Universität Rostock Traditio et Innovatio

Final Report for Master Module: Projektseminar Eingebettete Systeme

Topic: Early warning systems for seizure detection

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Introduction

Epilepsy is a significant neurological condition prevalent worldwide, characterized by abnormal electrical discharges in the brain. The clinical manifestation of this disorder often presents as epileptic seizures, representing prevalent positive signs of brain disturbance. Epilepsy stands as one of the most frequent primary brain disorders globally. Leading factors contributing to epilepsy include vascular issues, traumatic incidents, infections, brain abscesses, tumors, nutritional deficiencies, pyridoxine deficiency, and disorders related to calcium metabolism. Diagnosing epilepsy requires thorough research to enhance our comprehension of the mechanisms underlying epileptic disorders. [4]

“An epileptic seizure is a transient occurrence of signs and/or symptoms due to abnormal excessive or synchronous neuronal activity in the brain. Epilepsy is a disorder of the brain characterized by an enduring predisposition to generate epileptic seizures and by the neurobiologic, cognitive, psychological, and social consequences of this condition.” [5]

Figure 1. Occurrence of seizure [1]

Different types of epileptic seizures

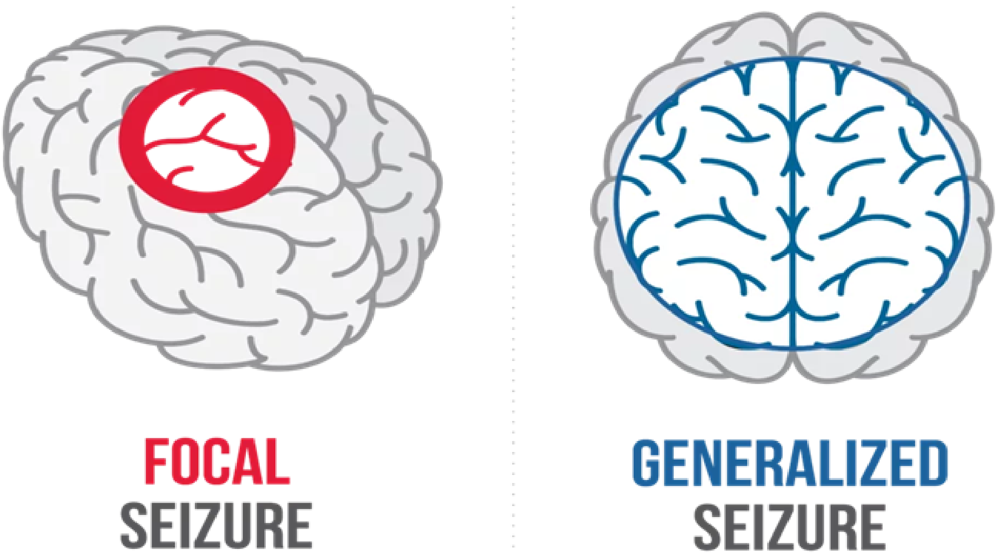


Figure 2. Focal and generalized seizure [2]

Focal Seizure

Focal onset aware seizures, formerly known as focal simple onset seizures, are characterized by the individual maintaining awareness of their surroundings and the ongoing events. Despite an inability to move or respond during these episodes, the person retains cognitive awareness throughout. [6]

Focal onset impaired awareness seizures, formerly labeled as focal complex seizures, involve a partial loss of awareness in the individual during the episode. [6]

Generalized Seizure

Absence seizures entail a brief loss of awareness, occasionally accompanied by subtle movements like eye blinking or lip smacking, commonly observed in children.

Tonic seizures involve the stiffening of muscles, often resulting in the person falling.

Atonic seizures manifest as a sudden loss of muscle tone, leading to falls or a drop of the head.

Clonic seizures are characterized by rhythmic, jerking muscle movements.

Myoclonic seizures are quick, involuntary muscle jerks.

Tonic-clonic seizures, also known as grand mal seizures, encompass a combination of tonic (muscle stiffness) and clonic (rhythmic jerking) phases, often associated with a loss of consciousness. [6]

- One of the most prevalent neurological disorders.
- Despite treatment, approximately one-third of individuals with epilepsy continue to experience seizures.
- The unpredictable nature of seizures and their consequences often leads to heightened anxiety, significantly diminishing the quality of life for affected individuals. [7]

Motivation

Our goal is to mitigate or ideally prevent seizures through the development of methods for detecting and predicting their occurrence.

State of the art for seizure detection and prediction

Seizure detection and ways

There are six primary methods for detecting seizures.

- **Electroencephalography (EEG)**

An electroencephalogram (EEG) is a diagnostic test designed to measure and record the electrical activity of the brain. This procedure entails the placement of small electrodes on the scalp, which detect and amplify the brain's electrical signals. The resultant EEG data offers valuable insights into the functioning of the brain. Crucially, EEG serves as a vital tool in assessing abnormal electrical patterns in the brain. It plays a pivotal role in diagnosing and classifying seizures and epilepsy, providing essential information for understanding and managing these neurological conditions. [8]

- **Electrocorticography (ECoG)**

Electrocorticography (ECoG) is a neurophysiological technique that entails the placement of an electrode grid directly on the surface of the brain to record electrical activity. In contrast to EEG, during ECoG, the electrode grid is positioned on the exposed brain cortex, enabling more precise and localized recordings of brain activity. While ECoG is an invasive procedure with associated potential risks, it offers valuable insights into the dynamics of brain activity. Its application extends to both clinical diagnosis and scientific exploration of the brain's functions, providing a more detailed understanding of neural processes. [9]

- **Electrocardiography (ECG)**

A non-invasive medical test used to measure and record the electrical activity of the heart is known as an Electrocardiogram (ECG or EKG). This procedure involves placing electrodes on specific locations on the skin, usually on the chest, arms, and legs, to detect and amplify the electrical signals produced by the heart. Some personal devices, such as smartwatches, now offer ECG monitoring capabilities. The ECG provides crucial information about the heart's rhythm, rate, and overall electrical activity, aiding in the assessment of cardiac health [10].There are two types of abnormal activities related to the heart during a seizure **Tachycardia**, characterized by an increased heart rate, is typically observed during complex partial and tonic-clonic seizures. On the other hand, **bradycardia**, indicating a decreased heart rate, is commonly associated with other types of seizures. [11]

- **Accelerometry**

Accelerometry is a technique that entails measuring and recording acceleration or movement patterns through accelerometers. These compact sensors detect and quantify changes in velocity across multiple directions. Notably, they have been applied in the detection of motor seizures, including tonic-clonic or myoclonic seizures. [12]

- **Video detection**

Several models have been devised for seizure detection through video monitoring. Video systems analyze multiple elements to identify seizures. Motion trajectory methods focus on the path of moving objects in space over time, considering factors such as velocity, area, angular speed, and duration. Certain video analysis techniques utilize markers, which are detectable objects worn on joints and extremities of patients. [7]

- **Matress sensor**

The MP5 mattress monitor (Medpage Ltd., UK) is specifically designed to identify seizures occurring during sleep. Positioned between the mattress and box spring, its microphone detects tapping and spring noise, with adjustable sensitivity. In a study involving 64 subjects experiencing 8 tonic–clonic seizures each, the system successfully detected 5 events (62.5%). Although it exhibited a poor positive predictive value of 3.3%, its high negative predictive value of 99.8% could offer patients with these seizures a heightened sense of security. The Emfit movement monitor (Emfit Ltd., Finland) is a quasipiezoelectric seizure detector placed under the mattress system, alerting caregivers to unexpected motor activity. Additionally, the system includes a bedside monitor. In a trial involving 22 patients, the Emfit system successfully detected 80% of seizures. [7]

Advantages and Disadvantages of the ways

Methode	Advantage	Disadvantage
Electroencephalography (EEG)	Noninvasive with valuable data in detecting epileptic seizures.	Low spatial resolution
Electrocorticography (ECoG)	More accurate compared to EEG	Invasive procedure
Electrocardiogram (ECG)	Narrow relation of tachycardia in preictal phase	Rhythmic cardiac changes can be observed in other physiological and pathological conditions, especially in older patients
Accelerometry	Able to detect movement changes in x, y, and z planes. Used in seizures with motor component.	Any sudden movement can be registered as a seizure event
Video detection systems	Recognizing kinematic patterns of seizure	Miss the seizure when patient is under covers or out of the camera's range
Mattress sensor	Nocturnal seizures, especially tonic–clonic seizures.	High negative predictive value

`Table 1. Advantages and Disadvantages of the ways [7]`

Seizure Prediction

The potential advantages of predicting seizures surpass those of merely detecting them. Such predictive devices hold promise in preventing accidents and enhancing overall outcomes, enabling early treatment or even the prevention of seizures. In a survey involving 141 patients with epilepsy, over 90% of respondents emphasized the importance of developing means for predicting seizures. Interestingly, these patients expressed a preference for sensitivity over specificity in seizure prediction. [13]

For effective prediction, systems must be capable of identifying preictal changes that, if present, occur within minutes, hours, or days before seizures. It's crucial to note that the features used for predicting seizures in advance may or may not be the same as those employed for detecting the presence of a seizure. [7]

Combined ways

Combining multiple approaches can significantly enhance accuracy and specificity in mitigating problems associated with seizure prediction and detection. Three effective ways of such integration include:

1. **Combined EEG:**
   - Single EEG Channel: Utilizing a single EEG channel for monitoring electrical brain activity.
   - Multiple EEG Channels: Employing multiple EEG channels to capture a more comprehensive view of brain signals, enhancing the accuracy of detection. [7]
2. **EEG and ECG:**
   - Integrating both Electroencephalogram (EEG) and Electrocardiogram (ECG) data for a holistic approach. This combination provides a more thorough understanding

of both brain and heart activities, aiding in accurate prediction and detection. [7]

3. **Accelerometry and Electrodermal:**

    - Combining data from Accelerometry, which measures movement patterns, and Electrodermal activity, which monitors changes in skin conductance. This integration offers a multi-modal approach, capturing diverse physiological indicators and improving overall prediction accuracy. [7]

By integrating these different modalities, we can leverage complementary information from various physiological signals, resulting in a more robust and accurate system for mitigating problems associated with seizures. [7]

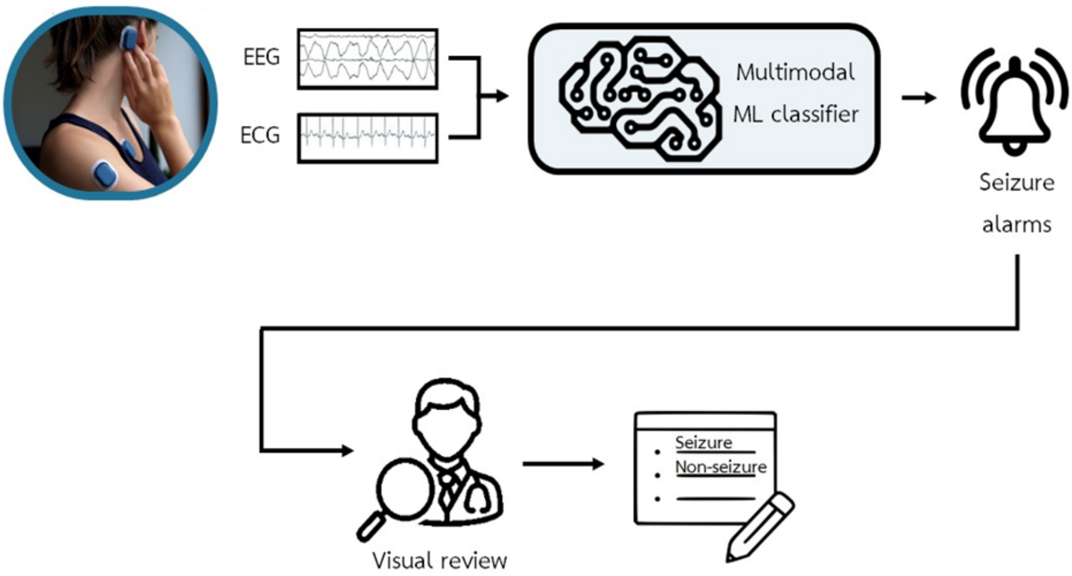


Figure 3. Combined EEG and ECG [3]

Closed-loop systems

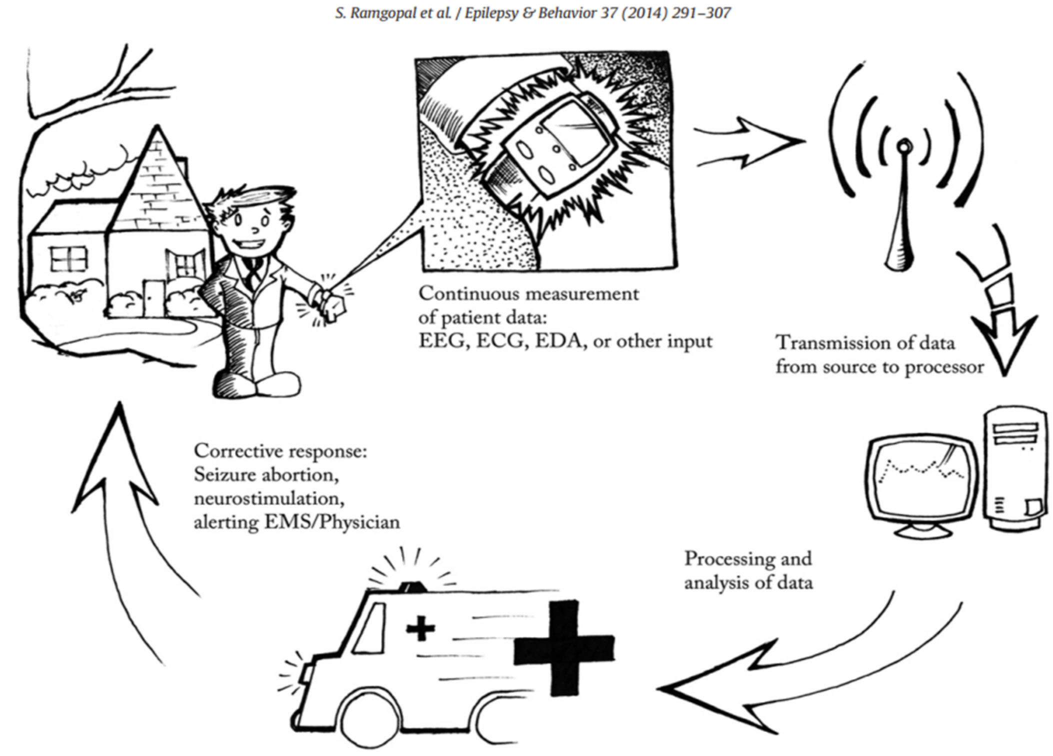


Figure 4. Closed loop systems [7]

Medical closed-loop systems are engineered to autonomously adjust and regulate a designated medical parameter in response to real-time feedback from the patient's physiological signals. These systems maintain continuous monitoring of the patient's condition and, based on the acquired data, deliver appropriate interventions or treatments.

In the realm of neurological conditions, closed-loop neurostimulation systems play a pivotal role, particularly in the treatment of conditions like epilepsy or movement disorders. These sophisticated systems constantly monitor brain activity or specific neural signals and, in turn, administer targeted electrical stimulation. The objective is to modulate or suppress abnormal brain activity, with the overarching goal of reducing seizure frequency or controlling motor symptoms effectively. [7]

It has four main parts:

1. Measuring device

In a closed-loop system, the continuous collection and processing of reliable and reproducible data are crucial for effective operation. Various sensor and detector tools, as previously discussed in the context of seizure detection, play a pivotal role in acquiring accurate data essential for the closed-loop system's functionality.

The selection of suitable sensors and detectors depends on the specific requirements of the closed-loop system. These tools encompass a range of devices such as EEG (Electroencephalogram), ECG (Electrocardiogram), accelerometers, and other specialized instruments designed for measuring specific physiological parameters. The meticulous choice of these devices ensures that the closed-loop system receives precise and relevant data, facilitating its ability to respond appropriately to the patient's physiological signals. [7]

2. Data transmission

Following data acquisition, the information must be transmitted to a system for analysis and processing. In experimental models of closed-loop systems, successful data transmission has been achieved using wireless technologies such as Wi-Fi and Bluetooth.

In the case of certain newer EEG headsets, signal processing, feature calculation, and classification can be executed directly on the device itself. This approach eliminates the need for transmitting raw data, streamlining the process.

From a security perspective, it is imperative to safeguard data transmission to prevent interception and protect patient privacy. Secure standards and protocols have been developed to ensure the encryption and restricted access of transmitted data.

In summary, ensuring rapid, secure, and reliable data transmission is pivotal for closed-loop systems. This facilitates accurate analysis, timely responses, and ultimately contributes to improved patient care. [7]

3. Data processing

In closed-loop systems, data processing holds a pivotal role in interpreting signals collected by biometric devices and assessing the patient's seizure risk in real-time. The data processing systems need to efficiently and rapidly determine the patient's current status and the likelihood of imminent or ongoing seizures.

Methods like feature calculation and classification, as discussed earlier and utilizing data from EEG, ECG, and accelerometry, exemplify the data processing systems essential for closed-loop operations. The efficacy of a data processing system is assessed based on parameters such as sensitivity, specificity, and predictive values.

While the steps and algorithms used in closed-loop systems bear similarities to those in seizure prediction systems, the processing time requirements are typically more stringent. The need for quick processing arises from the imperative to promptly activate interventions, aiming to prevent seizures or provide timely warnings. This emphasis on speed is crucial for the overall effectiveness of closed-loop systems in managing and mitigating neurological events. [7]

4. Response system

Closed-loop devices in epilepsy exhibit diverse response mechanisms, serving to warn patients or caregivers, initiate activities like medication administration or neurostimulation, and even notify healthcare providers or emergency services. Examples of such devices include the SmartWatch and EpiLert, designed to alert caregivers.

Responsive neurostimulation systems (RNS) are capable of detecting abnormal brain activity and responding by delivering electrical pulses to normalize it. On the other hand, deep brain stimulation (DBS) targets specific parts of the brain for modulation.

A dependable seizure prediction system holds the potential to enable the aborting of imminent seizures using rapid-acting benzodiazepines or other innovative techniques. These may include the use of Peltier coolers, UV light, or local drug delivery systems. The

Practical work

The diagnosis of epilepsy relies significantly on the electroencephalogram (EEG), a critical tool for accurately classifying different forms of epilepsy and facilitating the evaluation and treatment of neurophysiological disorders.

Method Selection

I implemented the dataset using Support Vector Machines (SVM), Deep Neural Networks (DNN), and Convolutional Neural Networks (CNN), and I obtained the results for each of them.

About Dataset

This dataset is a pre-processed and re-structured/reshaped version of a very commonly used dataset featuring epileptic seizure detection [14][15][16][17].

Attribute Information

The original dataset, as referenced, comprises 5 folders, each containing 100 files, with each file representing the brain activity recording of a single subject. These recordings span 23.6 seconds and are sampled into 4097 data points. Consequently, there are a total of 500 individuals, each contributing 4097 data points for a duration of 23.5 seconds.

To enhance the dataset's organization, we partitioned and shuffled every 4097 data points into 23 chunks. Each chunk consists of 178 data points, representing a 1-second interval. Therefore, the dataset now comprises 11,500 entries (rows), each containing 178 data points for 1 second (columns). The final column denotes the label "y" with values {1, 2, 3, 4, 5}.

In summary, the response variable "y" is found in column 179, while the explanatory variables X1, X2, …, X178 provide the EEG recording values at different time points. [18]

y Definition

The variable "y" denotes the category of the 178-dimensional input vector and specifically takes values in {1, 2, 3, 4, 5}, each corresponding to different conditions:

- 5: Eyes open, indicating the EEG signal recording when the patient had their eyes open.

- 4: Eyes closed, representing the EEG signal recording when the patient had their eyes closed.

- 3: Identification of the tumor region in the brain, recording EEG activity from the **healthy brain area**.

- 2: EEG recorded from the area where the **tumor** was located.

- 1: Recording of **seizure activity**.

Subjects falling into classes 2, 3, 4, and 5 are those without epileptic seizures, while subjects in class 1 experience epileptic seizures. Despite the existence of five classes, many authors have simplified the classification task to binary, focusing on class 1 (Epileptic seizure) versus the rest. The motivation behind creating this dataset version in a .csv format is to streamline data access. [18]

Reference of datastet

This Dataset collect from UCI Machine Learning Repository (from the University of Bonn) [14][15][16][17][18].

In [1]:

```
import time
import numpy as np
import pandas as pd
import tensorflow as tf
from sklearn.svm import SVC
import matplotlib.pyplot as plt
from keras.models import Sequential
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from keras.layers import Conv1D, MaxPooling1D, Flatten, Dense, Dropout
from sklearn.metrics import confusion_matrix, classification_report, a
```

```
WARNING:tensorflow:From C:\Users\hosei\anaconda3\envs\tensorjoon\lib\site
-packages\keras\src\losses.py:2976: The name tf.losses.sparse_softmax_cro
ss_entropy is deprecated. Please use tf.compat.v1.losses.sparse_softmax_c
ross_entropy instead.
```

Load the data

In [2]:

```
data = pd.read_csv('Epileptic Seizure Recognition.csv')
```

Show the dataset

In [3]:

```
data.head()
```

Out[3]:

	Unnamed	X1	X2	X3	X4	X5	X6	X7	X8	X9	...	X170	X171	X172	X17
0	X21.V1.791	135	190	229	223	192	125	55	-9	-33	...	-17	-15	-31	-7
1	X15.V1.924	386	382	356	331	320	315	307	272	244	...	164	150	146	15
2	X8.V1.1	-32	-39	-47	-37	-32	-36	-57	-73	-85	...	57	64	48	1
3	X16.V1.60	-105	-101	-96	-92	-89	-95	-102	-100	-87	...	-82	-81	-80	-7
4	X20.V1.54	-9	-65	-98	-102	-78	-48	-16	0	-21	...	4	2	-12	-3

5 rows × 180 columns

SVM Model

In [4]:

```
X = data.iloc[:, 1:-1].values
y = data.iloc[:, -1:].values
y[y > 1] = 0  # Convert multi-class to binary

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.

# Standardize the data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

start_time_1_SVM = time.time()
# Build and train the SVM model
svm_model = SVC(kernel='linear', C=1.0, random_state=42)
svm_model.fit(X_train_scaled, y_train)

start_time_2_SVM = time.time()
# Make predictions on the test set
y_pred = svm_model.predict(X_test_scaled)

# Calculate and print the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)

# Calculate and print classification report
class_report = classification_report(y_test, y_pred)
print("Classification Report:")
print(class_report)

# Calculate and print accuracy
accuracy_1 = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy_1)

end_time_SVM = time.time()
# Calculate and print time
training_time_SVM = end_time_SVM - start_time_1_SVM
print("Running Time of training:", training_time_SVM, "seconds")

predicting_time_SVM = end_time_SVM - start_time_2_SVM
print("Running Time of prediction:", predicting_time_SVM, "seconds")
```

```
C:\Users\hosei\anaconda3\envs\tensorjoon\lib\site-packages\sklearn\utils
\validation.py:1183: DataConversionWarning: A column-vector y was passed
when a 1d array was expected. Please change the shape of y to (n_samples,
), for example using ravel().
  y = column_or_1d(y, warn=True)
```

```
Confusion Matrix:
[[2284    1]
 [ 518   72]]
Classification Report:
              precision    recall  f1-score   support

           0       0.82      1.00      0.90      2285
           1       0.99      0.12      0.22       590

    accuracy                           0.82      2875
   macro avg       0.90      0.56      0.56      2875
weighted avg       0.85      0.82      0.76      2875

Accuracy: 0.8194782608695652
Running Time of training: 125.96467995643616 seconds
Running Time of prediction: 1.3151307106018066 seconds
```

DNN Model

In [5]:

```
X = data.iloc[:, 1:-1].values
y = data.iloc[:, -1:].values
y[y > 1] = 0  # Convert multi-class to binary

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.

# Standardize the data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Build the DNN model
model = Sequential()
model.add(Dense(128, activation='relu', input_shape=(X_train_scaled.sh
model.add(Dropout(0.5))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(1, activation='sigmoid'))

# Compile the model
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['

start_time_1_DNN = time.time()
# Train the model
history = model.fit(X_train_scaled, y_train, epochs=150, batch_size=32

# Evaluate the model
start_time_2_DNN = time.time()

y_pred = model.predict(X_test_scaled)
y_pred_binary = (y_pred > 0.5).astype(int)

# Calculate and print the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_binary)
print("Confusion Matrix:")
print(conf_matrix)

# Calculate and print classification report
class_report = classification_report(y_test, y_pred_binary)
print("Classification Report:")
print(class_report)

# Calculate and print accuracy
accuracy_2 = accuracy_score(y_test, y_pred_binary)
print("Accuracy:", accuracy_2)

end_time_DNN = time.time()
# Calculate and print running time
training_time_DNN = end_time_DNN - start_time_1_DNN
print("Running Time of training:", training_time_DNN, "seconds")

predicting_time_DNN = end_time_DNN - start_time_2_DNN
print("Running Time of prediction:", predicting_time_DNN, "seconds")
```

```
WARNING:tensorflow:From C:\Users\hosei\anaconda3\envs\tensorjoon\lib\site
-packages\keras\src\backend.py:873: The name tf.get_default_graph is depr
ecated. Please use tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From C:\Users\hosei\anaconda3\envs\tensorjoon\lib\site
-packages\keras\src\optimizers\__init__.py:309: The name tf.train.Optimiz
er is deprecated. Please use tf.compat.v1.train.Optimizer instead.

WARNING:tensorflow:From C:\Users\hosei\anaconda3\envs\tensorjoon\lib\site
-packages\keras\src\utils\tf_utils.py:492: The name tf.ragged.RaggedTenso
rValue is deprecated. Please use tf.compat.v1.ragged.RaggedTensorValue in
stead.

WARNING:tensorflow:From C:\Users\hosei\anaconda3\envs\tensorjoon\lib\site
-packages\keras\src\engine\base_layer_utils.py:384: The name tf.executing
_eagerly_outside_functions is deprecated. Please use tf.compat.v1.executi
ng_eagerly_outside_functions instead.

90/90 [==============================] - 0s 2ms/step
Confusion Matrix:
[[2254   31]
 [  37  553]]
Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.99      0.99      2285
           1       0.95      0.94      0.94       590

    accuracy                           0.98      2875
   macro avg       0.97      0.96      0.96      2875
weighted avg       0.98      0.98      0.98      2875

Accuracy: 0.9763478260869565
Running Time of training: 133.95166850090027 seconds
Running Time of prediction: 0.6147251129150391 seconds
```

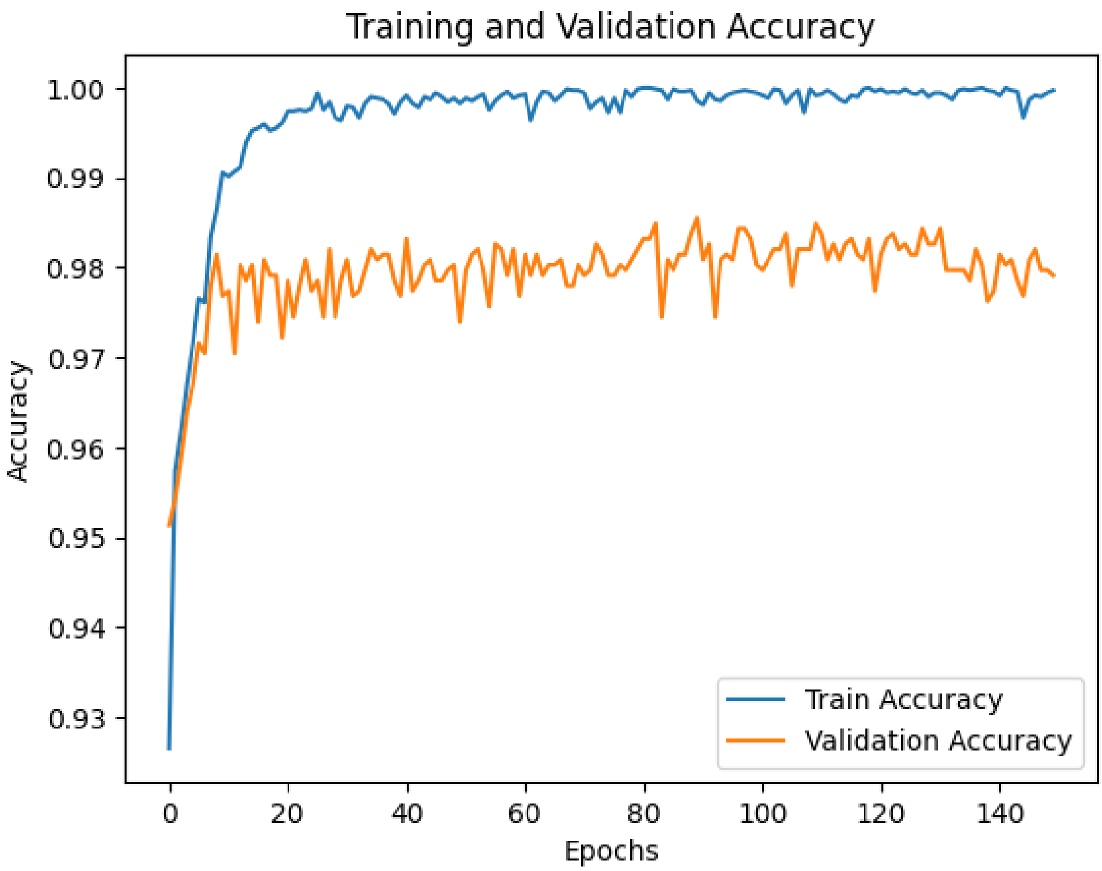
CNN Model

In [8]:

```
X = data.iloc[:, 1:-1].values
y = data.iloc[:, -1:].values
y[y > 1] = 0  # Convert multi-class to binary

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.

# Standardize the data

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Reshape the data for CNN
X_train_reshaped = X_train_scaled.reshape(X_train_scaled.shape[0], X_t
X_test_reshaped = X_test_scaled.reshape(X_test_scaled.shape[0], X_test

# Build the CNN model
model = Sequential()
model.add(Conv1D(filters=64, kernel_size=3, activation='relu', input_s
model.add(MaxPooling1D(pool_size=2))
model.add(Conv1D(filters=128, kernel_size=3, activation='relu'))
model.add(MaxPooling1D(pool_size=2))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(1, activation='sigmoid'))

# Compile the model
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['

start_time_1_CNN = time.time()
# Train the model
history = model.fit(X_train_reshaped, y_train, epochs=150, batch_size=
# Evaluate the model
start_time_2_CNN = time.time()

y_pred = model.predict(X_test_reshaped)
y_pred_binary = (y_pred > 0.5).astype(int)

# Calculate and print the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_binary)
print("Confusion Matrix:")
print(conf_matrix)

# Calculate and print classification report
class_report = classification_report(y_test, y_pred_binary)
print("Classification Report:")
print(class_report)

# Calculate and print accuracy
accuracy_3 = accuracy_score(y_test, y_pred_binary)
print("Accuracy:", accuracy_3)

end_time_CNN = time.time()
# Calculate and print running time
training_time_CNN = end_time_CNN - start_time_1_CNN
print("Running Time of training:", training_time_CNN, "seconds")

predicting_time_CNN = end_time_CNN - start_time_2_CNN
print("Running Time of prediction:", predicting_time_CNN, "seconds")
```

```python

# Plot training history
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

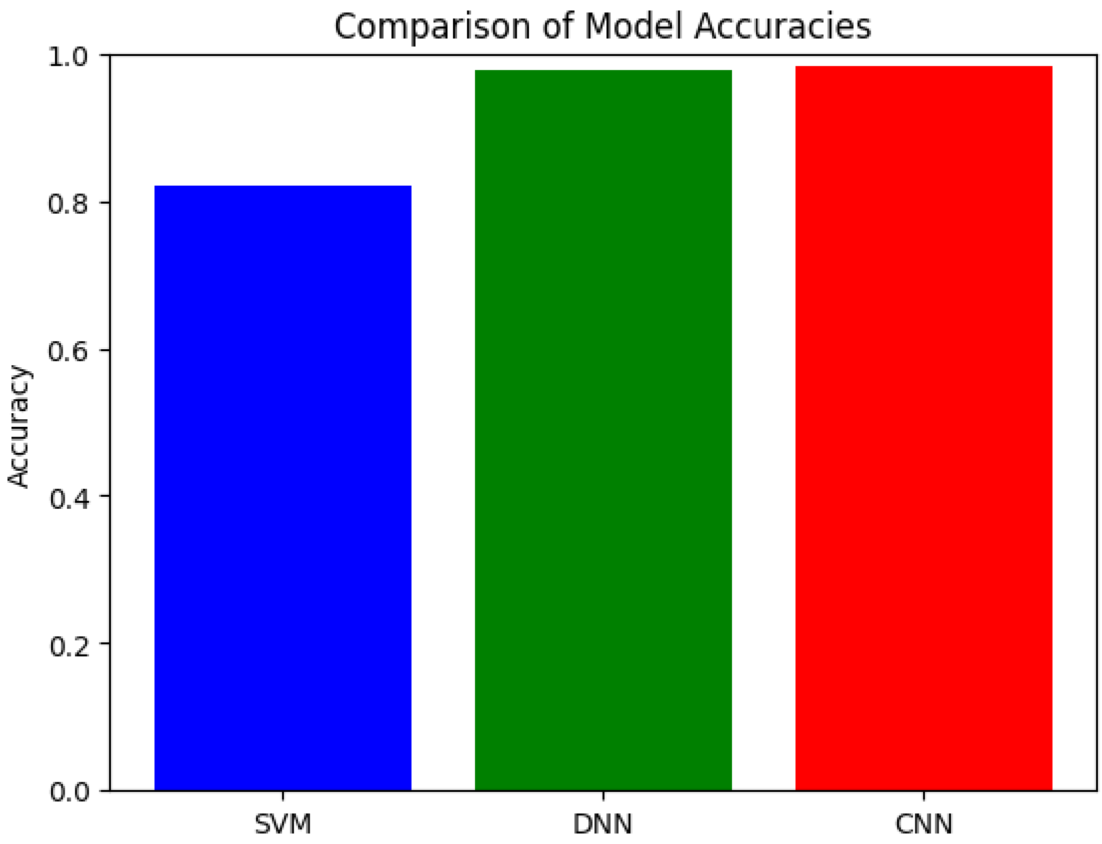
```
90/90 [==============================] - 1s 7ms/step
Confusion Matrix:
[[2274   11]
 [  41  549]]
Classification Report:
              precision    recall  f1-score   support

           0       0.98      1.00      0.99      2285
           1       0.98      0.93      0.95       590

    accuracy                           0.98      2875
   macro avg       0.98      0.96      0.97      2875
weighted avg       0.98      0.98      0.98      2875

Accuracy: 0.9819130434782609
Running Time of training: 516.7856051921844 seconds
Running Time of prediction: 1.0006401538848877 seconds
```



Comparison between the Models

In [9]:

```
svm_accuracy = accuracy_1  # accuracy variable for SVM
dnn_accuracy = accuracy_2  # accuracy variable for DNN
cnn_accuracy = accuracy_3  # accuracy variable for CNN

# Plotting
labels = ['SVM', 'DNN', 'CNN']
accuracies = [svm_accuracy, dnn_accuracy, cnn_accuracy]

plt.bar(labels, accuracies, color=['blue', 'green', 'red'])
plt.ylabel('Accuracy')
plt.title('Comparison of Model Accuracies')
plt.ylim([0, 1])  # Set the y-axis limit between 0 and 1 for accuracy
plt.show()
```



Challenges

Technical

- Ensuring device accuracy
- Minimal adverse effects
- Real-time data transmission
- Precise seizure description
- 24-hour service availability
- Limitations in autonomy [7]

Regulatory

- Establishing collaborations
- Validating technology
- Obtaining FDA approval
- Complying with safety and
- effectiveness regulations [7]

Market

- Addressing market needs
- Competition
- Prototype creation costs
- Patent maintenance
- Return on investment
- Potential rapid obsolescence [7]

Funding

- Organizations like CIMIT and the Epilepsy Therapy Project support innovation and early device development in epilepsy [7].

Link analytical method to Embedded system

Algorithmic Suitability:

While various algorithms, including Support Vector Machines (SVM), Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), etc., exhibit promising results in seizure detection and prediction, it is essential to prioritize those that align with the computational limitations of embedded systems. Complex algorithms with high computational demands may pose challenges in terms of real-time processing and responsiveness, making it crucial to strike a balance between accuracy and efficiency.

Computational Demands:

The chosen algorithm should be tailored to operate efficiently within the constraints of embedded systems. By considering factors such as model architecture, processing power, and memory availability, we aim to develop a system that not only meets the stringent computational demands of seizure detection but also ensures optimal performance on embedded hardware.

Energy Consumption Optimization:

To maximize the feasibility of deployment in resource-constrained environments, particular attention will be given to optimizing energy consumption. This involves careful selection of hardware components, model architecture,number of epochs and batch size. By implementing energy-efficient strategies, we aim to strike a balance between accurate seizure detection and minimized power consumption, ultimately enhancing the system's practicality and longevity in embedded deployments.

Result of Practical work

After conducting training and testing all three models SVM, DNN, and CNN, it is evident that CNN achieves the highest accuracy, followed by DNN and then SVM .

In terms of training time, it can be noted that SVM, DNN, and CNN rank in ascending order from least to most time consuming. Regarding prediction time, DNN leads, followed by CNN, with SVM requiring the most time.

When considering medical issues and their classification, minimizing both false positives and false negatives is crucial. However, if a choice must be made between the two, it is preferable to minimize false negatives. This is because if our case is indeed sick, failing to recognize it (false negative) can have severe consequences. In this context, the lowest false negative rate is attributed to SVM, followed by CNN, and then DNN.

In utilizing these three models, it's essential to acknowledge the existence of a trade-off. **Overall, considering both time and accuracy, the preference goes to the model built by CNN**. But we can also decide which architecture to use in which situation.

Accuracy Ranking: CNN > DNN > SVM

Training Time Ranking: SVM < DNN < CNN

Prediction Time Ranking: DNN < CNN < SVM

False Negative Ranking: SVM < CNN < DNN

Finally, it should be considered that all these results and times were with CPU, and if we use GPU, the times will certainly be faster."

Conclusion

We discussed four main parts of this project

- **Detection:** Primarily focused on identifying the occurrence of seizures.
- **Prediction:** Aims to forecast seizures, allowing for proactive measures such as aborting the seizure and preventing accidents.
- **Combined Ways:** Integrating various methods, like combining EEG and ECG, to enhance specificity and accuracy in seizure detection and prediction.
- **Best Approach:** Closed-loop systems, which seamlessly combine detection and prediction strategies, allowing for real-time monitoring and responsive interventions.

In essence, a comprehensive approach involves both detecting and predicting seizures,

References

[1] 1mg. (n.d.). National Epilepsy Day: 7 Common Epilepsy Myths Busted. Retrieved from 1mg: https://www.1mg.com/articles/national-epilepsy-day-7-common-epilepsy-myths-busted/ (https://www.1mg.com/articles/national-epilepsy-day-7-common-epilepsy-myths-busted/) on [20.01.2024].

[2] Cure Epilepsy. (n.d.). What Is Seizure? Retrieved from Cure Epilepsy: https://www.cureepilepsy.org/for-patients/understanding/basics/what-is-seizure/ (https://www.cureepilepsy.org/for-patients/understanding/basics/what-is-seizure/) on [03.01.2024].

[3] ResearchGate. (n.d.). Sketch of how to record an Electroencephalogram. Retrieved from ResearchGate: https://www.researchgate.net/figure/Sketch-of-how-to-record-an-Electroencephalogram-An-EEG-allows-measuring-the-electrical_fig1_338423585

(https://www.researchgate.net/figure/Sketch-of-how-to-record-an-Electroencephalogram-An-EEG-allows-measuring-the-electrical_fig1_338423585) on [31.01.2024].

[4] Kaggle. (n.d.). Machine Learning Algorithms for Epileptic Seizures. Retrieved from Kaggle: https://www.kaggle.com/code/myustips/machine-learning-algorithms-for-epileptic-seizures (https://www.kaggle.com/code/myustips/machine-learning-algorithms-for-epileptic-seizures) on [18.12.2023].

[5] Fisher RS, van Emde Boas W, Blume W, Elger C, Genton P, Lee P, Engel J Jr. Epileptic seizures and epilepsy: definitions proposed by the International League Against Epilepsy (ILAE) and the International Bureau for Epilepsy (IBE). Epilepsia. 2005 Apr;46(4):470-2. doi: 10.1111/j.0013-9580.2005.66104.x. PMID: 15816939

[6] Epilepsy Foundation. (n.d.). Seizure Types. Retrieved from Epilepsy Foundation: https://www.epilepsy.com/what-is-epilepsy/seizure-types (https://www.epilepsy.com/what-is-epilepsy/seizure-types) on [01.02.2024].

[7] Ramgopal, Sriram, et al. "Seizure detection, seizure prediction, and closed-loop warning systems in epilepsy." Epilepsy & behavior 37 (2014): 291-307.

[8] Verywell Health. (n.d.). What Is an EEG Test and What Is It Used For? Retrieved from Verywell Health: https://www.verywellhealth.com/what-is-an-eeg-test-and-what-is-it-used-for-3014879 (https://www.verywellhealth.com/what-is-an-eeg-test-and-what-is-it-used-for-3014879) on [29.01.2024].

[9] American Association of Neurological Surgeons (AANS). (n.d.). Epilepsy Electrocorticography. Retrieved from AANS: https://www.aans.org/Patients/Neurosurgical-Conditions-and-Treatments/Epilepsy%20Electrocorticography (https://www.aans.org/Patients/Neurosurgical-Conditions-and-Treatments/Epilepsy%20Electrocorticography) on [31.01.2024].

[10] Mayo Clinic. (n.d.). Electrocardiogram (EKG or ECG). Retrieved from Mayo Clinic: https://www.mayoclinic.org/tests-procedures/ekg/about/pac-20384983#dialogId13492854 (https://www.mayoclinic.org/tests-procedures/ekg/about/pac-20384983#dialogId13492854) on [31.01.2024].

[11] Burgess, Richard C. "Automatic seizure detection by ECG analysis." Handbook of Clinical Neurophysiology 3 (2003): 167-177.

[12] Kavanagh, Justin J., and Hylton B. Menz. "Accelerometry: a technique for quantifying movement patterns during walking." Gait & posture 28.1 (2008): 1-15.

[13] Schulze-Bonhage A, Sales F, Wagner K, Teotonio R, Carius A, Schelle A, et al. Views of patients with epilepsy on seizure prediction devices. Epilepsy Behav 2010;18:388–96.

[14] UPF Digital Repository. (n.d.). [Title of the specific dataset]. Retrieved from UPF Digital Repository: https://repositori.upf.edu/handle/ (https://repositori.upf.edu/handle/) [specific dataset URL] on [22.11.2023].

[15] UPF Digital Repository. (n.d.). [Title of the specific dataset]. Retrieved from UPF Digital Repository: https://repositori.upf.edu/handle/ (https://repositori.upf.edu/handle/) [specific dataset URL] on [22.11.2023].

[16] Handa, Palak, Monika Mathur, and Nidhi Goel. "Open and free EEG datasets for epilepsy diagnosis." arXiv preprint arXiv:2108.01030 (2021).

[17] Andrzejak, Ralph G., et al. "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state." Physical Review E 64.6 (2001): 061907.

[18] Kaggle. (n.d.). Epileptic Seizure Recognition. Retrieved from Kaggle: https://www.kaggle.com/datasets/harunshimanto/epileptic-seizure-recognition/data (https://www.kaggle.com/datasets/harunshimanto/epileptic-seizure-recognition/data) on [09.11.2023]