XIAMEN UNIVERSITY MALAYSIA
厦門大學馬來西亞分校

School of Computing and Data Science (SCDS)
Reference No. : XMUM.SCDS (V4)
Effective Date : 15 Sept 2023

Undergraduate FYP Proposal Form[1]

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Section II : Industry Information: (Complete this section if your project is going to be conducted in partnership with any company)

Company Name			
Contact Person			
Designation		**Phone**	
Email ID			

Section III : Declaration by the Student

By signing this form, I confirm that I have read and will adhere to the **Final Year Project Proposal Guidelines** of Xiamen University Malaysia as applicable to this application.

Signature of Student: 曾子聪 Date: Sept 25,2023

Section VI : Supervisor Approval

Name of Supervisor	Dr. Goh Sim Kuan		
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Signature		**Date**	Dec 11, 2023

[1] The length of the proposal should be between 2000-3000 (Excluding proposed title & references)

Note: the supervisor comment has been *removed* in this document

SECTION V : Proposal Information

Proposed Title	Designing Hybrid Network for EEG-based Seizure Detection
Introduction/Problem Statement	**1. Introduction** The brain serves as the central nervous system's core in the human body, exerting control over essential functions such as perception, movement, and cognition (Teng & Kravitz, 2019). Its intricate structure and complex functionality render it a subject of great mystery and ongoing scientific exploration. Disruptions in brain function can give rise to various disorders that profoundly affect an individual's quality of life and overall well-being (A. H. Shoeb & Guttag, 2010). Brain disorders include stroke, epilepsy, addiction, Parkinson's disease, and many other types, are characterized by distinct pathogenesis and symptomatology, exhibiting substantial inter-individual variations. Epilepsy is a type of serious neurological disease caused by abnormal nerve activity, with patients having recurrent seizures within one day. These sudden seizures pose risks not only to the person with epilepsy but also to those around them. Unpredictable seizures create challenges and limitations in many aspects of a person's daily life. Furthermore, the types and severity of epilepsy can vary greatly from person to person, making it more difficult for doctors to diagnose. In the modern epoch, neuro-imaging techniques in healthcare have revolutionized the way in diagnosis of epilepsy. Among these techniques, Electroencephalography (EEG) may be the most typical method to observe and analyze patterns of seizure activity, via monitoring the electronic potential over the scalp. Meanwhile, Deep Learning (DL) is recently prevalent and displays a great potential in aiding medical professionals in their decision-making processes, by embedding in the neuro-imaging system. During seizures, individuals may lose their consciousness and it is a challenge for them to call for help. This makes timely intervention and treatment more difficult. Therefore, it is often necessary for caregivers to monitor individuals with epilepsy to ensure they receive prompt emergency care when needed. These years, with the gradually increased cost in guardianship, the utilization of automated epilepsy detection systems has garnered increasing attention among researchers. These systems have high expectations in accurately detecting and predicting epileptic seizures, enabling medical professionals to intervene earlier and ensure the safety of patients.

	2. Problem statement Although seizure detection algorithms today have been widely applied to EEG and have advanced rapidly over the years, some problems remain in: ● **Problem 1:** Lack of exploration on hybrid structure Current work has focused on developing a deeper single feature extractor (FE), but the potential for horizontal scaling by integrating multiple FEs has often been overlooked. By combining the predictive results of multiple models, model ensemble approaches can combine their strengths to outperform the performance of a single model. This approach has had some notable success in other fields, notably computer vision. However, in the field of epilepsy detection, little research has been conducted on model integration. ● **Problem 2:** Long detection latency in current algorithms Current epilepsy detection algorithms suffer from high latency. And it is believed that the reason is due to the long sliding window used by the algorithms (Xu et al., 2023). However, shortening the window length may result in reduced features that can be captured by the model. In fact, there is no consensus in the academic community about the best choice of window length. Hence, the proposal investigates the impact of window length. ● **Problem 3:** Automated methods encounter limitations in generalization. In existing works, algorithms are evaluated on only one (or two) benchmark datasets, which results in under-validated generalizations of the models. Although these algorithms perform well on specific datasets, their performance in new environments cannot be ensured. This situation can lead to challenges in applying the algorithms in real-world scenarios, as real-world data often have distributions and characteristics that are different from the training data. Thus, it is important to evaluate methods on multiple datasets.
Aims and Objectives	**Aim** The aim of this study is to improve the accuracy and early detection of seizures by introducing an advanced hybrid network. The study seeks to develop effective algorithms that can provide reliable decision-making assistance for medical practitioners. It will involve exploring various datasets related to epilepsy and evaluating different feature extractors to identify the most efficient one. By combining these feature extractors, the goal is to improve the performance of the network. Additionally, this research endeavor aims to gain a comprehensive

	understanding of the pathogenesis of epilepsy. **<u>Objective</u>** ➢ To investigate various Feature Extractor (FE) for seizure detection. ➢ To develop the hybrid structure of neural network with composite FEs for seizure detection. ➢ To examine the proposed network using carefully design experiment. ➢ To evaluate the generalization of the proposed network, by comparing with other works. **<u>Hypothesis</u>** This study is based on the following: ➢ Each FE can extract different information from the same EEG features. ➢ Each FE can be trained to focus on more than one aspect on EEG signals (Spatio, temporal, spectral). ➢ A hybrid network with different FE outperforms the network with a single FE. The hypothesis will be carefully evaluated during the experiment. More details about FE and hybrid network will be revealed in the ***Literature Review*** as followed.
Background Study/ Literature Review	**<u>General Review</u>** An electroencephalogram (EEG) is a type of technology that records the brain activity of humans by placing electrodes on the brain's scalp. This technique has many advantages such as high temporal resolution and low cost, which makes it widely used in medical diagnostics and research. In the diagnosis of brain disorders, EEG has been shown to be effective in diagnosing a variety of diseases, such as epilepsy (Liu et al., 2020; Xu et al., 2020, 2022a), substance addiction (Chen et al., 2023), PTSD (Pelin et al., 2021) and other psychiatric illness(Wang et al., 2023). More specifically, by analysing the EEG, doctors can identify abnormal firing activity and areas of the brain that can be used to diagnose and plan treatment. However, this usually requires the involvement of an experienced physician and can lead to errors in judgment. **Epilepsy** is a chronic neurological disorder, with patients making up 1% worldwide(Xu et al., 2022b). Long-term medication is the mainstay of treatment for people with epilepsy, but one-third of patients are still not cured by medication. For

those people with epilepsy, seizures are usually accompanied by loss of consciousness, which makes it difficult to seek help from a doctor. Therefore, it has become particularly important to develop timely seizure detection systems.

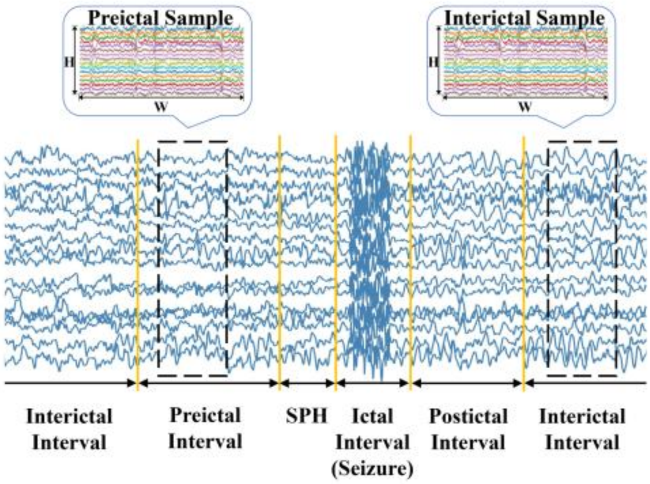

Figure 1: An example of EEG recording from epileptic patient (Xu et al., 2020)

<u>Diagnostic Challenges</u>

An accurate diagnosis of epilepsy presents several challenges. First, epilepsy requires a full understanding of the patient's past medical history(Syed et al., 2011). Next, the diagnosis in epilepsy requires professional doctors in case epilepsy has a wide variety of clinical features depending on its type (Liu et al., 2020). Thus, the medical community needs a reliable method to diagnose the epilepsy.

In this context, video-based EEG recordings have proved to be indispensable. Typically, EEG monitoring requires the patient to spend several days in the ward where EEG data with epilepsy are collected(A. H. Shoeb & Guttag, 2010). However, epilepsy is immediate and unpredictable. Timely detection and intervention of epilepsy through EEG can be difficult(Xu et al., 2023). Even the examination of the EEG after the fact is a time-consuming and labor-intensive way. In many countries, there is a shortage of doctors with experiential knowledge - manual examination of EEG recordings occupy technicians in a field already facing a shortage(Liu et al., 2020).

<u>Cutting-edge Machine learning technology</u>

The uncertainty in the diagnosis of epilepsy has also prompted the introduction of deep learning (DL) into this field. One typical scenario of utilizing DL is the automatic seizure detection system. Since the beginning of the last century, several studies have been published for detection algorithms. Early classic research comes from Shoeb, whose algorithm detected 131 out of 139 epileptic seizure events with a detection latency of 8 s and an FDR of 0.25/h in the year 2004(A. Shoeb et al., 2004). After 6 years, they published their dataset, under the name CHB-MIT, which is the most prevalent used nowadays (A. H. Shoeb & Guttag, 2010).

Subsequently, many tools and methods that can effectively diagnose epilepsy have emerged in this field, and research efforts have mainly focused on investigating newer feature extraction methods and model structures. For feature extraction, the EEG signal is rich in hidden information, both in the time domain and in the frequency domain, and different feature representations can be obtained by different signal processing methods, leading to different results. Some innovative results such as Vidyaratne et al. used a modified wavelet transform to extract the frequency information in spectrum and achieved 96% sensitivity on the CHB-MIT dataset(Vidyaratne & Iftekharuddin, 2017). The classical study for extracting time-domain information comes from the End-to-End architecture designed by Xu, which inputs the time-domain signal directly to CNN and classify for result(Xu et al., 2020).

In addition, the short-time Fourier transform (STFT) is also an efficient way to extract information, which extracts features from different time periods through a sliding time window. Its first introduction into epilepsy recognition came in 2018, when Truong et al. used a 30-second based time window to transform the signal, and this work has been hailed as one of the most classic papers in the field of epilepsy recognition(Truong et al., 2018). Inspired by this, Yuan proposed a multi-window multi-view deep learning framework based on STFT, which obtained an accuracy of 94.37% under cross-validation. It is worth mentioning that the empirical pattern-based decomposition method is a proven effective feature extraction technique, and in the past decade, it and its variants have been used by authors to achieve satisfactory performances(Alickovic et al., 2018; Hassan et al., 2020).

In terms of model structure, the design based on convolutional layers is a typical model architecture. The CNN-base architecture treats the EEG signal with processed features as a image for processing, in this case 2D convolutional kernel will be used in learning the relevant features(Xu et al., 2020). Different from the traditional construction, there are also many studies using 1D CNNs for model training with satisfactory results(O'Shea et al., 2020). In recent years, as novel models such as transformer (Vaswani et al., 2017) and GNN (Zhou et al., 2020) have been proposed, a lot of work has been done applying them to the field of epilepsy detection. Yan et.al used the 3-gate transformer as an encoder to transpose the time-frequency features and feed them into the decoder for classification, and achieved 96.01 per cent(Yan et al., 2022).

In addition to pursuing DL structures, there have been many studies that have attempted to optimize models in terms of breadth using ensemble. For example, Liu used symmetric encoders and found that different types of encoders were able to produce different EEG representations separately, while the combination of CNN and RNN produced the maximum performance(Liu et al., 2020). Subsequently, Li proposed to combine two types of feature extractors, GNN and CNN, where GNN is responsible for extracting spatial dynamic features and CNN is responsible for extracting temporal spatial information. After their experiments, it is proved that the proposed feature extraction method does not need to define hyper-parameters manually and does not lag other approaches in terms of performance(Li et al., 2022).

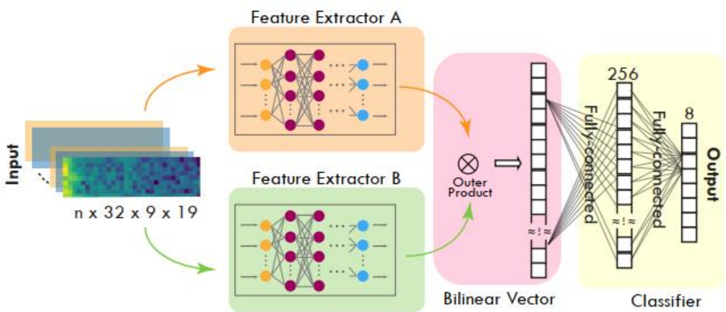

Figure 2: Symmetric FE Structure (Liu et al., 2020)

After in-depth exploration and analysis through the literature listed above, the main innovations of the typical studies with their drawbacks are shown in **Table 1**.

Form of feature	Feature Extractor	Innovation	Drawback
An End-to-End Deep Learning Approach for Epileptic Seizure Prediction			
Time domain	CNN	Directly send signal into classification	False use in evaluation metric
Automated EEG-Based Epileptic Seizure Detection Using Deep Neural Networks			
Frequency domain	MLP(DNN)	Filter out signal in different frequency signal	Only full-connected layers was utilized
Convolutional neural networks for seizure prediction using intracranial and scalp electroencephalogram			
Time-frequency domain	CNN	First study use STFT into feature extraction	Shallow CNN structure
Multichannel Synthetic Preictal EEG Signals to Enhance the Prediction of Epileptic Seizures			
Time-frequency	3D-CNN	Utilized 3D convolution	-

domain		kernel into classification	
Seizure Prediction Based on Transformer Using Scalp Electroencephalogram			
Time-frequency domain	Transformer	Utilized 3-gate transformer extractor into classification	Not suitable for real-time system
Graph-generative neural network for EEG-based epileptic seizure detection via discovery of dynamic brain functional connectivity			
Time-domain+ functional connectivity information	GNN+ Transformer + CNN	1) Combine the information from 3 type of FE 2) Compare with multiple advanced network	Only F1-score was applied
Epileptic Seizure Classification with Symmetric and Hybrid Bilinear Models			
Time-frequency domain	CNN+RNN	Applied hybrid network to achieve better performance	Not include cutting-edge tech(i.e.transformer)
Exploring the Applicability of Transfer Learning and Feature Engineering in Epilepsy Prediction Using Hybrid Transformer Model			
Time-frequency domain + frequency domain	Transformer	1) proposed the propobility to apply the algorithm into transfer learning 2) proposed mix-rhythm FE base on transformer	-

Table 1: Innovation and drawback of 8 mentioned publications

Research Methodology

<u>Research Strategy</u>

To better understand the state-of-the-art (SOTA) machine learning solutions in this field, especially in seizure diagnostic applications, this study will include comprehensive literature review at the first stage. This approach will ensure investigators gain a comprehensive understanding of cutting-edge solutions and apply them in their own research. After that, the quantitative research strategy will be adopted to yield the best Feature Extractor (FE). Subsequently, the top-N FE will be selected to build the hybrid network. In testing stage, two or even more EEG datasets will be used to evaluate the generalization of the network. This is expected to provide valuable insights into today's research in the field of seizure diagnosis and lay the foundation for the development of more effective diagnostic tools and treatments.

<u>Research Phases</u>

- **Phases 1: In-depth Literature Review**

Existing literature is collated and assessed to determine the best way to conduct experiments in the following step. This step will involve 2 sub-tasks: 1) Evaluation on the cutting-edge technique; 2) Evaluation of the open-source dataset. These will

	ensure that the proposed model is advanced and the dataset is properly organized. ➢ **Phases 2: Experimental Process** At the beginning of this phase, multiple FEs will be trained and tested one by one. Due to the control the variables, only one dataset will be used in this step. Through horizontal comparison, the performance of each FE will form a ranking, and the Top-N FEs will be selected for the following step. Subsequently, several hybrid structures will be proposed and trained on multiple datasets. To ensure the flexibility and adaptability of the model, I will use agile software development methods to iterate and adapt the model quickly. This means that during the development of the model, it will be adapted and improved in a timely manner based on the characteristics of the different datasets to ensure that the model is able to perform well in a variety of situations. After the in-depth evaluation, the final model structure will be determined. This will involve fine-tuning and optimizing the model to ensure it is robust and reliable. At this stage, I will evaluate multiple metrics to measure its performance in terms of accuracy, sensitivity and specificity by testing it on multiple datasets. At the same time, I will write a report describing the results of this study in detail. ➢ **Phase 3: Result Conclusion** In this phase, the findings will be concluded, aiming to derive valuable conclusions. Subsequently, I will document these findings in a thesis. If time permits, I intend to write it as a paper and submit it to a conference. I hope that my discoveries will provide novel insights for future researchers in the field of epilepsy detection.
Potential Project Significance	With continued innovations in the field of Deep Learning (DL) and strong demand from the healthcare industry, it is significant to conduct this study. Firstly, new DL techniques are emerging in other field (e.g. Computer Vision), which providing new insights and ideas for the study in epilepsy. These techniques have made tremendous progress in healthcare over the past few years, but there are still some challenges in seizure detection (refer to ***Literature review***). This means that now, more than pass, it is possible to develop efficient and reliable detection systems for brain disorders. Therefore, the importance of this study is to apply the latest machine learning algorithms to epilepsy diagnosis to provide more accurate and reliable diagnostic results. Secondly, current state-of-the-art (SOTA) detection network overly concerned with improving the performance in accuracy and false detection rate (FDR), however, the

<table>
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generalization often been neglected. It is notable that even though certain models perform well on specific datasets, they may not be able to adapt well when in the new environments. Therefore, this study will focus on <u>finding a balance</u> between performance and generalisability, which makes it significant for the practical application of epilepsy detection systems.

By integrating the latest DL algorithms and expertise in the field of seizure detection, this study will explore new cutting-edge strategies to improve the accuracy and generalization of epilepsy detection systems. This will also provide the healthcare field with more reliable and efficient epilepsy diagnostic (detection) tools to improve patient outcomes and quality of life.
</td></tr>
<tr><td>Expected Outcomes and/or Concluding Remarks</td><td>
<u>Expected Outcome</u>

The following are the project's expected results.

✓ Top-N Feature Extractor (FE) for seizure detection.

✓ Robust hybrid network with outstanding generation.

✓ End-to-end Detection System with graphic user interface (GUI)

<u>Concluding Remark</u>

There are several research gaps within the current field of study. To address these gaps, there is an urgent need for an in-depth study into the composite structure of neural networks. The primary focus of this study is to improve the current model performance on long latency and generation. Through continuous experiments with improvement, the advanced hybrid structure will be purposed and evaluated. However, trying to purpose robust structures can be challenging. While the proposed structure may not be the most cutting-edge solution, it serves the purpose of exposing techniques and knowledge useful to the future research in this field.
</td></tr>
<tr><td>Preliminary Result</td><td>
<u>Preliminary Result</u>

➢ Investigation on available dataset

Table 2 shows information about currently available datasets in open source. Most of the datasets can be categorical by acquisition location(Wong et al., 2023), and signal quality is closely related to signal acquisition location. Two common acquisition locations are: 1) scalp surface and 2) intracranial. Furthermore, a good EEG dataset should have multiple channels to contain more information. In terms of the number of channels, the TUHZ has up to 31 channels, which is the most.

<table><tr><th>Dataset</th><th>Channels Number</th><th>Type of Signal</th></tr></table>
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University of Bonn	1	Scalp/Intracranial EEG
CHB-MIT Scalp EEG	18	Scalp EEG
Melbourne-NeuroVista Seizure Trial	16	Intracranial EEG
Kaggle Upenn and Mayo Clinic's Detection Challenge	16-76	Intracranial EEG
Kaggle Amaerican Epilepsy Society Prediction Challenge	16	Intracranial EEG
Neurology and Sleep Centre Hauz Khas	1	Scalp EEG
Kaggle Melbourne-University Seizure Prediction	16	Intracranial EEG
TUH EEG Seizure Corpus(TUSZ)	23-31	Scalp EEG
Helsinkl University Hospital EEG	19	Scalp EEG
Siena Scalp EEG	20/29	Scalp EEG

Table 2: Details for open-source datasets

Given above, the following two datasets will be used in this experiment:

✓ TUH EEG Seizure Corpus(TUSZ)： TUSZ provides EEG data for 6 epilepsy types, which support multi-label classification. Moreover, it contains epilepsy data from more than 600 patients, the large sample size will ensures the training of more robust models. This dataset is constantly being repaired and updated for greater reliability.

✓ CHB-MIT Scalp EEG: CHB-MIT is the most classic dataset in the field. It contains epilepsy data from 23 patients and is used by many seizures detection study.

➢ **Pre-processing Result**

As the initial stage of the experiment, the CHB-MIT dataset was selected for the experiment. **Figure 2** demonstrates the preprocessing steps used in this experiment. According to the theory proposed by Liu in his paper(Liu et al., 2020), the EEG signals first need to be filtered. According to this, the band-pass filter was set at the range from 1Hz to 55Hz, which was to filter out high frequency noise and baseline drift phenomenon. Since AC power in the United States is concentrated around 60Hz, electrical noise at this frequency point should be removed. Subsequently, the EEG signals will be downsampled to 256 Hz to speed up the computation. Finally, the samples for training will be cut.

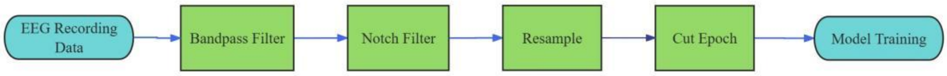

Figure 2: Pipeline of pre-processing

Figure 3 and **Figure 4** show the changes that occur in the spectrum of the EEG. It can be observed that the electronic noise around 60Hz is considered to be eliminated (log10(power)<-40). What's more, the ambient noise above 55Hz in the EEG signal is significantly reduced. After these steps, clean datasets will be generated and will be beneficial for subsequent model training.

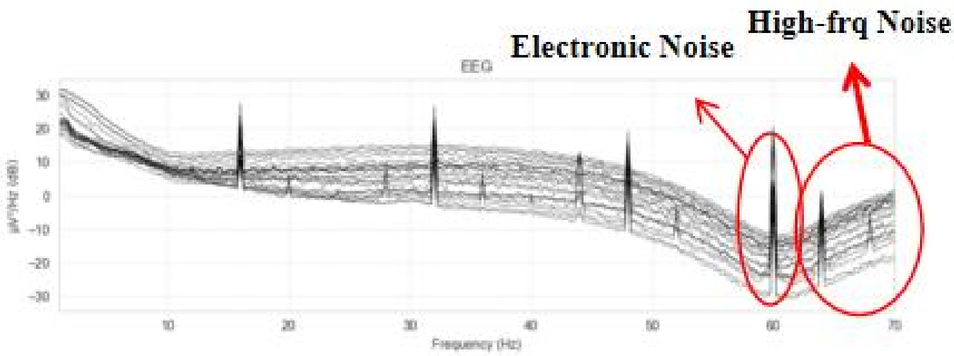

Figure 3: Spectrum of EEG Before Pre-processing

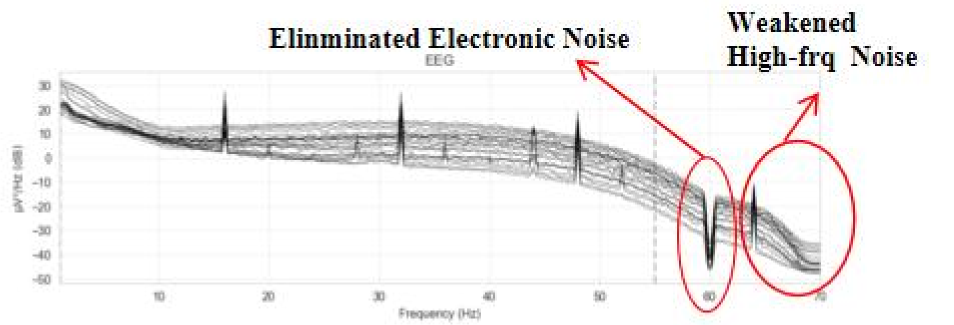

Figure 4: Spectrum of EEG After Pre-processing

Key References

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Gantt Chart

Breakdown of project

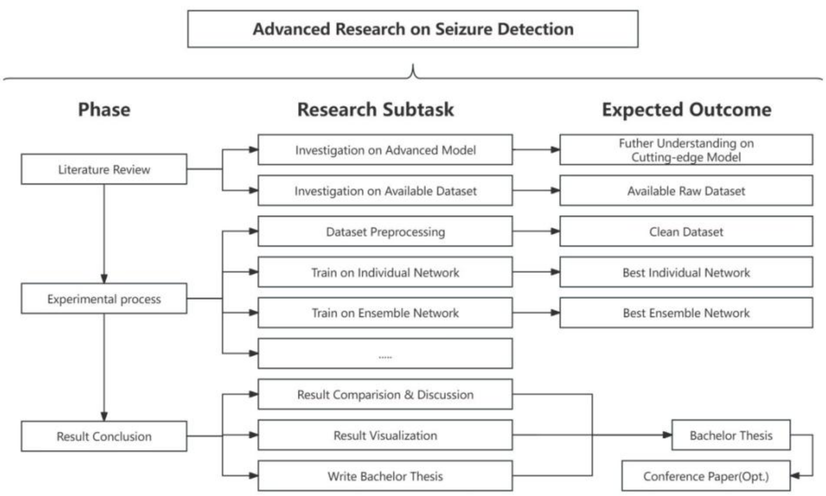

Figure 5: Breakdown of Final Year Research Project

Timetable for proposed activity

Task No.	Activity	Week No.	End Date	End Date
1	Overall Literature Review	1-4	2024/3/31	2023/4/13
2	Pre - process the datasets	1-4	2024/4/28	2024/5/4
	Train every FE one by one	4-8	2024/5/5	2023/5/25
	Evaluate each FE	5-8	2024/5/26	2024/6/22
	Build Hybrid Model	8-9	2024/6/16	2023/6/29
	Evaluate on 1st dataset	10-12	2024/6/2	2024/6/22
	Evaluate on 2nd dataset	11-12	2024/6/9	2023/6/22
3	Conclude experiment result	12-13	2024/6/16	2023/6/29
	Finish Draft of paper(opt.)	14	2024/6/30	2024/7/6
	Finish Report	14	2024/6/30	2024/7/6
	Prepare Presentation	15	2024/7/7	2024/7/13

Table 2: Activity involved in FYP

Gantt Chart for FYP

Figure 6:Gantt Chart of FYP

[2] Please follow APA style of referencing.