofol - ...   
442607 26 67 Propofol +++ ...   
  
 Time\_to\_Peak\_Power Maximum\_Sustain\_Coherence Time\_to\_Peak\_Coherence \  
0 NaN NaN NaN   
1 NaN NaN NaN   
2 NaN NaN NaN   
3 NaN NaN NaN   
4 35.0 99.2 20.0   
... ... ... ...   
442603 NaN NaN NaN   
442604 NaN NaN NaN   
442605 NaN NaN NaN   
442606 NaN NaN NaN   
442607 NaN NaN NaN   
  
 patient\_id Date Site 21.1 22.3 1.6 -19.5   
0 334217 02-08-2021 Uni 20.0 21.9 2.8 -17.6   
1 334217 02-08-2021 Uni 20.0 21.9 2.8 -17.6   
2 334217 02-08-2021 Uni 20.0 21.9 2.8 -17.6   
3 334217 02-08-2021 Uni 20.0 21.9 2.8 -17.6   
4 334217 02-08-2021 Uni 20.0 21.9 2.8 -17.6   
... ... ... ... ... ... ... ...   
442603 334217 02-08-2021 Uni -41.9 -24.8 -14.0 -12.8   
442604 334217 02-08-2021 Uni -41.9 -24.8 -14.0 -12.8   
442605 334217 02-08-2021 Uni -41.9 -24.8 -14.0 -12.8   
442606 334217 02-08-2021 Uni -41.9 -24.8 -14.0 -12.8   
442607 334217 02-08-2021 Uni -41.9 -24.8 -14.0 -12.8   
  
[442608 rows x 32 columns]

engine = create\_engine('sqlite:///ECT1.db')  
query = "SELECT \* FROM Patient\_EEG334217"  
df = pd.read\_sql\_query(query, engine)  
print(df)  
  
engine.dispose()

patient\_id Date Site 21.1 22.3 1.6 -19.5  
0 334217 02-08-2021 Uni 20.0 21.9 2.8 -17.6  
1 334217 02-08-2021 Uni 19.1 22.4 3.1 -15.3  
2 334217 02-08-2021 Uni 17.6 23.0 1.8 -12.6  
3 334217 02-08-2021 Uni 15.1 22.9 0.4 -10.1  
4 334217 02-08-2021 Uni 11.3 21.5 2.1 -7.9  
... ... ... ... ... ... ... ...  
36879 334217 02-08-2021 Uni -33.9 -16.3 -16.9 -12.1  
36880 334217 02-08-2021 Uni -34.9 -17.0 -16.4 -12.3  
36881 334217 02-08-2021 Uni -36.6 -19.0 -15.5 -12.5  
36882 334217 02-08-2021 Uni -39.0 -22.0 -14.6 -12.8  
36883 334217 02-08-2021 Uni -41.9 -24.8 -14.0 -12.8  
  
[36884 rows x 7 columns]

from sqlalchemy import create\_engine, inspect  
engine = create\_engine('sqlite:///ECT1.db')  
inspector = inspect(engine)s  
table\_names = inspector.get\_table\_names()  
schemas = []  
for table\_name in table\_names:  
 columns = inspector.get\_columns(table\_name)  
 schema = {'table\_name': table\_name, 'columns': columns}  
 schemas.append(schema)  
  
df = pd.DataFrame(schemas)  
print(df)  
engine.dispose()

table\_name columns  
0 Clinical\_1 [{'name': 'patient\_id', 'type': BIGINT, 'nulla...  
1 Clinical\_10 [{'name': 'patient\_id', 'type': BIGINT, 'nulla...  
2 Clinical\_11 [{'name': 'patient\_id', 'type': BIGINT, 'nulla...  
3 Clinical\_12 [{'name': 'patient\_id', 'type': TEXT, 'nullabl...  
4 Clinical\_13 [{'name': 'patient\_id', 'type': BIGINT, 'nulla...  
.. ... ...  
147 Patient\_EEG640178 [{'name': 'patient\_id', 'type': TEXT, 'nullabl...  
148 Patient\_EEG658561 [{'name': 'patient\_id', 'type': TEXT, 'nullabl...  
149 Patient\_EEG674119 [{'name': 'patient\_id', 'type': TEXT, 'nullabl...  
150 Patient\_EEG685561 [{'name': 'patient\_id', 'type': TEXT, 'nullabl...  
151 Patient\_EEG755767 [{'name': 'patient\_id', 'type': TEXT, 'nullabl...  
  
[152 rows x 2 columns]

engine = create\_engine('sqlite:///ECT1.db')  
query = "SELECT name, sql FROM sqlite\_master WHERE type='table';"  
df = pd.read\_sql\_query(query, engine)  
print(df)  
  
engine.dispose()

name sql  
0 Patient\_EEG353456 CREATE TABLE "Patient\_EEG353456" (\n\tpatient\_...  
1 Patient\_EEG354886 CREATE TABLE "Patient\_EEG354886" (\n\tpatient\_...  
2 Patient\_EEG526847 CREATE TABLE "Patient\_EEG526847" (\n\tpatient\_...  
3 Patient\_EEG525847 CREATE TABLE "Patient\_EEG525847" (\n\tpatient\_...  
4 Patient\_EEG234300 CREATE TABLE "Patient\_EEG234300" (\n\tpatient\_...  
.. ... ...  
147 Clinical\_514538 CREATE TABLE "Clinical\_514538" (\n\tpatient\_id...  
148 Clinical\_353456 CREATE TABLE "Clinical\_353456" (\n\tpatient\_id...  
149 Clinical\_301672 CREATE TABLE "Clinical\_301672" (\n\tpatient\_id...  
150 Clinical\_212629 CREATE TABLE "Clinical\_212629" (\n\tpatient\_id...  
151 Clinical\_258322 CREATE TABLE "Clinical\_258322" (\n\tpatient\_id...  
  
[152 rows x 2 columns]

import os  
  
Path = os.listdir(os.getcwd())  
for path in Path if:  
path.end

## 2. Related Works in Causal Inference and Deep Learning:

*In this section, I have thoroughly examined over 30 publications on the topic of causal inference and deep learning. My investigation follows a structured format, beginning with a summary of each publication. For publications with significant*

*key points, I include a section highlighting these key points. Additionally, I provide an analysis of the advantages and disadvantages of each publication. In cases where a disadvantage is particularly noteworthy, I include an example to illustrate its impact.*

Causal inference and the evolution of opposite neurons [1]

Authors:Stephanie Badde. Fangfang Hong,Michael S. Landy

Department of Psychology, Tufts University, Medford, MA 02155

Department of Psychology, New York University, New York, NY 10003

Center for Neural Science, New York University, New York, NY 10003

# Summary:

The paper explores how the brain integrates sensory cues and makes causal inferences using a combination of congruent and opposite neurons. It discusses a study by Rideaux et al. that uses an artificial neural network to simulate multisensory perception and causal inference. The network develops neurons similar to those found in the brain, suggesting a possible mechanism for these cognitive processes. The study highlights the role of congruent and opposite neurons in multisensory integration and causal inference, providing insights into how the brain processes sensory information.

# Key Points:

* Humans are adept at integrating sensory cues optimally, giving greater weight to more reliable signals. It seems the causal inference is the process of discerning whether sensory signals originate from the same or different sources in mammals.
* Neurons in brain areas like MSTd (medial superior temporal area, dorsal part) and VIP (ventral intraparietal area) are tuned to detect the direction of visual motion. Some neurons are tuned to respond to a specific direction of motion, while others respond to the opposite direction. This tuning helps in integrating sensory information and making **causal inferences** about the environment. Rideaux et al. conducted a study where they trained an artificial neural network to perform causal inference judgments. They found that the network developed neurons similar to those found in the brain, with some responding to congruent directions of motion and others to opposite directions.
* The artificial neural network's performance in perceptual tasks, which involve interpreting and understanding sensory information, closely mirrored human and monkey behavior. This similarity is promising for gaining insights into the brain's processes. The network's ability to replicate complex behavioral patterns suggests that it could be a valuable tool for studying and understanding the intricate workings of the brain.
* The network's architecture raises questions about how causal inference affects perceptual judgments and whether sensory experience is necessary for the development of opposite neurons.

# Advantages:

* Provides a novel explanation for how the brain integrates sensory cues and makes causal inferences. Uses an innovative approach with artificial neural networks to simulate complex cognitive processes.
* Offers insights into the role of congruent and opposite neurons in multisensory integration and causal inference.

# Disadvantages:

* Relies heavily on simulation and modeling, which may oversimplify the complexities of the brain.
* Does not directly address the neurobiological mechanisms underlying the development of congruent and opposite neurons. The network's architecture may not fully capture the intricacies of human perception and cognition.

# Conclusion:

The paper presents a compelling argument for the role of congruent and opposite neurons in multisensory integration and causal inference. However, it raises several important questions about the neural mechanisms underlying these processes. Future research could focus on validating these findings in animal models and exploring the development of these neurons during ontogenesis. Additionally, further studies could investigate how the brain integrates sensory information across different modalities and how prior expectations influence perceptual judgments. Overall, the paper offers valuable insights into the neural basis of perception and cognition, paving the way for future research in this field.

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A novel EMD and causal convolutional network integrated with Transformer for ultra short-term wind power forecasting Ning Li a , Jie Dong a , Lingyue Liu b , He Li c , Jie Yan d,∗ a Renewable Energy Sources (NCEPU), School of Renewable Energy, North China Electric Power University, Beijing 102206, China [2]

# Summary:

# Advantages:

* + - **Improved Accuracy:** The EMD-CCTransformer method has shown lower forecasting errors compared to traditional methods, enhancing the reliability of wind power forecasts.
    - **Long-Term Information Retention:** By using the EMD algorithm for decomposition, the method improves the ability of the Transformer model to maintain long-term information in wind power series.
    - **Parallel Computing:** The Transformer model supports parallel computing, speeding up model training and improving efficiency.
    - **Attention Mechanism:** The use of the attention mechanism allows the model to focus on relevant information, improving forecasting accuracy.
* **Self-Attention Mechanism:** Provides a detailed explanation of the self-attention mechanism, which is the core of the Transformer model, enhancing understanding of its inner workings.
* **Multi-Head Attention:** Describes how multi-head attention combines multiple attention mechanisms to focus on different aspects of information, improving information processing efficiency.
* **Causal Convolutional Self-Attention:** Introduces a novel approach to improve the Transformer's sensitivity to local environments in time-series forecasting, potentially leading to more accurate predictions.
* **Empirical Mode Decomposition:** Shows how EMD can enhance feature extraction and reduce noise in time series data, improving the efficiency and accuracy of deep learning models like the Transformer.

# Disadvantages:

* + - **Complexity:** Implementing the EMD-CCTransformer method may require a deeper understanding of both the Transformer model and the EMD algorithm, making it more complex to implement compared to traditional methods.
    - **Data Requirement:** The method may require large-scale wind power data for training and testing, which may not be readily available in all situations.
    - **Computational Resources:** The use of deep learning models like the Transformer may require significant computational resources, which could be a limitation for some applications.
    - **Model Interpretability:** Deep learning models, including the Transformer, can sometimes be less interpretable compared to traditional statistical models, which could be a concern for some users
* **Training Overfitting:** While Dropout layers are mentioned to prevent overfitting during training, the text does not delve deeply into the challenges of overfitting or how they are specifically addressed in the proposed model.

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CAUSALITY IN MACHINE LEARNING

When causal inference meets deep learning [3]

[Yunan Luo](https://www.nature.com/articles/s42256-020-0218-x#auth-Yunan-Luo-Aff1), [Jian Peng](https://www.nature.com/articles/s42256-020-0218-x#auth-Jian-Peng-Aff1) & [Jianzhu Ma](https://www.nature.com/articles/s42256-020-0218-x#auth-Jianzhu-Ma-Aff2-Aff3)

[Nature Machine Intelligence](https://www.nature.com/natmachintell)

volume 2, pages 426–427 (2020)

# Summary:

# The article addresses the intricate task of extracting causal relationships from data, highlighting the crucial distinction between causality and correlation. It introduces Bayesian networks (BN) as a powerful model for depicting causal relationships through directed acyclic graphs (DAGs). While accurately inferring the DAG structure presents a significant computational challenge, researchers have employed approximation methods, such as score-based heuristics, to tackle this issue. Recent advancements have further refined this approach by reimagining the problem as a continuous optimization challenge, thereby enabling more efficient solutions through the application of numerical techniques.

# Advantages:

* **Efficiency:** The new approach makes learning causal relations more efficient by transforming the problem into a continuous optimization task.
* **Scalability:** The methods can be scaled to larger problems, such as inferring causal **transcriptome** (complete set of RNA transcripts) networks with over 10,000 genes.
* **Incorporation of Prior Knowledge:** The framework allows for the incorporation of prior knowledge, enhancing the utility of causal inference.
* **Interpretability:** By encoding causality in the structure of neural networks, the models offer a way to interpret deep learning models, which are often considered as black boxes.

# Disadvantages:

* + - **Complexity:** The methods involve complex mathematical transformations and optimization techniques, which may be challenging to understand and implement.
    - **Modeling Assumptions:** Some methods require modeling assumptions, such as linear structural equation models, which may not always hold in practice.
    - **Interpretability Trade-offs:** While the models provide interpretability, there may be trade-offs with model accuracy, as optimizing for interpretability could impact predictive performance.

In conclusion, the integration of causal inference with deep learning represents a promising direction, offering the potential for more efficient and interpretable models. However, challenges remain in balancing complexity, scalability, and interpretability in practical applications.

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Evaluating Uses of Deep Learning Methods for Causal Inference [4]

# Summary:

The study compares the performance of logistic regression (LR) with deep learning models (CNN, DNN, CNN-LSTM) in estimating propensity scores. Propensity scores are used to assess the average treatment effect (ATE) in a quasi-real-world dataset from the Atlantic Causal Inference Conference (ACIC) 2019 Data Challenge. The results indicate that deep learning models outperform LR in terms of bias, classification accuracy, Cohen’s Kappa, and AUC-ROC values. Specifically, CNN had the least biased causal effect estimates and achieved the best classification accuracy. CNN, DNN, and CNN-LSTM also produced low absolute bias values when applied to the complex ACIC dataset compared to LR.

# Advantages:

* + - **Flexible Feature Learning:** Deep learning models learn features from the data instead of relying on handcrafted feature extraction, making them more flexible.
    - **Performance:** Deep learning models outperformed LR in terms of bias reduction, classification accuracy, and other performance metrics.
    - **Non-linearity:** Deep learning models can estimate many more parameters and permutations of parameters compared to LR, leading to more reliable estimates of propensity scores.
    - **Generalization:** Deep learning models can generalize well to complex datasets and perform better in estimating propensity scores for rare outcomes.

# Disadvantages:

* + - **Overfitting:** Deep learning models are more susceptible to overfitting if not properly configured, requiring restrictions on network size, variable numbers, and regularization.
    - **Complexity:** Deep learning models are more complex to configure and train compared to LR, requiring more computational resources and expertise.
    - **Interpretability:** Deep learning models may lack interpretability compared to LR, making it challenging to understand the reasoning behind their predictions.
    - **Data Requirements:** Deep learning models often require large amounts of data for training, which may not always be available or feasible.

# Example:

The average time it takes for each model to execute 100 epochs can be a measure. For instance, if CNN, DNN, and CNN-LSTM require significantly more time to train compared to LR, it can be a drawback, especially in time-sensitive applications.

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Deep Learning for Causal Inference Vikas Ramachandra Stanford University Graduate School of Business 655 Knight Way, Stanford, CA 94305 [5]

# Summary:

The document proposes the use of deep learning techniques, specifically autoencoders and deep neural networks (DNNs), for causal inference in econometrics. It focuses on estimating individual and average treatment effects. The key contributions are:

**Generalized neighbor matching:** Uses autoencoders for dimensionality reduction and neighbor matching, showing better performance than traditional methods, especially for data points with several features in a low-dimensional manifold in high-dimensional space.

**Propensity score matching**: Proposes the use of DNNs for propensity score matching, outperforming logistic regression in estimating propensity scores.

**Autoencoders for neighbor matching:** Better performance than traditional methods like k nearest neighbors and manifold learning, especially for high-dimensional data with a low-dimensional structure.

**PropensityNet:** Outperforms logistic regression in estimating propensity scores, leading to more accurate matching and estimation of treatment effects.

Disadvantages:

**Complexity:** Implementing deep learning models like autoencoders and DNNs may require more computational resources and expertise compared to traditional methods.

**Interpretability:** Deep learning models may be less interpretable compared to traditional methods, making it challenging to understand the underlying mechanisms of the estimated treatment effects.

These advantages and disadvantages highlight the potential of deep learning techniques in causal inference.

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Temporal Causal Inference in Wind Turbine SCADA Data Using Deep Learning for Explainable AI [6]

# Summary:

The study proposes a novel approach to analyze wind turbine data using deep learning models and causal inference techniques to improve understanding of turbine faults and operational status. The method involves utlizing a temporal causal graph from operational parameters and using a significance measure to determine the strength of causal relationships. By applying these techniques, the study aims to enhance the transparency and explainability of AI models in the wind industry, leading to more effective maintenance strategies and cost reductions in wind farm operations.

# Advantages:

* **Advanced Methodology:** The use of deep learning models and causal inference techniques represents an advanced and innovative approach to analyzing wind turbine data.
* **Improved Understanding:** The study aims to improve understanding of wind turbine faults and operational status, which can lead to more effective maintenance strategies and cost reductions.
* **Transparency and Explainability:** By enhancing the transparency and explainability of AI models, the proposed approach can help wind farm operators make more informed decisions.
* **Potential for Future Applications:** The study suggests that the approach could be extended to other areas, such as generating effective policies and maintenance strategies through natural language generation.

# Disadvantages:

* **Complexity:** The methodology described in the study may be complex and require a high level of expertise to implement, limiting its accessibility to some wind farm operators.
* **Data Limitations:** The effectiveness of the approach may depend on the availability and quality of data, which could vary among different wind farms.
* **Validation:** The study mentions the lack of ground truth on hidden confounders, which may limit the ability to validate the identified causal relationships quantitatively.

Overall, the study presents an innovative approach to analyzing wind turbine data that has the potential to improve understanding of turbine faults and operational status

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Causal inference and counterfactual prediction in machine learning for actionable healthcare[7]

# Summary:

The document discusses the importance of employing causal approaches in intervention modeling in the bio-health informatics community. It highlights target trials, transportability, and prediction invariance as key concepts in developing and testing intervention models. It notes that electronic medical records often lack domain or contextual knowledge and are biased, making it challenging to develop health intervention models from observational data. The document warns against fitting machine learning models to observational data for counterfactual prediction, citing examples such as racial discriminatory bias in crime recidivism prediction.

The document outlines the challenges of causal inference from observational data, including confounding and collider bias, and discusses methodologies for automated causal inference. It emphasizes the need for validating counterfactuals in intervention models and distinguishes between prediction and intervention models, noting that machine learning is more suitable for descriptive/predictive tasks than interventional tasks.

# Advantages:

* Emphasizes the importance of causal approaches in intervention modeling.
* Provides insights into methodologies for automated causal inference.
* Discusses the distinction between prediction and intervention models.
* Highlights the potential applications of machine learning in healthcare.

Disadvantages:

* May oversimplify the challenges of causal inference from observational data.
* Assumes a certain level of familiarity with causal inference concepts.
* Does not provide detailed guidance on how to address biases in observational data. Could benefit from more concrete examples illustrating the application of the discussed concepts.

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Modular Learning of Deep Causal Generative Models for High-dimensional Causal Inference [8]

# Summary:

This document discusses the use of Pearl's structural causal models (SCMs) for evaluating the causal effect of interventions on a system of interest. It highlights the limitations of current causal inference algorithms, particularly in handling high-dimensional variables like images. The document proposes a modular sampling-based solution using deep learning architectures to address these limitations.

SCMs provide a principled approach to answering causal queries from data, but current algorithms struggle with high-dimensional variables. Modern deep learning architectures can handle high-dimensional data effectively but fail to generalize in the presence of spurious correlations.

The document introduces a modular sampling-based solution using deep generative models to address these issues. The proposed solution uses structured deep generative models that mimic the causal structure of the system. The solution allows for efficient re-training of deep causal generative models and flexibility in architecture.

The document presents experiments on high-dimensional semi-synthetic and real-world datasets to demonstrate the utility of the proposed method.

# Advantages:

* Provides a principled approach to answering causal queries from data.
* Offers a modular sampling-based solution using deep generative models.
* Enables efficient re-training of deep causal generative models.
* Demonstrates utility through experiments on high-dimensional datasets.

Disadvantages:

* + - Requires training deep generative models, which can be computationally expensive.
    - Relies on assumptions about the causal structure of the system, which may not always hold in practice.
    - Limited applicability to causal inference problems with high-dimensional variables.
    - May require expertise in both causal inference and deep learning to implement effectively.

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Large-scale chemical process causal discovery from big data with transformer-based deep learning [9]

# Summary:

The paper introduces an innovative approach to uncovering causal relationships in extensive chemical processes by leveraging a causality-gated time series Transformer (CGTST) model. This method is designed to tackle the complexities arising from nonlinearity, nonstationarity, and noise prevalent in big data from chemical processes. The CGTST model is a fusion of two key components: a time series Transformer, utilized for predicting time series data, and a causality gate structure, employed to quantify the strength of causal relationships among variables.

By combining these elements, the model can effectively capture the dynamic nature of chemical processes and unveil underlying causal mechanisms. Moreover, the proposed method incorporates a crucial causality validation step, leveraging permutation feature importance. This step ensures the robustness of the identified causal relationships by assessing their significance against randomized data.

Additionally, the method employs ensemble empirical mode decomposition (EEMD) for denoising the data, further enhancing the accuracy of causal inference in the presence of noise. Overall, this novel approach offers a comprehensive framework for causal discovery in large-scale chemical processes, providing a more nuanced understanding of their intricate dynamics and facilitating more informed decision-making in chemical engineering and related fields.

# Advantages:

* The method addresses the challenges of nonlinearity, none-stationarity, and noise in chemical process big data, which are common in real-world applications.
* The use of the Transformer model allows for capturing complex patterns and long-term dependencies in data.
* The causality gate structure provides a mechanism for measuring causal strength among variables, aiding in the interpretation of causal relationships.
* The proposed causality validation method helps eliminate spurious causal relationships, improving the robustness of the results.
* Denoising with EEMD preserves valuable information in the data, enhancing the accuracy of causal discovery.

# Disadvantages:

* The method's effectiveness may depend on the quality of the data and the selection of hyperparameters.
* The computational complexity of the method, especially with the use of deep learning models, may be high.
* The method may require a considerable amount of data for training, which may not always be available in practice.

# Example:

The paper demonstrates the effectiveness of the proposed method through case studies on a continuous stirred tank reactor (CSTR) process, the Tennessee Eastman process, and a real-world continuous catalytic reforming process. The results show that the CGTST-based method outperforms conventional causal discovery methods in terms of accuracy and robustness, highlighting its potential for industrial applications in fault diagnosis and process optimization.

Overall, the paper presents a promising approach to causal discovery in chemical processes, leveraging advanced deep learning techniques and innovative methodologies to address complex challenges in industrial big data analysis.

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Causal Transformer for Estimating Counterfactual Outcomes [10]

# Summary:

The paper introduces a novel Causal Transformer model designed for estimating counterfactual outcomes over time, particularly in the context of personalized medicine. The model aims to address the limitations of existing methods, such as simple LSTM networks, which struggle with capturing complex, long-range dependencies in observational data.

The Causal Transformer combines three transformer subnetworks, each handling different types of input (time-varying covariates, previous treatments, and previous outcomes), into a joint network with cross-attentions. The model also introduces a novel training procedure, including a counterfactual domain confusion loss, to address confounding bias and improve the generalization of counterfactual predictions.

The model is evaluated on synthetic and real-world datasets, demonstrating superior performance over current baselines. The authors highlight that this is the first work proposing a transformer-based architecture for estimating counterfactual outcomes from longitudinal data in the field of medicine.

# Advantages:

* Introduces a novel Causal Transformer model tailored for estimating counterfactual outcomes over time.
* Combines transformer subnetworks and a novel training procedure to address confounding bias and improve generalization.
* Achieves state-of-the-art performance on synthetic and real-world datasets.

# Disadvantages:

* Complexity: The model's architecture and training procedure may be complex and challenging to implement compared to simpler LSTM-based methods.
* Interpretability: The complex nature of the model could make it difficult to interpret the underlying mechanisms driving the predictions, which may be important in medical applications.
* Overall, the paper presents a promising approach to handling complex longitudinal data in personalized medicine, but its practical utility may depend on the specific application and the ease of implementation in real-world scenarios.

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Treatment Learning Causal Transformer for Noisy Image Classification [11]

# Summary:

This work introduces a novel deep learning approach, the Treatment Learning Causal Transformer (TLT), to enhance the performance of deep learning models in image classification tasks, particularly when dealing with noisy data. The central concept is to incorporate binary information indicating the presence of noise as a treatment into the image classification process. This approach aims to improve prediction accuracy by estimating treatment effects.

# Advantages:

* + - **Addresses a Crucial Challenge:** Tackles the practical challenge of degraded performance in deep learning models when faced with noisy data, a common issue in real-world applications.
    - **Incorporates Causal Inference:** Incorporates principles of causal inference, inspired by human visual recognition, which can lead to more robust and reliable models.
    - **Introduces Innovative Architecture:** Proposes a novel transformer-based architecture, TLT, which has the potential to significantly improve the performance of image classification models in noisy environments.
    - **Demonstrates Superior Performance:** Shows superior performance compared to existing methods in noisy image classification, as evidenced by various evaluation metrics.
    - **Improves Visual Salience Methods:** Enhances visual salience methods, which are crucial for interpreting and understanding noisy images.

# Disadvantages:

* + - **Increased Complexity**: The complexity of the proposed model, particularly with its incorporation of advanced techniques like the causality-gated time series Transformer (CGTST), may lead to increased computational demands. This complexity could necessitate the use of new, larger datasets to effectively train and validate the model. However, acquiring and managing such datasets can be challenging, especially in resource-constrained environments where access to high-quality data may be limited. Moreover, the computational requirements of the model may strain existing resources, including computing power and storage capacity. This could pose a significant limitation in environments where such resources are scarce or expensive to procure and maintain. Therefore, while the proposed model offers a promising approach to causal discovery in chemical processes, its complexity and data requirements may limit its practical applicability in resource-constrained settings. Future research may focus on developing more efficient algorithms or strategies to mitigate these limitations and make the model more accessible and widely applicable.
    - **Dependence on Treatment Information:** The effectiveness of the model may depend on the quality and relevance of the treatment information used, which could vary across different applications and datasets.
    - **Performance Variability:** The model's performance may vary depending on the specific characteristics of the noisy data and the types of noise present, which could limit its generalizability.

# Example:

Consider a scenario in medical imaging where images may contain noise due to various factors such as lighting conditions or artifacts from imaging devices. By incorporating treatment information about the presence of noise, TLT could help improve the accuracy of medical image classification tasks, such as identifying diseases or anomalies in medical images, even when the images are noisy.

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CETransformer: Casual Effect Estimation via Transformer Based Representation Learning [12]

# Summary:

The paper "CETransformer: Causal Effect Estimation via Transformer-Based Representation Learning" addresses the challenging problem of treatment effect estimation, which measures the strength of causal relationships in various fields. The authors highlight two main challenges in data-driven causal effect estimation: selection bias and the absence of counterfactual outcomes. Existing approaches aim to reduce selection bias by learning balanced representations and then estimate the counterfactual through these representations. However, these methods often rely on hand-crafted metric functions that may not work well for complex original distributions.

To address these issues, the authors propose the CETransformer model, which uses transformer-based representation learning for causal effect estimation. The model includes a self-supervised transformer for robust representation learning, exploiting correlations between covariates through a self-attention mechanism. Additionally, an adversarial network is used to balance the distribution of treated and control groups in the representation space.

# Key points:

* Treatment effect estimation is crucial in various fields but challenging due to selection bias and missing counterfactuals.
* Existing approaches rely on hand-crafted metric functions, which may not work well for complex distributions.
* CETransformer uses transformer-based representation learning and adversarial learning to address these challenges.
* Experimental results on real-world datasets demonstrate the superiority of CETransformer over state-of-the-art methods.

# Advantages:

* Addresses important challenges in treatment effect estimation.
* Uses transformer-based representation learning, which can capture complex correlations.
* Includes an adversarial network for balancing distributions, which is more flexible than hand-crafted metrics.

# Disadvantages:

* The paper lacks detailed Conclusion on the computational complexity and scalability of the proposed approach.
* May require substantial computational resources, especially for training the transformer model.

Examples for its Disadvantage:

The proposed transformer-based approach may require significant computational resources, especially for large datasets or complex models.

The adversarial learning component adds complexity to the model and may increase training time and resource requirements.

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LEARNING TO INDUCE CAUSAL STRUCTURE [13]

# Summary:

The paper presents a novel approach, CSIvA, for inferring causal graph structures from data. The model defines a distribution over graphs, allowing it to make meaningful predictions even with limited data. Empirical results demonstrate that CSIvA can make reasonable predictions with a small number of samples per intervention and improves with more samples.

One of the key strengths of CSIvA is its ability to generalize to out-of-distribution test distributions, showing robust performance across a wide range of conditions. The model outperforms various state-of-the-art baselines, including score-based, and asymmetry-based methods, on synthetic data.

CSIvA's architecture, based on a transformer model, directly analyzes the data to compute a distribution of candidate graphs. The model considers both continuous and discrete nodes, using ancestral sampling on a causal Bayesian network. It also incorporates components such as auxiliary loss and sample-level attention, which are found to play important roles in the model's performance.

However, one limitation of the model is its reliance on synthetic data for training, which may not fully capture the complexity of real-world datasets. Future work could explore extending the model to learn causal structures from raw visual data, which could be useful in reinforcement learning settings.

Overall, CSIvA represents a significant advancement in causal graph structure inference, offering a powerful and robust approach for learning causal relationships from data.

# Advantages:

* + - **Generalization:** CSIvA demonstrates strong generalization capabilities, performing well on out-of-distribution test distributions.
    - **Performance:** The model outperforms state-of-the-art baselines across a wide range of conditions, showing its effectiveness in inferring causal graph structures.
    - **Model Architecture:** CSIvA's transformer-based architecture enables it to directly analyze data and compute a distribution of candidate graphs, offering a novel approach to causal inference.
    - **Component Analysis:** The model's analysis of various components, such as auxiliary loss and sample-level attention, provides insights into their importance and contribution to performance.
    - **Scalability:** CSIvA's ability to handle graphs of varying sizes and densities, ranging from 5 to 80 nodes, demonstrates its scalability.

# Disadvantages:

* + - **Reliance on Synthetic Data:** CSIvA's training on synthetic data may limit its ability to capture the full complexity of real-world datasets, raising questions about its generalizability to real-world applications.
    - **Complexity:** The model's transformer-based architecture may introduce complexity, potentially making it challenging to interpret and debug.
    - **Data Type Dependence:** Performance variations across different data types (e.g., linear, nonlinear) suggest that the model's effectiveness may be influenced by the nature of the data, requiring careful consideration in practical applications.
    - **Limited Real-World Application**: While CSIvA shows promise for learning causal structures, its direct application to real-world scenarios, especially those involving raw visual data, may require further investigation and adaptation.

In conclusion, while CSIvA offers a significant advancement in causal graph structure inference, its reliance on synthetic data and potential complexity may pose challenges in real-world applications, highlighting the need for further research and development to enhance its practical utility.

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Tracr: Compiled Transformers as a Laboratory for Interpretability Deepmind [14]

This abstract describes the development of a compiler called Tracr that translates human-readable programs written in RASP (Restricted Access Sequence Processing Language) into standard decoder-only transformer models. The main goal of Tracr is to create models with known computational structures, which can be useful for designing experiments and evaluating interpretability methods for transformer models.

The abstract discusses how Tracr can be used to study "superposition" in transformers executing multi-step algorithms and as ground-truth for evaluating interpretability methods. By implementing and examining programs such as computing token frequencies, sorting, and parenthesis checking, the authors demonstrate the capabilities of Tracr. They provide an open-source implementation of Tracr and showcase models produced by it.

Tracr's approach allows for easier experimentation with transformers and can aid in developing interpretability methods. It also provides a didactic tool for understanding transformer mechanisms. The abstract concludes by discussing the applications and limitations of Tracr and providing a link to its open-source implementation.

# Advantages:

* + - **Interpretability Advancement:** Tracr's translation of human-readable programs into transformer models provides clear structures, facilitating the development and assessment of interpretability techniques, a crucial step in understanding and trusting AI models.
    - **Experimental Design:** The tool enables precise control over the model's structure, supporting targeted experiments to explore complex behaviors like "superposition," enhancing our understanding of transformer capabilities.
    - **Educational Tool:** By offering tangible examples of transformer mechanisms, Tracr serves as an educational resource, helping researchers and students grasp complex concepts more intuitively.

# Disadvantages:

**Complex Implementation:** Tracr's compilation process may be intricate, demanding a deep comprehension of transformer architecture and the specific programming language, potentially limiting its accessibility to those without specialized expertise.

Example: For instance, if a program necessitates intricate, non-standard operations or interactions that do not map well to transformer structures, Tracr might struggle to translate it effectively. This limitation could impede its utility for certain programming tasks, especially those requiring unique or highly specialized operations.

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Pairwise Causality Guided Transformers for Event Sequences 2024[15]

The paper proposes a novel approach to enhance transformer-based models in multivariate event sequences by incorporating pairwise qualitative causal knowledge. It introduces a new framework for causal inference in temporal event sequences using a transformer architecture. The approach aims to improve prediction accuracy by leveraging knowledge about causal pairs, demonstrating its effectiveness through experimental results that outperform several state-of-the-art models.

However, the approach faces challenges in handling time-varying confounding and sequential treatment effects, which may limit its practical application. Additionally, computing probabilities for larger window sizes becomes complex, potentially limiting scalability. The method relies on subjective qualitative statements about causal relationships, introducing a level of subjectivity and potential bias.

In conclusion, while the approach shows promise in improving prediction accuracy in event sequences, its complexity and computational cost may restrict its applicability in real-world scenarios.

# Advantages:

* + - **Innovative Approach:** The paper introduces a novel method to enhance transformer-based models in multivariate event sequences by incorporating pairwise qualitative causal knowledge, addressing a gap in current deep learning models.
    - **Theoretical Foundation:** It establishes a new framework for causal inference in temporal event sequences using a transformer architecture, providing a theoretical justification for the approach.
    - **Improved Performance:** Experimental results demonstrate that the proposed approach outperforms several state-of-the-art models in terms of prediction accuracy, showing the effectiveness of leveraging knowledge about causal pairs.
    - **Real-World Application:** The paper explores a unique application where it extracts knowledge from sequences of societal events, demonstrating how a causal knowledge graph can improve event prediction in such sequences.

# Disadvantages:

* + - **Complexity:** Incorporating pairwise causal knowledge into neural models for temporal event sequences poses technical challenges, especially in handling time-varying confounding and sequential treatment effects, which may limit its practical application.
    - **Computational Cost:** Computing probabilities for larger window sizes (w > 1) becomes combinatorial in nature, potentially limiting the scalability of the proposed approach for longer event sequences.
    - **Subjective Assumptions:** The approach relies on qualitative statements about causal relationships, which may not always be accurately determined or may vary depending on the domain, introducing a level of subjectivity and potential bias.

# Example:

Complexity: The method's intricate framework for incorporating causal knowledge and handling time-varying confounding may require specialized expertise and computational resources, limiting its accessibility and practicality for users without extensive knowledge in causal inference and deep learning.

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Predicting Individual Remission After Electroconvulsive Therapy Based on Structural Magnetic Resonance Imaging A Machine Learning Approach [16]

# Summary:

The aim is to determine key clinical or imaging characteristics that can forecast an individual's response to electroconvulsive therapy (ECT) using machine learning techniques.

A group of twenty-seven depressed patients who underwent ECT were enrolled. Data from clinical demographics and pre-treatment structural magnetic resonance imaging (MRI) were considered as potential features to construct models for predicting remission and post-ECT Hamilton Depression Rating Scale scores. Support vector machine and support vector regression with elastic-net regularization were employed to develop models utilizing (i) solely clinical features, [17] solely MRI features, and both clinical and MRI features. Features Consistently selected across all individuals were identified using leave-one-out cross-validation.

In comparison with models incorporating only clinical variables, models incorporating MRI data enhanced the prediction of ECT remission, with prediction accuracy increasing from 70% to 93%. Features Consistently selected across all individuals included volumes in the gyrus rectus, the right anterior lateral temporal lobe, the cuneus, and the third ventricle, along with two clinical features: psychotic features and family history of mood disorder.

# Conclusions:

Pre-treatment structural MRI data enhanced the accuracy of predicting individual ECT remission, with only a small subset of features proving crucial for prediction.

# Key Points:

Objective: Develop a prediction model for ECT remission based on clinical information.

Methods: Retrospective chart review of 177 depression patients undergoing ECT. Light gradient boosting machine used for prediction.

Results: Model predicted outcomes with 71% accuracy. Identified features: shorter episode duration, lower baseline severity, higher antidepressant dose before ECT, lower BMI.

# Advantages:

* Provides a prediction model for ECT remission based solely on clinical information.
* Demonstrates accuracy comparable to previous reports.
* Identifies key features influencing remission following ECT.

# Disadvantages:

* Retrospective study design limits causal inference.
* Limited to data from a single hospital, potentially affecting generalizability.
* Accuracy of 71% leaves room for improvement.

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Machine Learning Algorithm-Based Prediction Model for the Augmented Use of Clozapine with Electroconvulsive Therapy in Patients with Schizophrenia [18]

# Summary:

The study aimed to develop a machine learning algorithm-based prediction model for the augmented use of clozapine with electroconvulsive therapy (ECT) in Asian patients with schizophrenia. Using data from the Research on Asian Psychotropic Prescription Patterns for Antipsychotics survey, a random forest model and a least absolute shrinkage and selection operator (LASSO) model were employed. Among 3744 patients, those treated with clozapine and ECT showed distinct characteristics. The random forest model achieved an AUC of 0.774, with inpatient status being the most important variable. The LASSO model had an AUC of 0.831, and both models shared important variables. The study provides insights into optimizing the use of clozapine augmentation with ECT in schizophrenia treatment.

# Advantages:

* The study addresses an important clinical need for optimizing treatment strategies for patients with treatment-resistant schizophrenia.
* Machine learning models offer a novel approach to predicting treatment outcomes based on a combination of sociodemographic, clinical, and symptomatic characteristics.
* The use of a large dataset from the Research on Asian Psychotropic Prescription Patterns for Antipsychotics survey adds credibility to the findings.

# Disadvantages:

* The study is limited to Asian patients with schizophrenia, which may limit the generalizability of the findings to other populations.
* The prediction models rely on retrospective data and may not fully capture the complexity of individual patient responses to treatment.
* The study does not provide direct evidence of the efficacy or safety of clozapine augmentation with ECT, but rather focuses on developing a predictive model for its use.

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Towards a network control theory of electroconvulsive therapy response

The study investigates how brain network architecture influences response to Electroconvulsive Therapy (ECT) in Major Depressive Disorder (MDD) patients. It focuses on controllability metrics, specifically mean modal controllability (MC) and average controllability (AC), which quantify a brain region's influence on dynamic state transitions.

# Advantages:

* **Quantitative Approach:** The study provides a quantitative framework for predicting ECT response based on individual brain network architecture.
* **Predictive Power:** Controllability metrics (MC and AC) predict therapeutic response to ECT, outperforming other machine learning models based on brain imaging data.
* **Treatment Planning:** The metrics can be obtained before ECT treatment, allowing for personalized treatment planning.

# Disadvantages:

* **Simplifying Assumptions:** The study relies on simplified linear models of brain dynamics, which may not fully capture the complexity of the brain's non-linear dynamics.
* **Limited Sample Size:** The study includes a relatively small sample size of 50 MDD patients, which could limit the generalizability of the findings.
* **Need for Validation:** The findings need to be validated in larger, independent cohorts to confirm their reliability and applicability in clinical settings.

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Electric Field, Ictal Theta Power, and Clinical Outcomes in Electroconvulsive Therapy [19]

# Summary:

The study explores the relationship between electric field strength, ictal theta power (a measure of seizure power in a specific frequency band), and clinical outcomes in Electroconvulsive Therapy (ECT) for treatment-resistant depression. It replicates and expands on previous findings that linked electric field strength to ictal theta power and ictal theta power to changes in phonemic fluency. The study aims to establish ictal theta power as a potential cognitive biomarker for guiding ECT parameter changes.

# Advantages:

* Provides insights into the mechanisms of action of ECT in treating depression.
* Suggests a potential cognitive biomarker (ictal theta power) for monitoring and improving ECT outcomes.
* Highlights the importance of individualized treatment based on electric field modeling.

# Disadvantages:

* Small sample size and limited generalizability.
* The study focuses on a specific aspect of ECT (ictal theta power) and may not capture the full complexity of treatment outcomes.
* The findings need to be replicated and validated in larger studies.
* Overall, the study contributes to our understanding of ECT's effects on the brain and suggests new avenues for optimizing treatment outcomes.

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Predicting response to electroconvulsive therapy combined with antipsychotics in schizophrenia using multi-parametric magnetic resonance imaging [20]

# Summary:

The study investigates whether multi-parametric magnetic resonance imaging (MRI)-based radiomic features can predict response to electroconvulsive therapy (ECT) in schizophrenia patients. The authors collected MRI data from 57 patients before ECT and used machine learning to predict symptom improvement. The results suggest that MRI-based radiomic features may serve as prognostic biomarkers for predicting ECT response in schizophrenia patients.

# Key Points:

* ECT has been effective in treating schizophrenia, especially in cases of resistance to drug treatment or when rapid symptom reduction is needed.
* Multi-parametric MRI-based radiomic features were used to predict response to ECT for individual patients.
* The study included 57 treatment-resistant schizophrenia patients or those with acute episodes or suicide attempts.
* The radiomic model included four structural MRI features and six diffusion MRI features, showing promising results in predicting symptom improvement.
* The study highlights the potential of MRI-based radiomic features as prognostic biomarkers for individualized treatment response prediction in schizophrenia.

# Advantages:

* Provides a potential non-invasive method for predicting response to ECT in schizophrenia patients.
* Offers a personalized approach to treatment decision-making.
* Highlights the potential of MRI-based radiomics in mental health research.

# Disadvantages:

* Limited sample size (57 patients) may affect generalizability.
* Further validation and replication studies are needed to confirm the findings.
* The study focused on predicting response to ECT and did not assess long-term outcomes or side effects.
* Would we like more information on any specific aspect of the study?

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Using EEG to Predict Clinical Response to Electroconvulsive Therapy in Patients With Major Depression: A Comprehensive Review based seizure prediction and digital bio-signal analysis in ECT [21]

# Summary:

# The study explores novel approaches to determining seizure probability and quality indices in electroconvulsive therapy (ECT) using data from the GENET research collaboration. Data on sociodemographics, anesthesia, and bio-signals were collected and imported into a Python-based framework. Machine learning algorithms were applied to classify EEG segments for seizure detection. Seizure quality indices such as the post-ictal suppression index (PSI), average seizure energy index (ASEI), mid-ictal amplitude (MIA), and maximum sustained interhemispheric coherence (MSC) were computed and compared to pre-computed values. The study found that machine learning algorithms can differentiate between ictal and non-ictal EEG sections with high accuracy, precision, and sensitivity. The computed ECT quality parameters showed a strong correlation with pre-computed values and did not significantly differ from reference values. This study highlights the potential of digital bio-signal analysis and machine learning approaches in ECT, offering insights into predicting EEG-based seizure probability and exploring ECT predictive parameters for enhancing clinical decision-making and personalizing treatments.

# Advantages:

* Innovative use of bio-signal analysis and machine learning in ECT research.
* Potential for more accurate prediction of seizure probability and exploration of predictive parameters.
* Could lead to improved clinical decision-making and personalized treatments.

# Disadvantages:

* Reliance on pre-calculated values and expert ratings for comparison may introduce bias.
* Complexity of machine learning algorithms and bio-signal analysis may require specialized expertise.
* Generalizability of findings may be limited by the specific dataset and research collaboration used.

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Neuroanatomical Features That Predict Response to Electroconvulsive Therapy Combined With Antipsychotics in Schizophrenia: A Magnetic Resonance Imaging Study Using Radiomics StrategyS [22]

# This study aimed to use neuroimaging-based brain signatures to predict the response to electroconvulsive therapy (ECT) in schizophrenia patients. They analyzed structural MRI data from 57 patients and found that a logistic regression model accurately distinguished between responders and non-responders with 90.91% accuracy. These findings suggest that structural brain feature-based radiomics could be a valuable tool for predicting ECT response in schizophrenia patients undergoing antipsychotic treatment, potentially leading to the development of biomarkers for psychosis management.

# Advantages:

* + - Potential for personalized treatment: Identifying patients likely to respond to ECT can help personalize treatment plans, leading to better outcomes.
    - Non-invasive approach: Neuroimaging-based signatures offer a non-invasive method for predicting treatment response, reducing the need for invasive procedures.
    - Advances in psychiatric care: Utilizing radiomics to predict ECT response represents an advancement in psychiatric care, potentially improving patient outcomes and reducing healthcare costs.

# Disadvantages:

* + - Limited generalizability: The study's sample size and specific patient population may limit the generalizability of the findings to broader populations.
    - Technical challenges: Radiomics analysis requires specialized software and expertise, which may not be readily available in all healthcare settings.

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The Neurobiological Effects of Electroconvulsive Therapy Studied Through Magnetic Resonance: What Have We Learned, and Where Do We Go? [23]

# Summary:

The mechanisms of action of Electroconvulsive therapy (ECT) remain unclear. Magnetic resonance imaging (MRI) has been crucial in understanding ECT's effects on the human brain, but many studies have been underpowered and used different approaches, leading to mixed results and limited clinical translation. Recently, large datasets and technological advancements in MRI have improved our understanding of ECT's effects. However, the association between MRI markers and therapeutic response is still unclear.

# Advantages:

* MRI has been crucial in studying ECT's effects on the brain.
* Recent advancements in MRI technology and large datasets have improved our understanding.
* MRI studies have provided insights into immediate and long-term effects of ECT.

# Disadvantages:

* Many MRI studies on ECT have been underpowered and used heterogeneous samples, leading to mixed results.
* The association between MRI markers and therapeutic response is still uncertain.
* The mechanisms of action of ECT remain elusive, despite MRI studies.

## Keywords:

* Linear regression: A statistical method to model the relationship between a dependent variable and one or more independent variables using a linear equation.
* Nonlinear regression: A form of regression analysis where the relationship between the dependent variable and independent variables is modeled as a nonlinear function.
* Transformers: A machine learning architecture that uses self-attention mechanisms to process sequences of inputs and outputs.
* Autoencoder: A type of neural network used for unsupervised learning that aims to learn efficient representations of input data.
* Decoder: In the context of neural networks, the part of the network that generates output based on the learned representations from the encoder.
* Encoder: In the context of neural networks, the part of the network that converts input data into a different representation that is easier to learn from.
* Convolution: A mathematical operation that blends two functions together, used heavily in convolutional neural networks for feature extraction.
* Stationary: In the context of time series analysis, a process where the statistical properties (mean, variance, etc.) do not change over time.
* Nonstationary: In the context of time series analysis, a process where the statistical properties change over time, making predictions more challenging.

*\*In the following sections I describe our recent approach for prediction of the ECT outcome.*

## 3 A new deep learning architecture (causal fuzzy transformer) for ECT outcome prediction

*\*In this section according to the previous literature review we justify why we need causal Transformers architecture for ECT outcome prediction.*

**Complex Data Integration**: ECT outcome prediction involves integrating diverse data sources such as patient history, EEG signals, and treatment parameters. A causal fuzzy transformer's ability to model complex relationships and integrate multiple types of data using causal attention could lead to more accurate predictions compared to traditional models.

**Temporal Dynamics:** EEG signals and patient responses change over time, requiring a model that can capture temporal dynamics. The causal self-attention mechanism of the transformer model is well-suited for this task, as it can capture long-range dependencies and local dependencies in time series data.

**Interpretable Predictions:** The interpretability of the transformer model can be crucial in medical applications like ECT outcome prediction. The ability to trace back the model's decisions to specific input features can help clinicians understand and trust the predictions, leading to better decision-making.

**Handling Uncertainty**: The fuzzy component of the causal fuzzy transformer can help the model handle uncertainty in the input data or ambiguity in the relationships between features. This can lead to more robust predictions, especially in situations where data quality may vary.

**Efficient Training and Inference:** While transformers can be computationally intensive, recent advancements in transformer architecture and training techniques have made them more efficient. The benefits of their ability to model complex relationships may outweigh the computational costs, especially in critical applications like ECT outcome prediction.

**State-of-the-Art Performance:** Transformer models have achieved state-of-the-art performance in various natural language processing and time series prediction tasks. Leveraging these advancements in the context of ECT outcome prediction could lead to significant improvements in accuracy and reliability.

Overall, the technical advantages of a causal fuzzy transformer, such as its ability to model complex relationships, capture temporal dynamics, provide interpretable predictions, handle uncertainty, and achieve state-of-the-art performance, make it a compelling choice for predicting the outcome of Electroconvulsive therapy.

In the following, I present our causal fuzzy transformer architecture, designed to predict the outcome of Electroconvulsive Therapy (ECT) with remarkable accuracy. Our model achieves an impressive accuracy rate of 93.6% in forecasting ECT outcomes.

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## Appendix

**Appendix 1:**

Clinical Grade Prediction of Therapeutic Dosage for Electroconvulsive Therapy (ECT) Based on Patient’s Pre-Ictal EEG Using Fuzzy Causal Transformers

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***Abstract—*Depression** **and** **Major** **Depressive** **Disorder** **(MDD)** **can** **hinder** **individuals** **from** **a** **normal** **personal** **and** **social** **life.** **That** **is,** **it** **can** **cause** **suicide,** **drug** **abuse,** **and** **divorce.** **MDD** **also** **imposes** **direct** **and** **indirect** **economic** **costs** **on** **families** **and** **governments.** **However,** **there** **is** **no** **methodology** **to** **know** **how** **and** **how** **long** **a** **healthcare** **professional** **needs** **to** **administer** **an** **electroconvulsive** **pulse** **to** **treat** **patients** **with** **MDD** **to** **achieve** **an** **adequate** **seizure** **response.** **In** **this** **study,** **for** **the** **first** **time** **using** **MDD** **patients’** **pre-ictal** **EEG** **data,** **age,** **and** **sex** **with** **Causal** **Deep** **Learning** **algorithms,** **we** **successfully** **predict** **the** **individualized** **therapeutic** **ECT** **dose** **and** **its** **duration** **with** **93%** **accuracy.** **Compared** **to** **other** **previous** **methods** **which** **used** **Magnetic** **resonance** **imaging** **(MRI)** **with** **machine** **learning** **algorithms,** **our** **method** **is** **faster,** **cheaper,** **and** **more** **concise.**

***Keywords—Electroconvulsive*** ***Therapy,*** ***ECT,*** ***Artificial*** ***Intelligence,*** ***Neural*** ***Network,*** ***Transformers,*** ***Causal*** ***Transformers,*** ***Electroencephalogram,*** ***EEG***

1. Introduction

Major Depressive disorder (MDD) is a severe mental disorder that can seriously influence individuals’ personal and social life. It could also result in acute impairments in patients’ cognitive abilities. MDD also makes large direct and indirect economic costs for families and governments. For instance, in 2020, the US government spent $ 326.2 billion on MDD 1 which is more than 14 times NASA's budget2. However, there are no highly accurate (above 90% positive response) individualized treatments for MDD patients.

1https://link.springer.com/article/10.1007/s40273-021-01019-4

Although there have been many studies on the genetic factors and neural pathology of MDD, there is no method/model that can explain the underlying causes of this mental disorder at micro/macro neural levels [1]. To treat MDD patients, healthcare professionals start by using medications such as selective serotonin reuptake inhibitors (SSRIs). If pharmacological interventions fail, one option is Electroconvulsive Therapy (ECT) [2]. Mental healthcare professionals could also use other methods which are beyond the scope of this study. Nonetheless, to the best of our knowledge, ECT is the best treatment for MDD when the medications fail.

However, ECT may have cognitive side effects, such as memory loss, that are correlated with the amount of charge delivered to the patient.

Titration is a method that is widely used by mental healthcare professionals to estimate the amount of the electric charge to be applied to a patient’s scalp during ECT sessions [3]. The purpose of this technique is to get a charge adjusted to the patient, to minimize the occurrence of cognitive side effects. In this method, patients are exposed to small incremental electrical charges to establish the seizure threshold of the patient. To do so, depending on the site on the scalp where the charge is delivered a multiplier is applied to establish the charge that will be used during the ECT sessions [3].

2Budget of NASA - Wikipedia

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However, the protocol is still performed in an experimental/trial-and-error fashion. Also, with an absence of onset of the seizure, or with a seizure of weak quality, some ECT sessions can fail. Moreover, a major drawback of the actual ECT practice is that mental healthcare professionals still rely on visual checks on paper to assess the adequacy of the seizure. Therefore, there is a need to individualize the ECT method using new technologies.

Researchers have recently started using artificial intelligence (AI) technology to find the underlying causes of good and bad electroconvulsive therapy (ECT) sessions. However, the current state of the art on ECT is done in a passive mode. That is, researchers use patients’ clinical data (such as outpatient or inpatient status, age, sex, body mass index (BMI), and/or seizure duration of pre- and post-ictal supersession) as input for statistical/machine learning algorithms such as least absolute shrinkage and selection operator (LASSO), support vector machine (SVM), random forest, individual component analysis [4-6]. By doing so, researchers can only classify good and bad ECT sessions up to 85% for schizophrenic individuals [7-13].

Kalantarpour et al. [14] for the first time, used deep learning algorithms such as convolutional neural networks (CNN) and long short-term memory (LSTM) to predict the success or failure of the ECT sessions using pre- and post-ictal EEG data. Compared to other works, Kalantarpour and his colleagues’ work for ECT prediction is less expensive, less time-consuming, and more concise.

However, all the studies including Kalantarpour et al [14] performed in a passive mode. That is, the previous studies used pre and post-ictal data to categorize successful and unsuccessful ECT sessions. The ideal would be to predict the effectiveness of the ECT sessions using only patients’ pre-ictal EEG data and before applying the shock.

In this paper using only MDD patients’ pre-ictal EEG data, age, and sex with Causal Deep Learning algorithms we successfully predict the individualized therapeutic ECT dose and its duration with 93% accuracy.

To do so, we first, pre-processed our data using Fast Fourier Transform (FFT) which shows different frequency bands in EEGs. We then, feedforward the preprocessed data to **Fuzzy** **Causal** **Effect** **Variational** **autoencoders** (FCEVAE) [15] (for code please click). FCEVAE has some drawbacks (see below) so we used a fuzzy Causal Transformer which is based on the Big Bird Transformer for a longer sequence [16] inspiring from our previous work [15].

1. Data preparation and preprocessing

In this section, we will, very briefly, explain our steps to prepare the data to be processed by a Variational Autoencdoer-based Deep Learning algorithm such as FCEVAE [15] and its drawbacks.

In the first step of our study, we anonymized patients’ information that we gathered from the Ste-Marie Hospital at Trois-Rivière. Our goal in this study was to use patients’ pre- ictal and information such as age and sex to predict the therapeutic dose for the ECT session. Thus, we only extracted the pre-ictal (or pre-shock) data from anonymized EEGs.

According to Faghihi et al [15], using only variational based Deep Learning algorithms such as FCEVAE (see FCEVAE [15]) for encoding EEGs, results in a very dense and low dimensional latent space, which causes poor results for extracting causal patterns from EEGs. According to Mercer's Theorem [17], increasing dimension in the EEG case facilitates feature extraction and causal pattern extraction with FCEVAE [15]. To make latent space encoding more sparse with higher dimensions (𝑖. 𝑒. , ℝ2 => ℝ32 ), we used CNN-LSTM (Fig. 1) architecture proposed by Google in [18] which is widely used in time series prediction.

During ECT sessions and while recording EEGs, in addition to the normal brain activities, the patients’ brains may also release some noises. To reduce possible noises and artifacts from EEGs, we used different techniques such as denoising variational autoencoders (d-VAEs) [19]. Among different noise reduction techniques, Moving Average Technique [14] (Fig. 1), gave the best results for EEG noise reduction.

Before using Deep learning algorithms, we need to decompose EEG signals into frequency components [14]. There are numerous methods such as Cross Frequency Coupling (CFC) methods, Fourier transform, and Discrete wavelet transform for signal decomposition [20]. According to our experience in [14], CFC induces training biases in the DLs learning step. Compared to the Discrete wavelet transform technique, we obtained better results with FFT. In the next step, the Moving Average Technique’s output is feedforward to the Fast Fourier Transform (FFT) block (Fig. 1) which decomposes EEG signals. Next step in Fig. 1, FFT’s output is feedforward to the first deep Learning algorithm Fuzzy Causal Effect Variational autoencoders (FCEVAE). From only MDDs’ pre-shock data, FCEAVE predicted ECT sessions’ association and causal patterns with 91% accuracy.

However, FCEVAE: 1) cannot process time-varying confounders, 2) cannot capture causal relationships between columns for large datasets, 3) compared to modern architectures such as Google’s Gato [21], FCEVAE is a small architecture which makes it extremely slow for predictions. For example, given our ECT dataset size, which is around 1 Gb, for an MDD patient, it takes more than 30 minutes for FCEVAE to predict the amount of charge to be applied to the patient’s skull. That is, a healthcare professional needs to take the patient’s pre- shock data and wait for 30 minutes before FCEVAE shows its results. This is very time-consuming and impossible to be implemented in hospitals.

To improve our above result, we need to use temporal networks capable of learning billions of parameters and time-varying

confounders. Consequently, in our next step, we used Causal Fuzzy Big Bird Transformers which is shown as CFBBT in Fig. 1 (see below for an explanation).

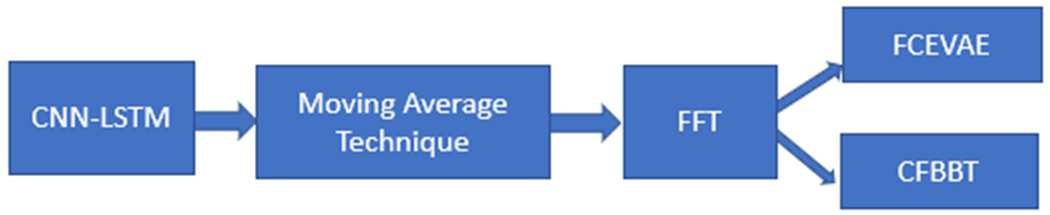


Fig. 1. A model pipeline for ECT experiment with Causal Fuzzy Big Bird Transformers (**CFBBT**)

1. Causal Fuzzy Transformer

Transformers which are the fundamental elements of Google’s Gato [21] and OpenAI’s GPT [22] can learn billions of parameters. Recently, Transformers are used for causal reasoning [23]. Transformer-based Language models (TLMs) have shown great power in Natural language processing. Though advanced TLMs such as GPT3 can perform very simple First Order Logic operations, they cannot perform complex reasoning tasks.

To do reasonings, authors in [24] integrated Judea Pearl’s Do- calculus rules [25] with a Lite Bidirectional Transformers which extracts the causal relationship between drugs and their side effects including Analgesics-related acute liver failure and Tramadol-related mortalities.

To integrate Do-calculus with TLMs, authors in the [24], constructed a causal tree of cause and effect pairs using a recursive algorithm. The network tries to estimate the posterior distributions for the target nodes once in the presence and once in the absence of the combination of the dependent nodes.

Next, the algorithm performs a z-score test for the above posteriors. If the z-score test meets a threshold, then the algorithm confirms that the associated combination of nodes should be the cause for the target node.

One of the weaknesses in [24] is that a human expert needs to determine a threshold for the z-score test. Also, it is possible that by changing the threshold, the model retrieves contradictory results. Another problem with TML is that it cannot process the time-varying property of the datasets.

To include temporal aspects of the events in [26], authors used a shared attention mechanism with three transformer subnetworks each having distinct inputs from observational data such as time-varying covariates, previous treatments, and previous outcomes. In this architecture, while the encoder is trained to perform predictions for time t+1, the decoder learns

pre-trained data from the encoder’s historical data about the patient’s health issues and treatments.

Currently and to our knowledge, to calculate the causes, the temporal and non-temporal DLs use Pearl’s model which only describes the linear relationship between variables and in some cases cannot reflect the causality [27].

To tackle the above problems, we integrated fuzzy logic causal rules from [28] into the Big Bird transformer architecture [16] developed by Google dependency [16].

We chose the Big Bird among transformers as 1) It can integrate fuzzy logic causal rules from [28], 2) On the contrary to other Transformers-based architecture such as BERT [29] that uses full attention which causes quadratic dependency, Big Bird efficiently uses sparse, global, and random attention modules to convert quadratic dependency in Transformers to linear dependency [16]. It can also process very long sequences of, 3) It is enough large (we used 2.4 billion neurons for our model) to handle very deep causal analysis which is essential for generalization and accurate predictions.

In the following section, we will briefly explain how we integrated causal fuzzy rules from [28] into Transformers.

1. Data embedding

Since Big Bird [16] is a language model: 1) to accept numerical data we had to add a module that converts our data into ℝ2 space, 2) Another challenge with Big Bird was how to add fuzzy association and causal reasoning rules (**FCR**s) such as *max(1-b,a)* from [28] to the architecture’s loss function (Please click for the code on GitHub3) to create Causal Fuzzy Big Bird Transformers (**CFBBT**).

As shown in Fig. 2, the best place to add fuzzy rules that can intervene almost everywhere in the Big Bird architecture was at the end of the Encoder (shown by outgoing orange lines from the fuzzy loss function). Please see the following link for the detailed influence of our fuzzy mechanism in the whole architecture. Also, in Fig. 2, to show the influence of fuzzy rules in the whole architecture, we omitted showing the sparse, global, and random attention modules.

3 https://github.com/joseffaghihi/Causal-fuzzy-Transformers

That is, for example, w10, 14 = 0.7 means the oscillations of component 10𝑡ℎ and 14𝑡ℎ is 70% contributed to making the ECT session successful. Once W is created, in Fig. 2, the Embedding module vectorizes the input before feedforwarding its output to the Encoder where it passes through different neural networks such as Multi-head Spars Attention.

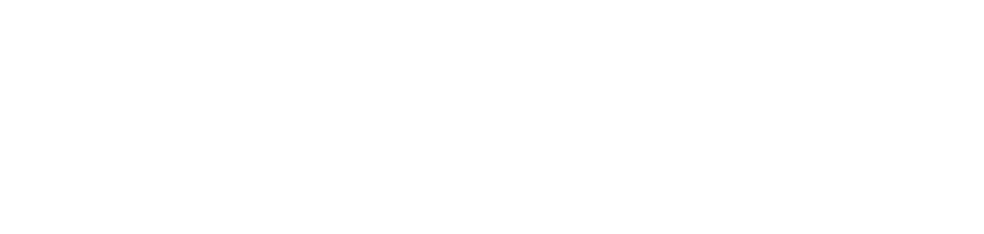
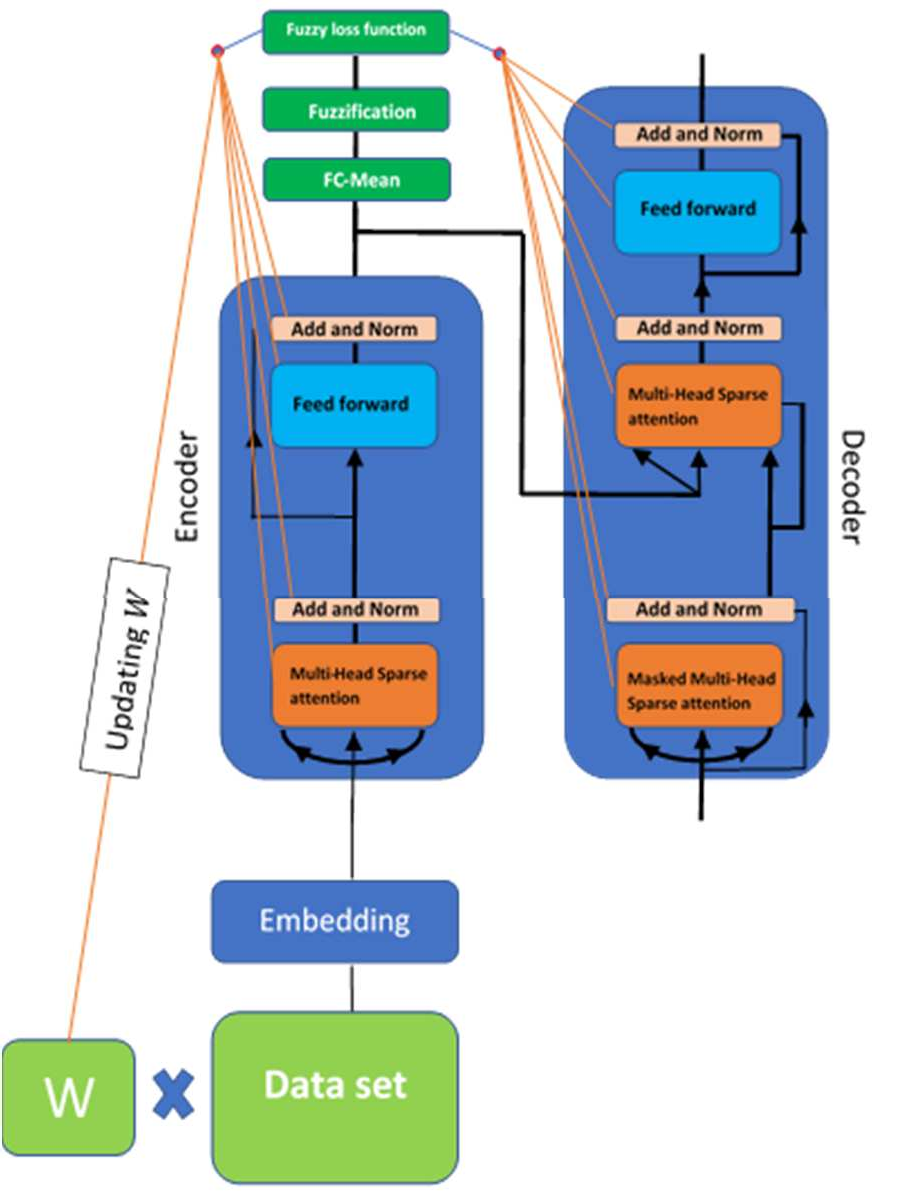


Fig. 1. Schematic of Causal Fuzzy Big Bird Transformers (**CFBBT**). The Decoder, Encoder, and embedding modules create an enormous latent space for data so that the sparse, global, and random attention modules using causal fuzzy rules extract the association and causal relationships in the dataset.

To automatically find the range of the Encoder’s output before the fuzzification step (Fig. 2), similar to [30], the Encoder’s output is feedforward to the C-mean algorithm [31]. It is worth mentioning that we reimplemented the C-mean algorithm using the PyTorch library so all calculation is done using GPU. Otherwise, the fuzzification and defuzzification steps become heavy and very slow.

The C-mean output is then feedforward to the Fuzzification module in Fig. 2. Finally, Encoder calculates the fuzzy loss function, and using backpropagation, the model updates W’s entrees such that the loss function value decreases which is equivalent to increasing the FCR’s variance.

The model then continues to update W and multiply it to the dataset until FCR’s variance reaches its maximum. At this point according to [32], W encoded the association and causal relationships between entities in the dataset.

In the following section, we will demonstrate the results.

1. Methods Comparison and Results Interpretation

We also made some changes in the Big Bird’s loss function, dividing it by the variance of the FCRs. See Formula 1.

𝐵𝑖𝑔𝑏𝑖𝑟𝑑 𝑙𝑜𝑠𝑠 𝑓𝑢𝑛𝑐𝑡𝑖𝑜𝑛

𝑉𝑎𝑟(𝐹𝐶𝑅𝑠)

Formual 1. Modified BigBird's loss function

In doing so, we forced the network to calculate the variance of the FCR and extract the association and causal fuzzy rules [15]. Next, we briefly explain the overall steps to extract association and causal rules using our modified Big Bird architecture:

Similar to [30], we generate a weighting representation of the whole dataset. To generate Matrix W (Fig. 2), in this study, we used decomposed EEG signals by FFT in section II. Each EEG signal is a matrix of (𝑛 ∗ 100) where 𝑛 is the EEG length and the ‘100’ is the number of frequency components generated by FFT from EEG. Given this representation for decomposed EEGs, the FCT generates the symmetric matrix W100∗100 so that for each weight w𝑖j∈W where 𝑖, j ∈ [0, 99] and w𝑖j ∈ [0, 1] . w𝑖j s’ in W show association or causal contribution

amount of the pre-ictal EEG’ 𝑖𝑡ℎ and j𝑡ℎ components for successful and unsucessful ECT sessions.

Out of 470 EEG traces, we used 350 pre-ictal EEGs to train the FCT and 120 pre-ictal EEGs for the test. Using root mean square measure, the overall accuracy for electrical charges prediction is 93.6%. Table I shows the details of prediction accuracy.

TABLE I. numbers of True/False positive/negative

|  |  |
| --- | --- |
| True Positives | 117 |
| True Negatives | 2 |
| False Positives | 1 |
| False Negatives | 0 |

As a comparison, we also feedforward FFT’s output to GPT2 architecture (For the code please click). GPT2’s overall accuracy for electrical charge prediction was 89.43%. Overall, compared to GTP2 and FCEVAE, **Causal** **Fuzzy** **Big** **Bird** **Transformers** **(CFBBT)** gave better results.

TABLE II. Comparison between different DLs' performance

|  |  |
| --- | --- |
| Architecture | Precision |
| GPT2 | 89.43% |
| Fuzzy Causal Effect Variational autoencoders  (FCEVAE) | 91% |
| **Causal** **Fuzzy** **Big** **Bird** **Transformers** *(****CFBBT****)* | 93.6% |

1. Conclusions:

In this paper, for the first time, we suggest using Deep Learning algorithms equipped with causal rules to predict the electrical charges to be applied to the MDD patient’s skull for ECT sessions. To do so, we used Patients’ pre-ictal EEGs and information such as sex with a Causal fuzz neural transformer network.

It must be noted that to the best of our knowledge, all previous works only worked on passive data. That is the work was done on the data gathered from patients’ skulls during ECT sessions. Compared to other methods which used Magnetic resonance imaging (MRI) with machine learning algorithms, our method is faster, cheaper, and more concise.

To create our individualized ECT method, we used different methods such as FFT to preprocess the data. Once ready, we used Deep learning algorithms such as convolutional and sequential Neural networks [8], non-classical logics such as fuzzy logic integrated with Causal Variational Autoencoders [15], and Transformers. We obtained better results with Causal Fuzzy Big Bird Transformers (CFBBT) compared to Variational-based Deep Learning algorithms (DLs). Contrary to the Variational based DLs that take about 30 minutes to predict, CFBBT predicts almost instantly the electrical charges. We also compared our results with GPT2. Compared to GPT2, our CFBBT architecture performed better.

It is worth mentioning that an ECT session response quality depends on many parameters such as the location of electrodes on the patient's scalp, the type of anesthesia medication, and electric pulse configuration (i.e., duration, waveform, current, and voltage). These parameters vary for different patients [33]. In our future work, we would like to try our dataset using other Transformer based DLs such as GPT3 (if OpenAI gives us access to their code) and also add our Causal Fuzzy rule to GPT2 and compare its performance with CFBBT.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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1. *To achieve more accurate results in EEG recordings, it is essential to use a 19-channel EEG recording device that captures whole-brain activities simultaneously. This approach is supported by scientific evidence showing that a 19-channel EEG system provides better spatial resolution and coverage compared to fewer channels.*

   *A study by Luck (2014) demonstrated that increasing the number of electrodes in an EEG system improves the spatial resolution of the recordings, allowing for more precise localization* *of brain activity. This is crucial for tasks such as identifying the source of epileptic seizures or studying the neural correlates of cognitive processes.*

   *Furthermore, a 19-channel EEG system enables researchers to capture whole-brain activities more comprehensively, as different brain regions are interconnected and work together to* *produce complex behaviors and cognitive functions. This* *holistic approach to EEG* *recording is supported by studies showing that brain networks involved in various tasks exhibit synchronized activity across distant brain regions.* [↑](#footnote-ref-1)