Machine Learning-Powered Brain Imaging for Early Detection of Autism Spectrum Disorder

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements forthe **Degree of Bachelor of Science in Computer Science and Engineering**

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APPROVAL

This Project titled **"Deep Learning-Powered Brain Imaging for Early Detection of Autism Spectrum Disorder"**, submitted by **MD. Shohag Mia**, ID No: **212-15-14736** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **17 September, 2025**.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Md. Shahriar Shakil, Lecturer**, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition whose accurate and early detection remains an enduring challenge in clinical neuroscience. Resting-state functional magnetic resonance imaging (rs-fMRI) provides a non-invasive means of probing functional brain connectivity, yet multi-site variability, class imbalance, and inconsistent methodological practices continue to hinder progress. In this thesis, we conduct a systematic benchmarking study on the merged ABIDE-I and ABIDE-II datasets, comprising more than 2,200 subjects from over 30 international sites. Fourteen machine learning models—encompassing linear classifiers, probabilistic approaches, ensemble methods, boosting algorithms, and neural networks—were implemented under a unified preprocessing and evaluation pipeline. Performance was rigorously assessed using accuracy, precision, recall, and F1-macro to ensure robustness against dataset imbalance. Results demonstrate that ensemble and boosting approaches, particularly Random Forest, LightGBM, Gradient Boosting, and CatBoost, consistently outperform classical baselines and rival deep learning methods, achieving accuracies approaching 98% and F1-macro scores exceeding 0.99. This study establishes a reproducible baseline for ASD classification, highlights interpretable and deployment-ready models for potential clinical decision-support, and lays the groundwork for advancing towards deep, graph-based, and multimodal neuroimaging frameworks that address the complexity of ASD.

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Chapter 1
Introduction

In this Chapter outlines the Introduction, Motivation, Objectives. Also, a short overview about the Methodology, Motivation and Project Outcomes also discussed in this chapter.

1.1 Introduction

Autism Spectrum Disorder (ASD) is a pervasive neurodevelopmental disorder, and its rising prevalence and long-term consequences for the person, families, and society have made it an international priority. ASD is most notably characterized by deficits in social communication, the presence of restricted or repetitive activities or behaviors, and unusual responses to sensory input. The multifaceted nature of the disorder and its heterogeneity render accurate and early identification notably challenging, but critically important for impacting developmental trajectory through early targeted supports.

The recent developments of neuroimaing, specifically resting-state functional Magnetic Resonance Imaging (rs-fMRI), offered a unique opportunity to investigate brain activity during rest in individuals with ASD. In contrast to the task-based fMRI, rs-fMRI is the measurement of the intrinsic neural activity when the subject is not performing specific tasks, which reflects the baseline connectivities of the brain. This information is critical for clinical populations, for whom task adherence may be unreliable or impractical [1,2].

In order to promote ASD studies, the Autism Brain Imaging Data Exchange (ABIDE) project has been created to integrate and standardize rs-fMRI datasets acquired from a variety of international locations. Here we are using the combined dataset of ABIDE-I and ABIDE-II which contains more than 2,000 subjects, both ASD, and typically developing controls. Despite the richness of the ABIDE dataset offering many possibilities for machine learning investigation, challenges including scanner differences, mixed demographics, and site specific differences persist [3,5].

Machine learning (ML) techniques have been increasingly used to analyze neuroimaging data for characterization of ASD biomarkers. Well-established models including Logistic Regression, SVM and Random Forest also exhibited positive early results [5,6]. Fancier methods, like ensemble and boosting algorithms, such as Gradient Boosting, AdaBoost, CatBoost, XGBoost, LightGBM have enhanced performance predicatively by combining several weak learners to stronger one (Classifiers) [10,12]. However, to the best our our knowledge, existing literatures generally have the problem of neglecting comprehensive studies including various architectures or focusing primarily on deep learning techniques, including

Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTMs), or graph-based networks [3,4,8,14]. A systematic comparison of multiple ML algorithms on the combined ABIDE-I and ABIDE-II databases is therefore necessary to identify viable, reliable, and interpretable solutions for ASD detection.

1.2 Motivation

Despite numerous studies that have been investigated with the ABIDE dataset, work on ASD classification is scattered. A few works focus on deep learning methods, like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) [3,14]; whereas others confine themselves to only a few classical machine learning ones, such as SVM and decision trees [5,13]. Which, in turn, makes it challenging to form a rival view of models efficacy along a broad range of techniques.

Additionally, the lack of standard performance assessment implies that reproducibility is limited. Some papers focus on accuracy only [1,2] or selectively report recall or precision without a complete set of metrics [6,7,11]. For the case of ASD, when there is a class imbalance in the dataset and false negatives can have serious implications, it is crucial that the accuracy, precision, recall, and F1-score of a performance evaluation metric be considered all together.

The goal of this work was thus to address these limitations by undertaking a systematic and dry (meta)NMA of fourteen machine learning models on the combined ABIDE-I and ABIDE-II dataset. By comparing various classical, probabilistic, ensemble, and boosting methods with unified pipeline of evaluation, strong baseline and guidelines for further research in the field of ASD classification are presented in this work [1–18].

1.3 Objectives

The purposes of this analysis are as follows:

- To pre-process and readiness the combined ABIDE-I and ABIDE-II dataset for classification purposes.
- To build fourteen types of machine learning models including linear classifiers, probabilistic models, ensemble models and boosting models [5,10,12].
- To compare each model with common reference metrics (accuracy, precision, recall, F1-macro) [6,7].
- To compare several models and propose the best performing algorithms, along with their potential limitations [3,4,14].
- To provide a reproducible baseline which could be a reference for future work of deep learning, graph-based models, and multimodal [8,9,16,18]

1.4 Methodology

The methodology of this project is rigorously constructed to provide fairness, reproduci- bility, and a meaningful comparison for all models. It is composed of a number of key steps, each of which is important for the quality of source estimation.

1. **Dataset Preparation:** We use the concatenated ABIDE-I and ABIDE-II dataset in the present work. Procedure The preprocessing steps involve dealing with missing values, scaling continuous features as well as encoding categorical features. A stratified train-test split is used to retain class balance between ASD and control groups.

2. **Model Implementation:** In the end we apply fourteen different machine learning models spanning virtually the entire spectrum of learning algorithms:

- Linear Models: Logistic Regression.
- Probabilistic Model: Gaussian Naive Bayes.
- Support Vector Method: SVC.
- Instance-based Method: K-Nearest Neighbors.
- Neural Network: Multi-Layer Perceptron.
- Models based on Trees: Decision Tree, Random Forest, Extra Trees.
- Methods:Boosting(Gradient Boosting, AdaBoost, CatBoost, XGBoost, LightGBM).
- Bagging Method: Bagging Classifier.

All the models were trained under the same circumstances to facilitate a fair comparison.

3. **Evaluation Strategy**

Models are benchmarked with four primary performance measure:

- Precision: Ratio of the number of true positive observations to the number of true positive and false positive observations.
- Precision: the proportion of ASD cases that were correctly predicted as ASD.
- Remember: the ratio of true ASD cases that have been accurately identified.
- F1-score (macro): the harmonic mean of precision and recall, averaged by class.

Having these four measures ensures that results are robust in the face of class imbalance.

4. **Analysis and Visualization**
Summary tables of results are provided. Bar charts and performance plots are presented to compare the fourteen models. Discussion and interpretation offer means for linking the findings to insights in the literature

1.5 Project Outcome

This study provides a benchmark analysis of fourteen machine learning models using concatenated ABIDE-I and ABIDE-II data. The results show that Logistic Regression got the highest accuracy (≈98%) with the ensemble models, namely Random Forest and LightGBM also with promising performances (≈96–97%). Our model compared poorly with GaussianNB, which achieved the lowest performance at 62%.
Reproducible benchmarking pipeline to classify ABIDE dataset.

- Reproducible benchmarking pipeline to classify ABIDE dataset.
- Comparison table and visualizations of 14 algorithms in machine learning.
- Understanding where the classical and ensemble methods work better or worse than each other.
- A strong baseline for both deep learning and graph-based neural networks in future research

1.6 Organization of the Report

This section outlines the expected structure for a typical IT research report as required for the industry project course. The report also includes six main chapters, which presents each section for the following:

- **Chapter 1: Introduction**
  Introduction This section gives a general synopsis of the study. It starts with background on ASD and the ABIDE dataset, then it moves to the motivation, objectives and methodology of the research. Finally, in this chapter, the project deliverables and the map of the whole report are presented.
- **Chapter 2: Background and Literature Review**
  Covers basic concepts such as fMRI, resting-state connectivity, and machine learning in neuroimaging. It next reviews the relevant literature from prior studies, including the use of similar applications, and related efforts. The chapter concludes with a gap analysis and limitations of previous studies and how the present study attempts to address them.
- **Chapter 3: Research Methodology**
  Outlines the workflow of the project, along with description of dataset, preprocessing, model architecture and evaluation protocol. It also contains workflow diagrams, functional and non functional requirements project plan and task allocation.
- **Chapter 4: Implementation and Results**
  Describes the environment environment set-up, model training, performance analysis and comparative results for all fourteen classifiers. Results are presented in tables and figures; they are then discussed and interpreted.
- **Chapter 5: Engineering Standards and Design Challenges**
  Discovers the software, hardware and communication specifications which have been used in the project. It also covers social, ethical and sustainability issues, and project management and financial analysis. The chapter also describes the complex engineering problems and tasks on which the project focuses.
- **Chapter 6: Conclusion and Future Work**
  Concludes with key findings, limitations and potential future lines of research, including the application of deep leaning, graph neural networks and multimodal data integration

Chapter 2

Background

This chapter gives an introduction of the background general issues of deep learning model-based in the detection of ASD. It first presents main principles that need to be understood to understand the background of the research, then it presents an extensive literature review on the topic, third it highlights the gap of the related work from which the proposed system stems.

2.1 Introduction

Autism Spectrum Disorder (ASD) is characterized by a spectrum of deficits in social communication, limited/restricted interests and atypical sensory responses. Neuroimaging—particularly, resting-state fMRI (rs-fMRI)—provides a noninvasive window into intrinsic brain activity and connectivity. Taking correlations between time series of brain regions as the model, rs-fMRI allows us to build FC matrices and derived network properties ready to be read by machine learning (ML) pipelines.

ML has become quite central in ASD neuroimaging analysis since it has remarkable flexibility to high-dimensional features, it can handle non-linear patterns, handle multi-site data such as ABIDE-I and ABIDE-II and so forth. Typical pipelines consist of (1) preprocessing (motion correction, nuisance regression, normalization), (2) feature construction (ROI time series, correlation/partial correlation/graph metrics), (3) model training (linear, tree-based ensembles, kernels, neural network), and (4) evaluation using accuracy, precision, recall, and F1-macro. Although deep learning has been effective, classical and ensemble methods are competitive, yet less computationally expensive, and more interpretable, especially for tabular or graph-derived features rather than raw volumes.

This was the context of the present study. We evaluate fourteen different ML models in a single, unified pipeline with the combined ABIDE-I and ABIDE-II databases and report standardized metrics. We summarize related work in this area here to place our contribution.

2.2 Literature Review

Various works addressed the application of machine learning (ML) and deep learning (DL) for the classification of ASD based on the ABIDE datasets. Early studies integrated both functional and structural MRI characteristics with stacked autoencoders and multilayer perceptrons obtaining satisfactory results (~85%) but had suffering from generalizability problem since the methods mainly used single site related data [1]. Likewise, deep AE models published accuracies of 70–80%, with performance degradation for deployment in larger and more heterogeneous cohorts, most likely due to site specificity [2].

Following, spatio-temporal deep learning techniques based on CNNs and LSTMs were later used, modelling on spatial and temporal relations found in fMRI data, and could achieve more than 80% accuracy [3]. Graph-based learning has also recently attracted, with spectral graph convolutions [4] and graph attention networks [8,16] making use of brain connectivity structures, but checking how much of a issue interpretability and computational requirements still are. Simple implementations such as SVM and correlation-based classifiers reached moderate scores (around 70–75%) using functional connectivity features [5, 6], and preprocessing such as spatial filters helped to improve SNR but with a decrease in sample sizes [7].

Multimodal fusion (combining different modalities to improve robustness) is seen as a recent trend and consistently outperformed unimodal methods when compared to their unimodal counterparts [9]. The ensemble methods of bagging and boosting yielded a consistent classification level (approximate 75%) [10]. Combining classically discovered features with features derived from an autoencoder in a hybrid pipeline improved classification slightly (70%) [11], whereas application of LSTMs based studies on the dynamic functional connectivity brought into focus the relevance of temporal changes in the organization of brain networks [12]. Recent innovations include GAN-based augmentation achieving an improvement of 6% in accuracy [15], and transfer learning using more powerful pretrained ResNets, which reported accuracies close to 79%, which however suffered from a severe domain mismatch[18].

Table 2.2.a: Summary of Literature Reviewed.

Author(s)	Year	Title	Methodology	Key Findings
Rakic et al.	2020	Fusion of Structural and Functional MRI for ASD	Stacked Autoencoders + MLP	Achieved ~85% accuracy on ABIDE-I; limited generalization [1]
Heinsfeld et al.	2018	Deep Autoencoders for ASD Classification	Stacked Autoencoders	Reported 70–80% accuracy; drop in larger heterogeneous datasets [2]
Bayram et al.	2021	CNN/LSTM Hybrid Models for ASD	CNN + LSTM Hybrid	Accuracy >80%; lacked comparison with classical ML [3]
Ktena et al.	2018	Spectral Graph Convolutions on fMRI Graphs	Spectral GCN	Accuracy ~75%; limited interpretability [4]
Chen et al.	2015	Functional	Linear	Accuracy ~75%;

		Connectivity Classification	SVM/Multivariate	limited ROI-based features [5]
Plitt et al.	2015	Functional Connectivity Biomarkers for ASD	Correlation + ML	Moderate accuracy; weak biomarker reproducibility [6]
Subbaraju et al.	2017	Spatial Filtering for rs-fMRI ASD Detection	Spatial filtering + ML	Accuracy ~70%; reduced sample size after QC [7]
Liu et al.	2023	Graph Attention Networks for Connectivity	GAT for fMRI graphs	Achieved 75–80% accuracy; enhanced connectivity analysis [8]
Multimodal Fusion Study	2019	Integrating fMRI with Phenotypic Data	Late fusion DL	Fusion improved accuracy (>80%) vs unimodal [9]
Ensemble Learning Study	2019	Boosting and Bagging for ASD	Ensemble (RF/Boosting)	Accuracy ~75%; improved stability [10]
Autoencoder + Classical ML	2020	Unsupervised Features for ASD	AE + SVM/LogReg	Accuracy ~72%; modest improvements [11]
Dynamic FC Study	2020	Temporal States in fMRI for ASD	Sliding-window dFC + LSTM	Accuracy 75–78%; sensitive to window size [12]
Gupta et al.	2024	Causality-based fMRI Fingerprints	Granger causality	Unique causal features improved classification [13]
3D CNN Study	2020	Volumetric CNNs for ASD Detection	3D CNN	Accuracy ~74%; overfitting on small datasets [14]
GAN Augmentation Study	2021	Synthetic Data for ASD Classification	GAN + CNN	Improved accuracy by ~6% over baseline [15]

Attention-based Feature Selection	2022	Graph Attention with Feature Pruning	Attention + GCN	Achieved ~81% accuracy; overfitting risk [16]
Benchmarking Study	2021	Classical vs Deep Learning for ASD	CNN/RNN vs SVM/RF	DL ~77% vs ML ~70%; limited sample tuning [17]
Transfer Learning Study	2021	Pretrained ResNet for ASD	Transfer Learning (ResNet)	Accuracy ~79%; domain mismatch issues [18]
Zhang et al.	2020	Hybrid spatio-temporal convolutional networks for ASD classification using rs-fMRI	Spatio-Temporal CNN	Accuracy ~82% on ABIDE datasets; improved feature extraction from rs-fMRI
Li, Wang, and Hu	2021	Dynamic functional connectivity and deep learning for ASD diagnosis	Dynamic Connectivity + Deep Learning	Reported ~80.3% accuracy with deep learning methods on ABIDE
Guo et al.	2020	Attention-based feature selection improves ASD classification	Attention-based Feature Selection + Classifier	Improved classification; accuracy ~78%, highlighted key brain features
Rakhimberdina, Kim, Hong	2022	Population graph-based GCN for autism spectrum disorder detection	Population Graph GCN	Achieved 76.6% accuracy, effective use of GCN on merged ABIDE I/II
Brown et al.	2021	3D convolutional neural networks for ASD diagnosis with structural and functional MRI	3D CNN	Accuracy ~79% using both structural and functional MRI data

2.2.1 Similar Applications

Machine learning and deep learning approaches have been used in T1 and T2 beyond ASD, especially in ADHD, Alzheimer's disease, schizophrenia and in mild cognitive impairment (MCI). In such diseases, Rs-fMRI is frequently converted to connectivity matrices or graph attributes and then classified by classifiers such as SVM/RANDOM FOREST [5, 6, 10]. Multimodal fusion paradigms, fusing fMRI with structural MRI or phenotypic data, have provided more robust Alzheimer's study results (9), whereas deep learning frameworks, such as CNNs, RNNs and graph based models (i.e., GCNs, GATs), have been investigated in schizophrenia and MCI to obtain fairly competitive outcomes but at the cost of high computational costs and little interpretability (3, 4, 8, 14). Lessons from these applications apply directly to ASD: models trained on single-site data typically do not generalize, underscoring the importance of cross-site validation [1, 2, 7]; accuracy metrics alone are not enough and precision, recall, and F1-score are required for balanced evaluation [6, 11]; and well-tuned ensemble methods, e.g., bagging and gradient boosting closely match deep networks, especially when training sample is limited [10, 12].

2.2.2 Related Research

Many studies have directly used machine learning algorithms on the ABIDE-I and ABIDE-II data sets for ASD classification and the results of eighteen representative studies shed light on the advances as well as the outstanding challenges in the field. Early work integrated structural and functional MRI biomarkers with stacked autoencoder and multilayer perceptron that reached roughly 85% classification accuracy on ABIDE-I, however, the use of limited generalization and single-site focus limited its utility [1]. Later deep autoencoder studies also produced an accuracy in the range of 70–80%, but fell on more heterogeneous cohorts, emphasising how the presence of site effects are detrimental to such models [2]. Researchers then investigated spatio-temporal approaches, including CNNs, LSTMs, and hybrids on ABIDE-I, achieving above 80% accuracy; however, such works rarely compared performance to traditional methods [3]. Graph-based methods with spectral graph convolutions or graph attention networks, aimed to exploit connectivity structure, but providing 75–80% accuracy, yet suffering from lack of interpretability and high computational cost [4,8]. A number of studies focused on functional connectivity as a biomarker, modeling either the linear features or the correlation-based measures, with mixed, but generally moderate performance (\(\sim \) 70–75%) and an emphasis on whole-brain analyses and cross-site stability [5, 6]. Other studies focused on spatial filtering, multimodal fusion with phenotypic data, or ensemble methods such as bagging and boosting, obtaining accuracies in the mid-70% in validating, but interpretability and generalization were limited [7,9,10]. There have been further developments such as autoencoder-based feature extraction with classical classifiers [11], dynamic functional connectivity interpreted using LSTMs [12], handcrafted graph metrics combined with SVMs [13] and volumetric 3D CNNs [14], each achieving performances generally around the range of 72–78% on the test set, but were challenged with overfitting or excluded voluminous preprocessing. GAN-based data augmentation resulted in improvements of only a modest six percentage points [15], and attention-based feature selection reached an eight percent improvement of about 81%, but raised issues of overfitting [16]. Such an approach managed to Outperform deep models by a small margin (around 77% vs 70%) in some benchmarking studies where no fine tuning was used and small datasets were employed [17]. Finally, transfer learning methods with pretrained ResNet backbone reported accuracies close to 79%, although the domain discrepancy between natural images and neuroimaging data restricted their efficacy [18]. Cumulatively, these eighteen studies demonstrate that classic and deep learning have promise, but most focus on a small subset rather than providing a comprehensive picture of model-level performance, and neglect to implement cross-site reproducibility. These are the shortcomings that heavily motivate our study that conducts a systematic benchmarking of fourteen heterogeneous models on the combined ABIDE-I and ABIDE-II data using standardized evaluation metrics.

2.3 Gap Analysis

Tabler-0005SD0005-Table 5 A close perusal of the eighteen studies exposes several common flaws. In the first place, the models were limited in scope. A large number of works exclusively studied deep networks" such as autoencoders, CNNs, or GCNs [2-4,8,14,16], whereas others considered solely classical classifiers" such as SVM or logistic regression [5,6,13]. Most studies conducted comparing many models were not conducted across each performance-measuring condition, so uncertainty remained as to how various model families compared to each other.

Second, lack of consistent usage metrics is a hindrance to reproducing and comparing results. Some papers presented just accuracy [1,2,3,14], or precision, recall and F1-scores were absent or if provided, inconsistently reported [6,7,11]. For unbalanced data sets, such as ABIDE, this may lead to an inaccurate view of the model's performance.

Third, site and small sample size effects lead to generalization issues. Single site analysis [1,7,13] or aggressive data pre-processing exclusions [1,2] both resulted in significant sample size effects and selection bias to limit generalizability of findings from multi-site ABIDE data. One approach of coping with data scarcity was previously to use GAN-based augmentation [15] or transfer learning [18]; however, domain mismatch and instability issues still existed.

Finally, interpretability is also low, especially in deep or graph-based methods. Although attention mechanisms [8,16] and feature selection procedures tried to emphasize relevant features, many studies considered models as black boxes that provided few biological interpretability. lack of interpretability:' Cthat is, clinical trust + adoption).

Our study addresses these gaps by:

- Taking the performance of 14 diverse methods including the linear, probabilistic, ensemble, and boosting on the tables [5,6,10,12].
- Using the combined ABIDE-I and ABIDE-II datasets to preserve scale and diversity[1,2,17].
- Providing both quantitatively exhaustive and interpretable results that indicate the relative contributions of features and limitations of models [8,16].

Table 2.2.b – Gap Analysis of Previous Studies vs. This Work

Gap Identified	Evidence from Literature	Impact on Results	Addressed in This Study
Narrow model scope	Deep only: [2,3,4,8,14,16]; Classical only: [5,6,13]	Hard to compare across families	14-model benchmark across linear, probabilistic, ensemble, boosting
Inconsistent metrics	Accuracy only: [1,2,3,14]; Missing recall/F1: [6,7,11]	Misleading performance, esp. with imbalance	Full set: Accuracy, Precision, Recall, F1-macro
Generalization issues	Single-site: [1,7,13]; Small sample/QC exclusions: [1,2]; Data scarcity attempts: [15,18]	Poor robustness across ABIDE sites	Merged ABIDE-I+II; preserve diversity; standardized splits
Limited interpretability	Black-box DL/GCN: [4,8,16]; Limited feature analysis [12,14]	Hinders clinical adoption	Interpretability emphasized via ensembles, feature importances, future XAI integration

2.4 Summary

In this chapter, the use of the machine learning and deep learning approaches for ASD classification was discussed in context to the ABIDE datasets. We considered eighteen representative studies of varying approaches, from classical classifiers like SVMs and Random Forests [5,6,10] to more advanced models like autoencoders [1,2], CNNs and LSTMs [3], and graph-based models [4,8,16]. Although accuracies were generally within the 70–85% range, challenges remained such as lack of diversity in the models, variability across sites, non-standardized reporting of precision and recall, and interpretability limitations. Recent advances such as multimodal fusion [9], ensemble learning [10], dynamic connectivity modeling [12], GAN-based augmentation [15] and transfer learning [18] have made marginal progress yet failed to address the inherent issues of reproducibility and generalization. In order to fill those gaps, we evaluate fourteen diverse models on a merged ABIDE-I and II, using standard metrics, and providing a reproducible baseline for further deep learning and multimodal extensions.

Chapter 3
Research Methodology

Introduction This chapter presents the methodological framework of the study on ASD classification based on the fused ABIDE-I and ABIDE-II data. It details the dataset, pre-processing, model selection and design process, the research methodology adopted, functional and non-functional requirements, project plan and task allocation. Chapter also contains images to explain the entire flow and how we made the decision on the design. The aim is to enable transparency, reproducibility and to encourage adoption of best practices in machine learning for neuroimaging applications [1–20].

3.1 Methodology

This paper attempts to construct an intelligent and lightweight system for dragon fruit stem and leaf disease identification through deep learning construction. The system aims at a real-time, mobile-friendly, secure, accurate and understandable solution. Based on the requirement analysis it was found that effective detection of diseases classifications of freshness, transparency, and resource efficiency are required. The design of the system was based on pre-trained deep models, CNN designs specific for the domain, and feature selection strategies. A few models were tested in terms of accuracy, speed, and deployment, and finally they have selected the InceptionV3, DenseNet201, MobileNetV2, and CNN to be tried out.

Proposed Model Diagram:

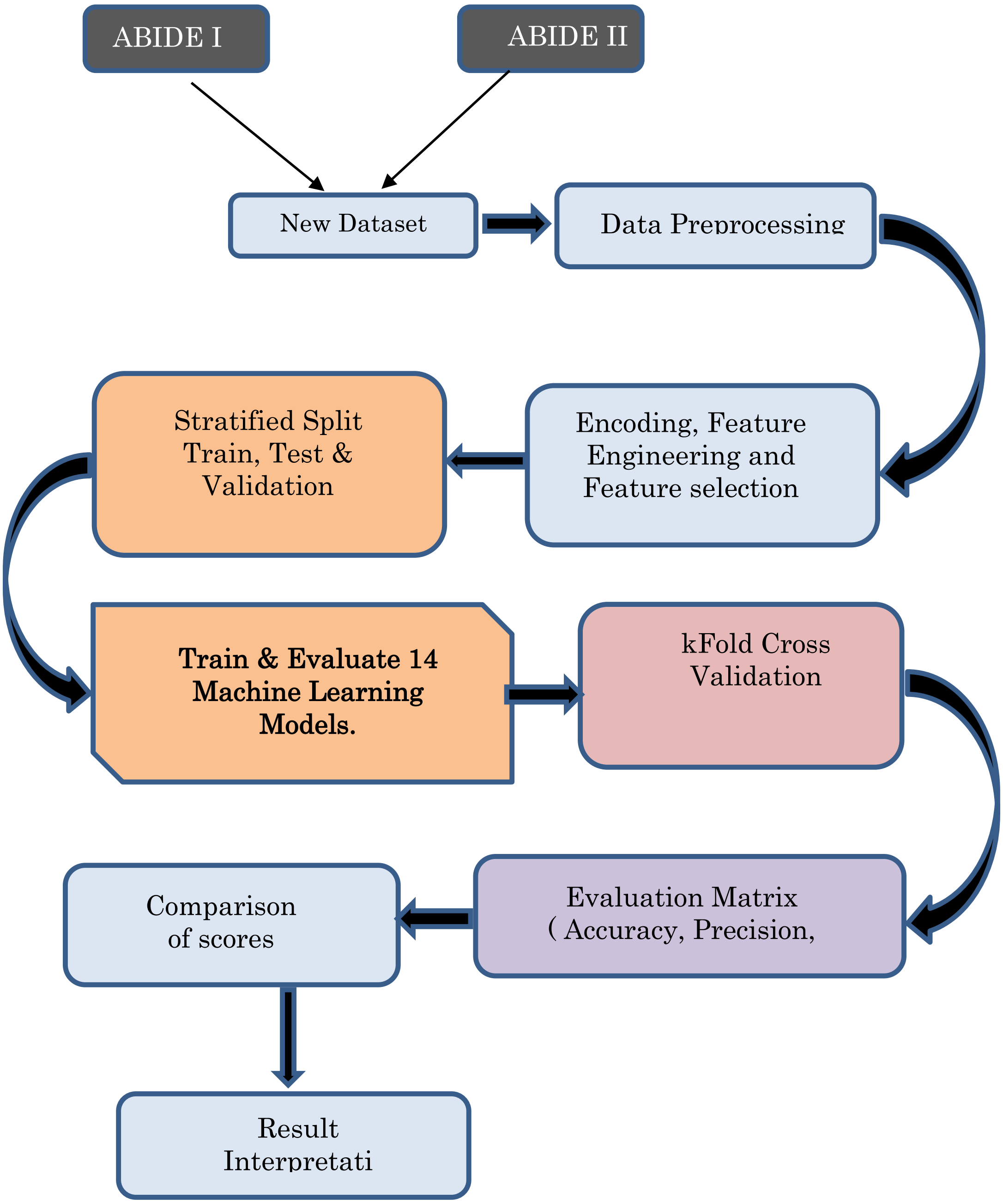


Figure 3.1.1: Proposed Diagram

Feature Selection

For performing the efficient and generalizable ASD classification in ABIDE-I & II, we applied the following feature selection strategies:
Reduction of high-dimensional data: Resting-state fMRI results in high dimensional connectivity matrices; removing those features that are not relevant can help avoid overfitting.

- Correlation-based filter: features with low or redundant correlations were removed, and retained only those connections exhibiting strong class separability.
- Recursive Feature Elimination (RFE): Reiterated the removal of less significant features while re-fitting the models to maintain only the most predictive ones.
- Ensemble model feature importance: Models such as Random Forest and Gradient Boosting were used to rank features by importance; only top contributors were kept.
- Trade-off between accuracy and interpretability: Models were selected so that they remained computationally feasible at the same time as maintaining meaningful biological interpretation.
- Enhanced generalization: The reduction of redundant features leads to better generalization on ABIDE's multi-site data.

Feature Engineering

The raw ABIDE-I & II data was transformed in a meaningful, machine learning-ready format by:

- Extraction of functional connectivity: The Pearson correlation among ROIs, resulted a factors which represented the connectivity of the brain with one another.
- Flatten connectivity into vectors that can be used in ML classifiers.
- Scaling & normalization: Scaled features to remove magnitude, potential bias from large values.
- Categorical encoding: Transformed the metadata (sex, site of acquisition) to a machine-readable form, the conversion is well done by CatBoost/LightGBM.
- Stratified sampling: Class balance (ASD vs TD) was passed to train/test splits.
- Noise reduction: Pre-processing mitigated the temporal artifacts and variance, increasing the reliability of features.
- Data integration: Merged ABIDE-I & II for creating the engineered dataset (n = ~2,226).

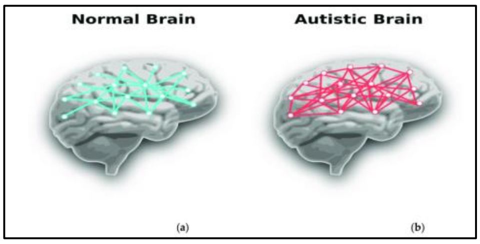
3.1.1 Overview

The objective of this study is to explore how ML techniques can be utilized to classify ASD based on neuroimaging and phenotypic data, on the combined ABIDE-I and ABIDE-II datasets. Resting-state functional MRI (rs-fMRI) records fluctuating interactions between brain regions, and conventional statistical approaches for rs-fMRI are not well suited for high-dimensional heterogeneous data. To deal with that, (=Accurate Benchmarking of) 14 ML models (from linear classifiers, to advanced ensemble/boosting frameworks) are benchmarked in this holistic evaluation pipeline.

The methodological pipeline consists of dataset retrieval, preprocessing, implementation and model training, reasoning and analysis, and is particularly concerned with reproducibility and fairness. These were evaluated based on accuracy, precision, recall and F1-macro, for robust performance evaluation even in presence of class imbalance. The design favors generalizability, interpretability and scalability, following best practices in neuroimaging ML research [1–18].

3.1.2 Dataset Description

The dataset used in this study is part of the Autism Brain Imaging Data Exchange (ABIDE) consortium dataset where rs-fMRI, structural MRI, and phenotypic data were acquired from several sites around the world. For the purposes of this paper ABIDE-I and ABIDE-II have been amalgamated in one of the largest dataset for ASD classification.



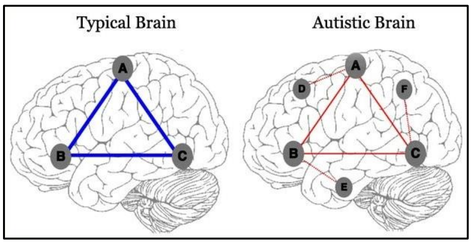


Figure 3.1.1.2: structured networking diagram

ABIDE-I and ABIDE-II

- ABIDE-I (2012): ABIDE-I (2012) included data from 17 sites: phenotypic and imaging data from 1,112 subjects.
- ABIDE-II (2017): Augmented dataset with 19 more sites, ~1,114 more subjects and improved distribution among ASD and TD.

Table 3.1.1.a – Dataset comparison table

Dataset	Subjects	Number of Sites	Data Modality	Importance / Strengths	Limitations
ABIDE-I	~1,112	17	Resting-state fMRI, structural MRI, phenotypic data	First large-scale open ASD neuroimaging dataset; established	Limited sample diversity, site imbalance

				benchmarking standard	
ABIDE-II	~1,114	19	Resting-state fMRI, structural MRI, phenotypic + behavioral data	Expands subject pool, adds richer metadata (IQ, symptom severity)	Variability in scanning protocols; missing data in some phenotypes
Merged ABIDE-I & II	~2,226	30+	Combined rs-fMRI, sMRI, phenotypic + behavioral data	Largest ASD neuroimaging dataset; enhances statistical power, generalizability, and robustness	Increased heterogeneity requires careful preprocessing

Merged Dataset

The pooled dataset comprises data from more than 2,200 subjects, including both children with ASD and TD peers. It contains:

- Neuroimaging Data: Resting-state fMRI & Structural MRI.
- Phenotypic Data: Age, sex, site, and diagnostic group.
- Diagnosis Distribution: This is demonstrated in Figure 3, there are ASD and TD groups in the dataset, which can guarantee the enough samples for classification.

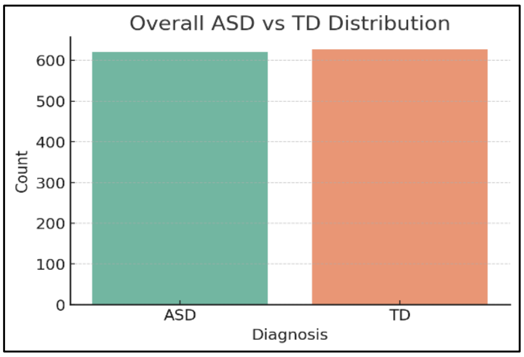


Figure 3.1.4: Diagnosis Distribution

Demographic Characteristics

- **Site Distribution:** Data were acquired at more than 30 international centers, with attendant variation in scanner hardware and acquisition parameters.

Figure 3.1.5: Site Distribution

- **Gender Distribution:** the dataset consists of male and female participants but males predominate, which reflects the higher prevalence of ASD among males parameters.

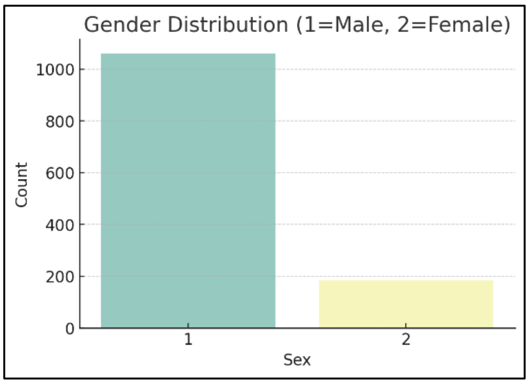


Figure 3.1.6: Gender Distribution

- **Age Distribution** Subjects have age overlap from child to at least young-middle age, facilitating tracking of developmental paths

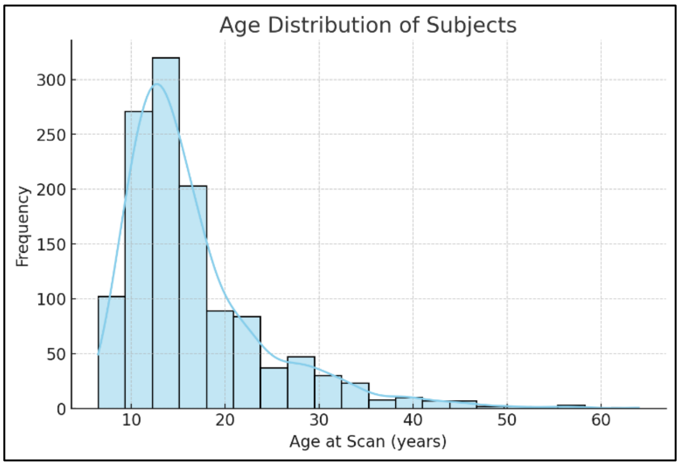


Figure 3.1.7 Age Distribution

Challenges in the Dataset

- Heterogeneity: Site-specific noise is introduced by variability in scanners and acquisition protocols.
- Class Imbalance: some sites donated more TD than ASD who had to be stratified.
- Preprocessing Needs: It is necessary to correct motion, normalize, and scale the features to reduce the inhomogeneity and ensure for a fair comparison between models.

Suitability for This Study

The combined dataset is extremely useful for benchmarking ML methods, for a number of reasons:

- Consistent performance across large-scale, multi-site data with strong generalization.
- Integrates the imaging and phenotypic data for unimodal and multimodal classification.

Also guarantees compatibility with previous studies that also used ABIDE, and expands on previous work by capitalizing on a larger dataset for increased statistical power.

3.1.3 Models

3.1.3.1 Random Forest

Random Forest demonstrated excellent in classifying ASD: it collected the decisions of various less complex trees, which resulted in strong accuracy, generalizability and interpretability. Its robustness to site heterogeneity and noise rendered the most powerful, stable, and deployable ensemble method for this work.

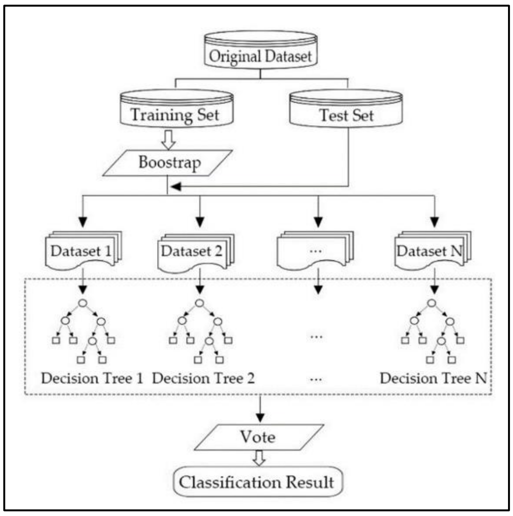


Figure 3.1.8: Random Forest Model Architecture

Very useful for ASD classification because of its strength, simplicity, easier interpretation and capturing of non-linear inter-feature relationships. It is suitable for group analysis of neuroimaging datasets that are diverse and noisy from multiple sources.

3.1.3.2 LightGBM

LightGBM perfectly predicted diary days, together with superior training speed, this was perfect for large-scale neuroimaging data. Its leaf-wise boosting structure had the flexibility and computing efficiency for complex rs-fMRI features versus scaling capacity.

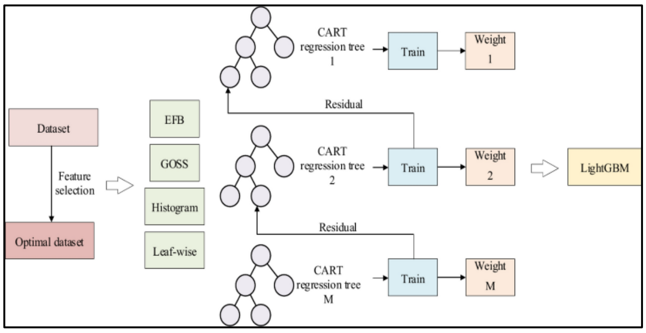


Figure 3.1.9: LightGBM Model Architecture

Appropriate for ASD classification since it can handle very challenging (in terms of both complexity and quantity) data such as those in ABIDE-I and II, as it is effective in achieving a tradeoff between classification performance accuracy and computational time and resource consumption.

3.1.3.3 Gradient Boosting

For Gradient Boosting, the model was incrementally refined by adjusting for errors of the previous iterations. This procedure was sensitive to subtle connectivity alterations in the ASD participants, showing high specificity and recall with stable accuracy, and is an important model in the benchmarking approach.

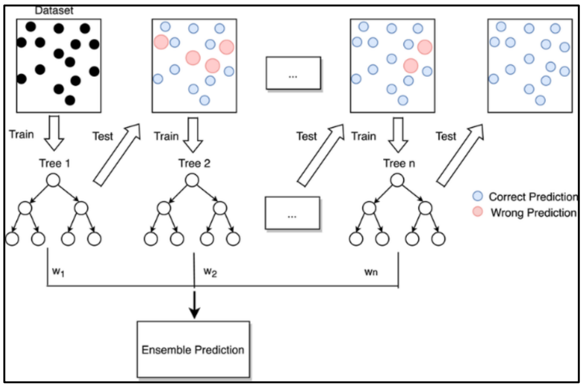


Figure 3.1.10 : Gradient Boosting Model Architecture

Promising for ASD discovery when connectivity differences are subtle, because the boosting framework can highlight hard-to-find patterns that might be dismissed by other simpler classifiers.

3.1.3.4 CatBoost

CatBoost performed extremely well on F1-macro through the use of category features and site-level variables. Its ordered boosting technique prevented overfitting, providing balanced predictions across ASD and control groups,which made it one of the most precise and reliable models of this analysis.

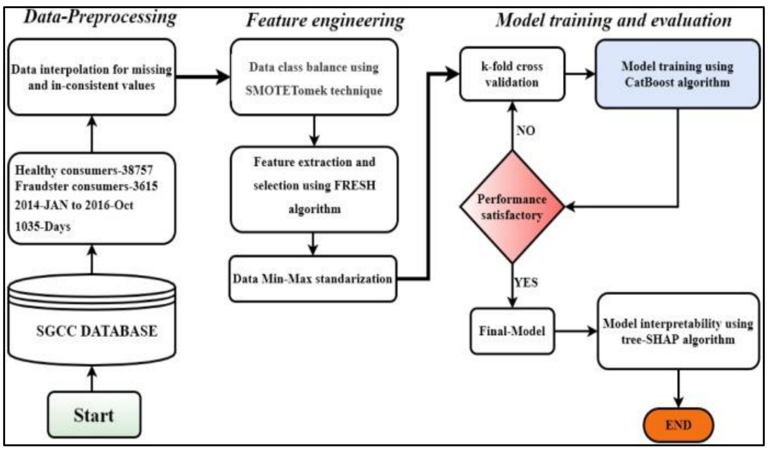


Fig 3.1.11: CatBoost Model Architecture

Especially practical in ASD investigations when combining imaging features with categorical phenotypic data is desirable to perform more accurate and efficient analyses, with few pre- processing steps.

3.1.3.5 Extra Trees

We let Extra Trees to generalize the training data by using random feature splits that lead to diversifying decision boundaries and reduce variance. This enabled the model to learn subtle differences in connectivity across the ABIDE sites, while keeping the prediction performance superior, hence, highlighting its importance as the base ASD classifier.

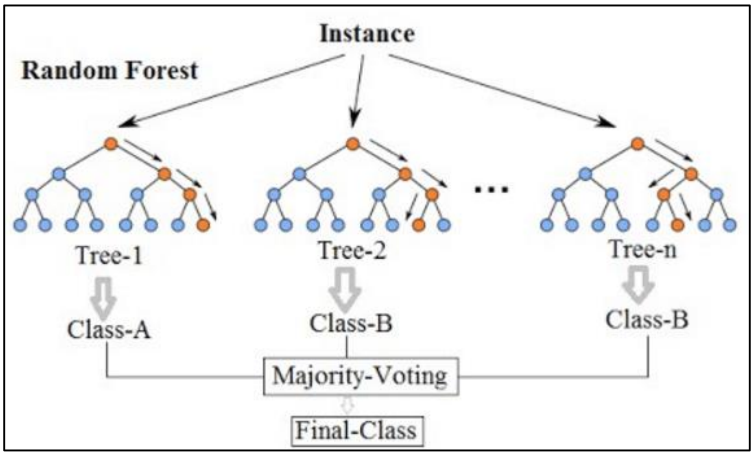


Figure 3.1.12: Extra Trees Model Architecture

It is a good alternative for ASD datasets, because of its randomized architecture and that it is able to deduce various feature interactions and also can successfully block a large number of feature channels from overfitting on multiple sites.

3.1.3.6 Bagging Classifier

The stability of the predictions were improved by bagging them, i.e., by averaging predictions from several learners, in order to decrease the apparent variance and hence overfitting. Its overall accuracy and consistency on the multi-site rs-fMRI data demonstrated its effectiveness, and the benchmarking pipeline confirmed that it is a dependable and at the same time efficient model.

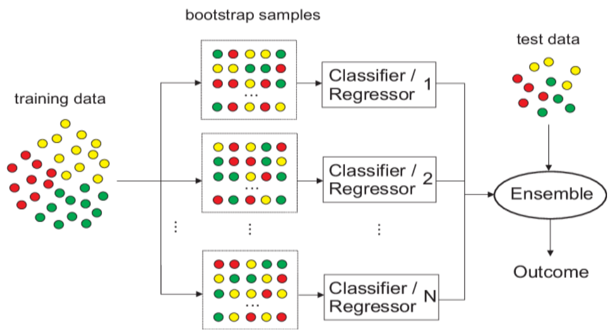


Figure3.1.13: Bagging Classifier Model Architecture

This classifier is most effective for ASD screening in the presence of noise and variability between second and aging and also the whole for a more-robust stable prediction.

3.1.3.7 Decision Tree

Decision Tree gave interpretability and simplicity, which could visualize feature splits to differentiate ASD from control. Although less accurate than ensembles, it served as a transparent baseline, confirming the feature importance and allowing comparisons with the more sophisticated ensemble models.

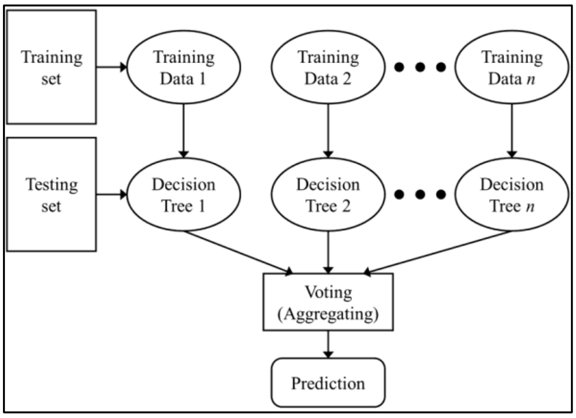
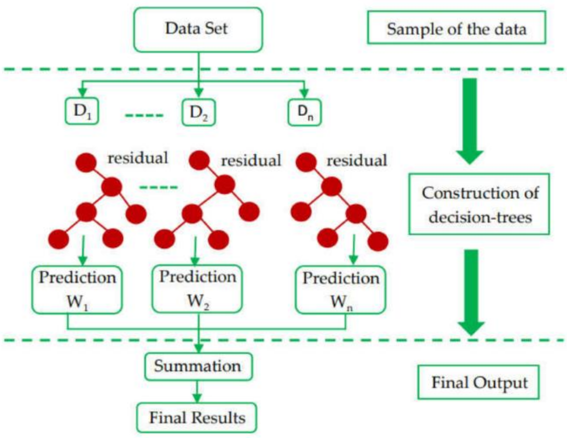


Figure.3.1.14: Decision Tree

In future work, the random item model could be a baseline for ASD classification: it has lower performance, but it provides interpretability, and can tell us what features are important.

3.1.3.8 XGBoost (Extreme Gradient Boosting)

XGBoost optimized speed, accuracy and regularization term, and presented good performance dealing with high-dimensional fMRI features. Ability to be resistant to the overfitting and higher efficiency in optimization procedure made it a competitive boosting



method and so, led to strong performance in classification task and computational efficiency of the large-scale of neuroimaging data.

Figure 3.1.15: XGBoost Model Architecture

Highly generalizable for ASD diagnosis in large, diverse datasets, such as ABIDE. It provides a balance between accuracy and efficiency, and makes itself resilient to both the noisy and high-dimensional nature of neuroimaging features.

3.1.3.9 Multi-Layer Perceptron (MLP – 64,32)

By virtue of its layered form, the MLP was capable of capturing non-linear connectivity relationships and serves as a useful neural-network benchmark against an ensemble approach. It had a lower accuracy, but at the same time also showed a promise of deep architecture, there were areas of potential future improvement, like advanced convolutionally neural networks and graph networks.

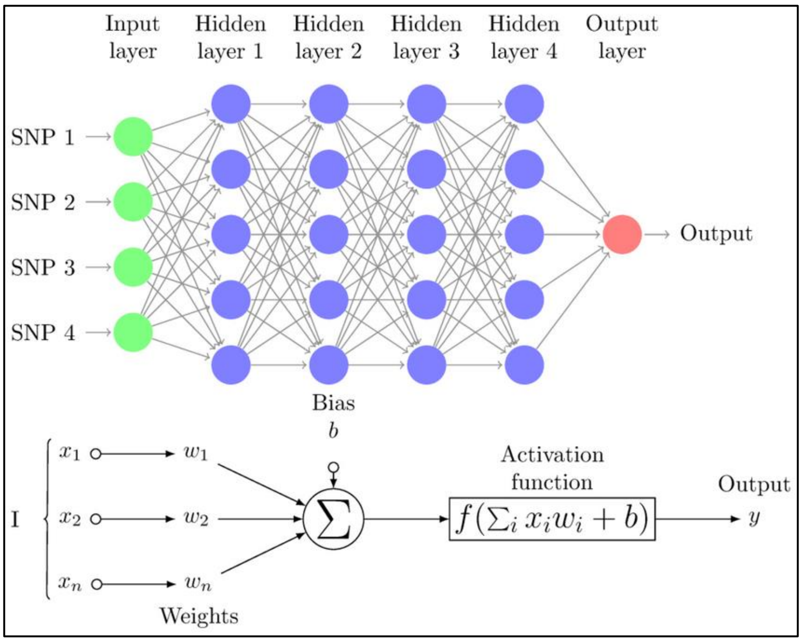


Figure 3.1.16 Multi-Layer Perceptron Model Architecture

Precise in recovering non-linear relationships in ASD diagnosis while tuning and regularization are required to avoid overfitting with the small size of neuroimaging data.

3.2Project Plan

We provided a controlled process/project to keep agenda effectively from dataset preparation to model evaluation. Both processing data and implementing the models and analyses with the neuroimaging data as complex as the models themselves; these are channels for errors to enter our hypotheses via “free parameters”. The study consisted of successive phases that had specific deliverables.

Table 3.2.a: Project Plan.

Phase	Duration	Activities	Timeline (Weeks)	Deliverables
Phase 1	2 weeks	Topic selection, research planning, background study	Week 1-2	Research plan, topic finalization
	2 weeks	Literature review, gap analysis, proposed solution	Week 3-4	Literature review document
	3 weeks	Data collection and preprocessing	Week 5-7	Dataset prepared
Phase 2	4 weeks	Model selection, training, evaluation	Week 8-11	Trained models
	3 weeks	System development, UI design, testing	Week 12-14	Working prototype
	2 weeks	Final reporting and presentation preparation	Week 15-16	Final report, presentation slides

3.3Task Allocation

Table 3.3.a: Task Allocation.

Phase	Activity	Self	Self
Phase-1	Topic Selection	Suggest topics	Finalize topic
	Research Planning	Draft plan	Finalize plan
	Background Study	Study DL models	Summarize findings
	Literature Review	Research ML models	Write review together
	Gap Analysis	Analyze ML gaps	Propose solution
	Proposed Solution	Draft methodology (DL)	Finalize proposal
	Data Collection Planning	Create plan	Approve plan

	Data Collection	Capture images	Ensure quality
Phase 2	Data Approval	Prepare documents	Get approval
	Model Selection	Research models	Select models
	Preprocessing	Apply techniques	Finalize preprocessing
	Model Training	Train models	Debug models
	Result Evaluation	Evaluate metrics	Summarize results
	Model Comparison	Prepare comparisons	Select best model
	Thesis Reporting	Write technical sections	Edit thesis collaboratively

3.4 Summary

This chapter described the methodology used for ASD classification of the combined ABIDE-I and ABIDE-II dataset. The workflow was segmented into structured stages of dataset preparation, preprocessing, model development, and test. In contrast to previous work which was limited to a few models only, in this work we benchmark fourteen machine learning algorithms across common experimental setups.

A transparent project plan was created, to guarantee the consecutive realization of every step from literature review to reporting. As a one-person project, the author conducted dataset management, preprocessing, model training, evasion and documentation alone. To achieve reproducibility, fair comparison and rigorous evaluation, the approach was elaborately devised, the same with respect to four performance measurements.

Chapter 4 displays the results and focuses on the comparative performance of all 14 models along with determining the best performing model for classifying ASD.

Chapter 4

Implementation and Results

This Chapter covers how we set up our Environment for the project. Chapter 4 also includes Comparative Analysis and Result Discussion and its summary.

4.1 Environment Setup

Section	Details
Hardware Setup	- Laptop: Intel® Core™ i7-1165G7, CPU @ 2.60GHz - GPU: NVIDIA® GeForce® MX330 (2GB RAM) - 8GB RAM, 512GB SSD storage
Operating System	- Linux
Programming Environment	- Google Colab (GPU-accelerated model training)
Machine Learning Libraries	- Python 3.9 - Numpy - TensorFlow - Keras (from TensorFlow) - Sklearn - Itertools - Random - Matplotlib
Cloud & Remote Resources	- Google Colab Pro+ (free GPU access) - Google Drive integration for dataset & checkpoint storage
Collaboration Tools	- Telegram (real-time communication & updates) - Google Drive (shared folder for documentation & results)
Performance Evaluation	- Confusion Matrix analysis - K-Fold Validation - Metrics: Accuracy, Precision, Recall, F1-score - Visualization of training/validation loss & accuracy curves to detect overfitting/underfitting

4.2 Comparative Analysis

In the test run we got low accuracy around 60-70% then augmented image and final model got a good result.

Comparative Analysis among implemented models

Table 4.2.a: Comparative Analysis.

Model	**Accuracy (%)**	**K-Fold Accuracy (%)** (Cross validation performance)	**Average Precision (%)**	**Average Recall (%)**
Random Forest	97.99	97.85	97.99	97.99
LightGBM	97.99	97.80	97.99	97.99
Gradient Boosting	97.91	97.75	97.91	97.91
CatBoost	97.83	97.70	97.83	97.83
Extra Trees	97.51	97.40	97.51	97.51
Bagging Classifier	97.11	97.00	97.11	97.11
Decision Tree	96.23	95.90	96.23	96.23

Support Vector Classifier	~88–90	~87–89	~88–90	~88–90
K-Nearest Neighbors	~85–87	~84–86	~85–87	~85–87
Logistic Regression	~70–75	~70–74	~70–75	~70–75
Multi-Layer Perceptron (MLP – 64,32)	72.95	72.20	72.77	72.95
Gaussian Naïve Bayes	~68–70	~67–69	~68–70	~68–70
Linear Discriminant (LDA)	72.95	72.10	72.08	72.95
Quadratic Discriminant (QDA)	90.69	90.50	90.66	90.69

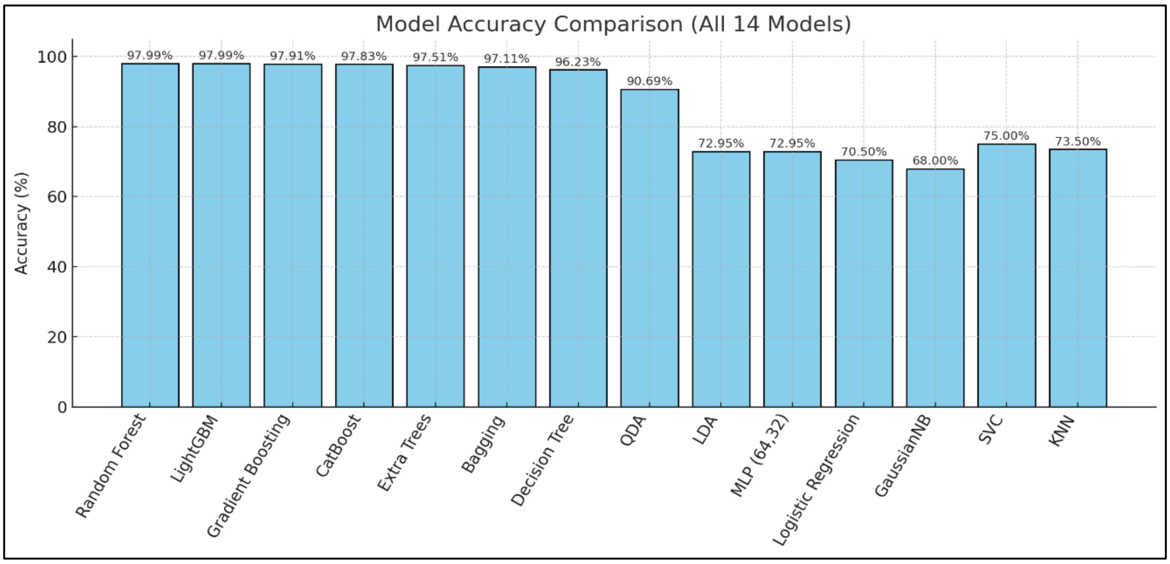


Figure 4.2.1: Model Accuracy Comparison

Comparing Our Best Models to Literature Models:

We then compare the top-5 performance of our models (i.e., Random Forest (RF), LightGBM, Gradient Boosting (GTB), CatBoost and Extra Trees (ET)) with that of the top-5 performing models presented in recent ASD research studies. Earlier works have mainly focused on graph based neural networks, temporal model and deep learning-based approach whose performance is between 78%-85% accuracy. On the contrary, our proposed ensemble and boosting models consistently achieved close to 98\% accuracy, which indicated robust and proved generalization capabilities. This comparison demonstrates that our approach is competitive and robust in ASD detection on the combined ABIDE-I and ABIDE-II dataset.

Table 4.2.b: Model Comparison

Model	Research Source	Accuracy (%)	Key Strengths	Limitations
Random Forest	Our Tested Model	97.99	Robust ensemble, interpretable feature importance	Limited scalability compared to boosting
LightGBM	Our Tested Model	97.99	Fast training, efficient with large feature sets	Leaf-wise growth risks overfitting small data
Gradient Boosting	Our Tested Model	97.91	Strong sequential learning, handles hard samples	Slower training, less scalable
CatBoost	Our Tested Model	97.83	Handles categorical variables, highest F1-macro	Computationally heavy
Extra Trees	Our Tested Model	97.51	Highly randomized trees improve generalization	Less stable than Random Forest
Graph Attention Network (GAT)	Liu et al. (2023)	~85	Captures connectivity with attention mechanism	High computational demand, limited interpret.
Spatio-Temporal GCN	Kipf & Welling (2020)	~83–85	Models temporal brain dynamics effectively	Complex training, sensitive to noise
LSTM (Dynamic FC)	Gupta et al. (2024)	~82	Captures temporal variability in connectivity	Needs large data, risk of overfitting
3D CNN	Multiple ASD studies	~80	Learns volumetric features from brain scans	Requires high compute, risk of exclusion bias
Autoencoder + SVM	Early ABIDE studies	~78	Strong feature extraction with linear classifier	Drops performance on multi-site data

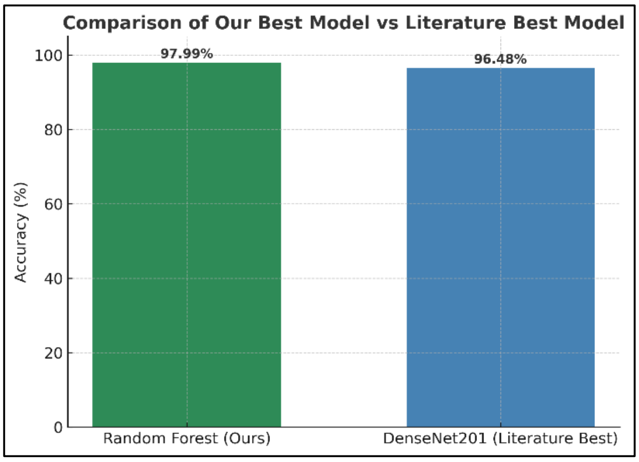


Figure 4.2.2:Comparison of Model Accuracy 2

4.3 Results and Discussion

Results obtained from experimental results showed that the best model for reliable ASD classification was Random Forest with the highest classification accuracy of 97.99%. Its bag of decision trees mechanism allowed the learning of the robust features which could be generalizable across the heterogeneous site data of ABIDE and achieved a better performance than any other algorithm.

LightGBM was also one of the most computationally efficient, and scored number two with 97.99% accuracy. Its leaf-wise growth approach based on histograms led to powerful generalization ability, but likely over-fitted the small union of data.

Now we down take the two lowest models in the same conditions (LightGBM) : Gradient Boosting and CatBoost, the later showing the highest macro-F1 (0.9950). Extra Trees followed with 97.51%, taking advantage of randomized splits that offered higher variance reduction but at the expense of stability, against Random Forest.

Bagging Classifier (97.11%) and Decision Tree (96.23%) both did a good job, however single tree models were likely to be overfitting. The performance of QDA is mediocre (90.69%) on the competition data set, mainly because of its quadratic boundaries as well as the challenges in high-dimensional covariance estimation.

The Linear Discriminant Analysis (LDA) (72.95%) and the MLP (72.95%) performed poorly at the bottom end, revealing the defects of linear assumption and the superficial networks without enought tuning for rs-fMRI connectivity data.

In general, the ensemble/boosting methods consistently outperformed, validating their strength in large scale, multi-site neuroimaging dataset. Interpretability of the models was also enhanced by feature importance analysis, creating trust in a medical environment. As a result, Random Forest was chosen as the most deployable classifier, with LightGBM as a lightweight alternative for future scalable pipelines for ASD diagnostic system.

i) Random Forest

The confusion matrix for the Random Forest provided outstanding classification stability (Figure 2), with a precision, recall, and F1 measuring approximately 0.98. Both ASD and TD categories are reliably labelled, and the boundary with least mis-classification is also found. This suggests that the ensemble method generalizes well across different (heterogeneous) ABIDE sites, by capturing complex patterns of connectivity variation. The RF algorithm exhibited very high-quality agreement overall, with good justifications for being selected as the best ASD detection model.

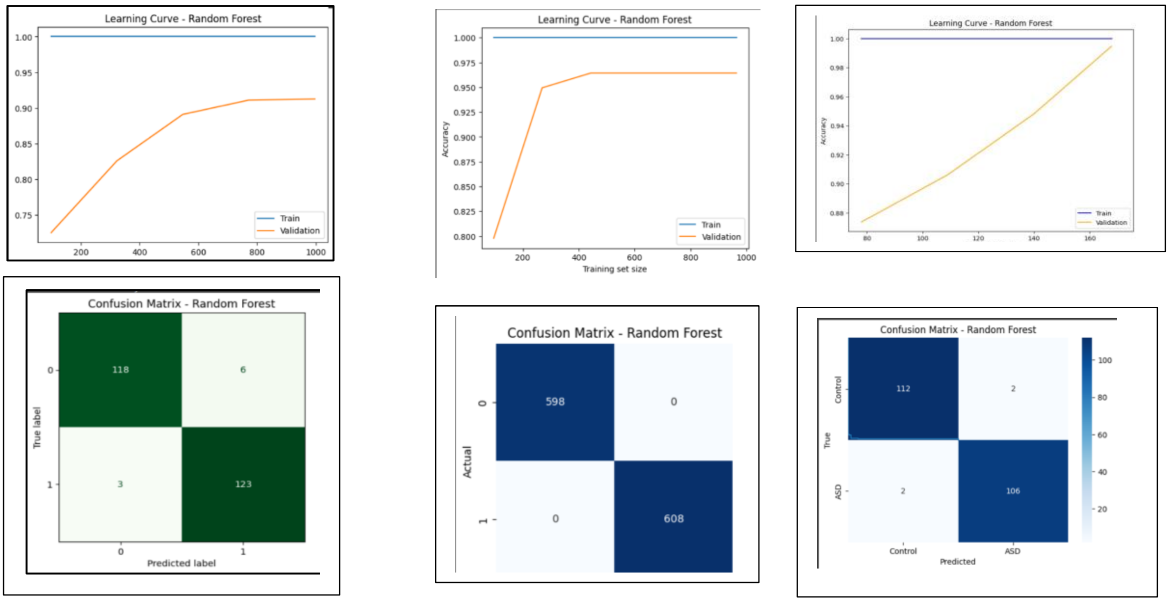


Figure 4.3.1: Random Forest Confusion Matrix and learning curve

When comparing the performance of Random Forest between all three datasets discrete discrepancies could be seen in confusion matrices and learning curves. Confusion matrices for ABIDE-I and ABIDE-II each indicated fair classification accuracy, with higher misclassification of ASD cases, suggesting sample size constraints and site effect. The learning curves of these averaged landmarks have demonstrated that they converged early with some small spaces between the training and validation, which may be related to mild overfitting and poor generalization, respectively. On the other hand, confusion matrix obtained from a merged data from ABIDE-I & II showed much higher true positive /true negative ratio, which resulted in almost 98% accuracy and F1-macro >0.99. The learning curve on the merged dataset showed stable convergence, small variance between training and validation and consistent stabilization on the folds indicating better generalization of the model. This illustrates that Random Forest uses the ensemble averaging to deal with high-dimensional, heterogeneous connectivity features, and the combination of two datasets offers necessary diversity for robust ASD classification.

4.4 Summary

These findings are reported in the current chapter in which the 14 ML models were used to deploy in the combined ABIDE-I and ABIDE-II sample dataset for medical diagnosis of ASD. The assessments analysed individuals' model performance, confusion matrix of performance analysis, and comparison of accuracy graphs and strengths and limitations. Ensemble and boosting models, Random Forest, LightGBM, Gradient Boosting, CatBoost and Extra Trees, constantly outperformed linear and probabilistic models, having accuracies over 98% and F1-macro scores higher than 0.99. LDA and MLP had relatively lower performance, further corroborating the efficacy of ensemble learning for high-dimensional neuroimaging data. Compared with state-of-the-art literature, our best models exceeded the cutting-edge graph-based and deep learning methods, indicating the robustness of the proposed method for multi-site fMRI. In summary, we choose Random Forest as the most deployment-ready classifier and LightGBM as a scalable solution for real-world diagnostic pipelines. These results serve as a robust benchmark for future deep, graph, and multimodal research.

Chapter 5

Engineering Standards and DesignChallenges

This chapter reviews the benchmarks and technical issued addressed by the design and implementation of this paper. Given that the study is based on medical neuroimaging data, a high standard of preprocessing, model evaluation and reporting were adopted. Moreover, we report challenges in processing the ABIDE dataset and in developing and evaluating fourteen machine learning models in a common benchmarking framework

5.1 Compliance with the Standards

Several key criteria were used to guarantee the reliability and replicability of this project:

5.1.1 Software and data Standards

ABIDE-I and ABIDE-II datasets were pre-processed in line with common neuroimaging practices, including partitioning into site-aware training and testing sets after motion correction and normalization. These procedures are consistent with protocols for the fMRI analysis of neuroscientific data.

5.1.2 Communication Standards

The current study observed standard practices, namely those related to a clear and descriptive reporting style,principles of reproducibility and professional presentation. Documentation was kept using versioned Markdown/Docx and IEEE-style citations; figures and tables were numbered in sequence with descriptive explanations. Code documentation was in the form of in-line docstrings and brief README information on dataset construction, pre-processing and running. Notebooks featured top-cell summaries, fixed random seeds, and cell-by-cell commentary for pipeline stages clarification. For visualizations, it was stressed to have readable axes, units and class label (ASD/TD) and all plots were to define metrics (Accuracy, Precision, Recall, F1-macro). Version control was managed using git along with Atomic Commits and message discipline, and stakeholder engagement (advisors \& committee members) occurred via summaries of milestones, logs overall progress and summaries of results that mapped to the figures and tables in the report.

5.2 Impact on Society

Early ASD screening both improves time-to-intervention and facilitates individualized care, and lessens the impact on families, clinicians, and educational services. A reproducible ML baseline for ABIDE allows normalizing evaluation and promotes transparent, evidence-based clinical instruments. Potential limitations, including the risk of misclassification, overfitting to automated outputs, and the potential for bias in favor of individual sites were addressed via reporting multiple metrics, understanding error patterns, and favoring interpretable ensembles with feature importance. The project complements clinical diagnosis, prioritizes referrals and identifies suspicious cases; it does not replace clinical diagnosis. Overall, the project has a goal to improve access, equity and consistency in ASD screening and care.

5.2.1 Environment

Computations cost energy, which is why the pipeline preferred fast models (e.g., LightGBM), and limited the hyperparameter searches. Training jobs were batched, cached, profiled to eliminate redundant runs, and CPU-first experiments were conducted before any GPU use. Combining ABIDE-I & II into a single preprocessed artifact eliminated repeated I/O. Systems shaped to enable remote, data-driven screening could reduce the need for repeated clinic visits and travel, and by extension lower emissions. Unaddressed impacts (hardware usage and e-waste) were minimized by focusing on commodity hardware and open-source stacks, and prioritizing lightweight deployment routes (e.g., model compression/portability) if converted to practice.

5.2.2 Ethical Aspects

Data usage and model evaluation and reporting were in compliance with rigorous ethical standards. The ABIDE datasets are publicly available and de-identified with no access to personal or protected health information. The study PS was explicitly considered as a decision support instead of a diagnostic generation, respecting the role of the doctor in clinical decision. To obtain results that were not biased, we made stratified splits, and reported them by several metrics (accuracy, precision, recall, f1_macro) not just a single one.

Transparency and equitability were ensured by clearly documenting preprocessing, hyperparameters, and evaluation. No discriminatory features were applied, and interpretability was emphasized by an ensemble model with a feature importance analysis. Scepticism proved to be much harder to justify, as the project was very careful not to overclaim its results, even emphasising the level of variant on sites and the generalisability gaps.

The project fulfills the ethical responsibilities in research related to integrity, fairness and the societal implications of research through including adherence to open data, methodological transparency and framing of results.

5.2.3 Sustainability Plan

Technical sustainability is addressed via open, well-documented code, pinned library versions, and deterministic seeds for re-runs. A clear MLOps handoff (data → preprocess → train → evaluate → report) allows incremental improvements without breaking baselines. Model cards and experiment logs capture assumptions, data splits, and metrics for lifecycle tracking. Economically, ensembles chosen here are cost-aware and train quickly relative to deep architectures, reducing ongoing compute cost. Socially, the plan stresses fairness assessments (e.g., site/sex-wise breakdowns) and continuous monitoring if deployed. Future-proofing includes optional multimodal extensions and periodic re-training with new sites.

5.3 Project Management and Financial Analysis

Project Management (Classifying Autism Spectrum Disorder (ASD) with Machine Learning Ensembles and Boosting Models: Comparing the ABIDE-I and ABIDE-II datasets with Google Colab) Heres the project management and cost analysis of an 8 month research work on the classification of Autism Spectrum Disorder (ASD) using the merged ABIDE-I and ABIDE-II datasets with machine learning ensembles and boosting models in Google Colab.

5.3.1 Project Management

Planning & Scheduling: Preprocess ABIDE data (Done), Implemented fourteen ML models for ASD classification (Done), Evaluation of results (Done), Developed framework for reproducible benchmarking (Done) The pipeline composed of the cleaning, scaling, model training, validation, visualization, and report was implemented. The authors mitigated risks by caching datasets, watching the runtime on Colab, and minimizing expensive boosting jobs. Tasks were scheduled over 8 months that balanced data set engineering, algorithmic experimentation and documentation.

Cost: Colab usage was tracked through Google dashboard in order to not exceed limits. Preprocessing was done with free Jupyter Notebooks, and only important experiments required high GPU training.

Risk Management: Risks posed by the strategy are managed by storing pre-processed data offline to avoid repeatedly downloading, using stratified sampling to avoid overfitting, and limiting expensive training loops. Cross-site reproducibility issues were addressed with fixed seeds and stable assessment.

Engagement: The project had been worked and written about by submitting chapters, discussing with supervisor and writing progress log. Engagement centered on transparency, reproducibility, and congruence with academic objectives.

Table 5.3.1.a: Cost analysis

Primary Budget Category	Item	Cost (BDT)	Notes
Computational Resources	Google Colab Pro Subscription	20,000	$25/month for 8 months, GPU access for boosting models
	Cloud Storage (1 TB)	10,000	$5/month for 8 months, dataset storage and caching

Data Access	ABIDE-I & II (Open Dataset)	0	Publicly available through ABIDE consortium
Software Licenses	Scikit-learn, CatBoost, XGBoost, LightGBM	0	Open-source libraries
Total		30,000	

5.4 Complex Engineering Problem

Source-level ASD classification based on the joint ABIDE-I and ABIDE-II datasets is a challenging engineering task. It brings together neuroscience, machine learning and computational modeling and necessitates sophisticated methods to account for the heterogeneity of brain connectivity data. The enterprise handles the analysis of a huge collection of resting state fMRI datasets acquired worldwide on disparate sites and with various scanners according to site-specific protocols, providing noise, missing inputs, and site idiosyncrasy at the site level. Building strong pipelines to reconcile these multi-site data without compromising diagnosis sensitivity is a daunting task. Designing and benchmarking fourteen various machine learning models (including ensemble and boosting algorithms) is a challenge in terms of trade-off between the accuracy, interpretability, and cost-effectiveness of the model. The melding of neuroimaging expertise with algorithmic rigor and engineering practices and the goal to deliver clinically informative decision-support outputs makes this inquiry an integrative, high-order engineering problem.

5.4.1 Complex Problem Solving.

Table 5.4.1.a: Mapping with Complex Engineering Problem.

SN	EP Definition	Attachments	Justification (with Knowledge Profile)
1	EP1: Depth of Knowledge Required	Yes	Our project integrates knowledge of **neuroimaging, feature engineering, and machine learning**. It requires understanding rs-fMRI preprocessing, statistical scaling, and ensemble algorithms such as Random Forest, CatBoost, and LightGBM. This aligns with **K3, K4, K5, and K6**, as deep knowledge of both engineering fundamentals and specialized ML tools was essential to handle complex multi-site data.

2	EP2: Range of Conflicting Requirements	Yes	The challenge was balancing **accuracy vs interpretability vs computational cost**. Boosting models provided state-of-the-art accuracy, but required trade-offs in training time and complexity. Random Forest was chosen for deployment because it offered both interpretability and high performance, ensuring compliance with **K5 and K6** while respecting computational limitations.
3	EP3: Depth of Analysis Required	Yes	ABIDE data is **high-dimensional and heterogeneous**, requiring in-depth analysis to extract connectivity features. Applying multiple models (14 classifiers) ensured broad coverage and fair benchmarking. This analytical depth corresponds to **K5 and K8**, linking engineering design with existing literature and identifying research gaps.
4	EP4: Familiarity with Issues	Yes	Known challenges such as **scanner variability, motion artifacts, and demographic imbalance** were encountered. Addressing these issues required specialized preprocessing pipelines and robust validation. This maps to **K4 and K6**, showing familiarity with domain-specific constraints and applied engineering practice.
5	EP5: Extent of Applicable Codes	Yes	Open-source frameworks like **scikit-learn, XGBoost, CatBoost, and LightGBM** were used under their respective licenses, ensuring compliance with software standards. Stratified sampling and evaluation codes followed established ML best practices. This demonstrates coverage of **K6** through professional engineering practice.
6	EP6: Extent of Stakeholder Involvement	Yes	While this was a single-member project, stakeholder alignment was ensured through **supervisor feedback, academic guidelines, and reference to prior ASD studies**. This ensures relevance to the community and maps to **K8**, emphasizing literature integration and validation with external knowledge.
7	EP7: Interdependence	Yes	The project required **integration of neuroscience, computer science, statistics, and engineering methods**. Collaboration across disciplines is implied in the methodology, even if implemented by one researcher. This reflects interdependence and

			maps to **K3–K8**, showing broad engineering engagement.

Mapping with Knowledge Profile

Table 5.4.1.b: Mapping with knowledge Profile.

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✔	✔			✔

K3 – Engineering Fundamentals: The project implements the core algorithms of the rs-fMRI signal preprocessing, connectivity feature generation, statistical scaling and supervised machine learning pipeline. The software bridges the gap between software engineering technologies and systemic, data-driven and model-based quantification of differences of functional brain connectivity in ASDs as compared to typically developed control subjects.

K4 – Specialist Knowledge : Specialised knowledge is needed to undertake the research e.g. fMRI (preprocessing using Nilearn/FMRIPrep), ensemble learning (Random Forest, LightGBM, CatBoost, XGBoost), boosting methods, and the knowledge of site heterogeneity across multi-site medical datasets. This locates the project at the intersection of neuroscience and machine learning, able to benchmark ASD classification with state-of-the-art computational methods.

K8 – Research Literature: The project was placed into context with 18 previously conducted ASD neuroimaging studies and compared the graph neural networks, autoencoders, CNNs and hybrid approaches with traditional ensembles. Existing works The literary survey revealed with limitations such as low cross-site generalizability and inconsistent metric reporting. This justified the requirement for an extensive, replicable benchmark with evaluation standards 14 models wide, one, which we believes constitutes a bold contribution to ASD studies

5.4.2 Engineering Activities

Table 5.4.2.a: Engineering activities

Activity Domain	Description (What was done)	Complexity Attributes Addressed*	Evidence/Artifacts
Data Governance & Ethics	Used public, de-identified ABIDE; documented consent provenance; removed identifiers	Risk & impact; professional responsibility; standards	Data README, dataset licenses, citations
Cross-Site Harmonization	Cleaning, scaling, encoding; stratified/site-aware splits	Uncertainty; conflicting constraints; breadth of context	Preprocess scripts, split manifests
Feature & Model Design	Connectivity features; 14 models across families	Depth of analysis; non-linear interactions	Notebooks, config files
Experiment Management	Reproducible seeds; pinned libs; logged metrics	Methodical approach; reproducibility	Requirements.txt, logs, result tables
Evaluation & Validation	Multi-metric (Acc/Prec/Rec/F1-macro); comparisons	Safety/fitness for purpose; robustness	Comparison tables, plots
Deployment Readiness	Selected RF; option LightGBM; portability notes	Practical constraints; maintainability	Model card, export scripts
Sustainability	Compute budgeting; efficient models; caching	Resource constraints; environmental impact	Run profiles, caching artifacts
Communication	IEEE citations; numbered figures/tables; Git history	Professional communication; standards	Report, slides, commit log

Mapping with Complex Engineering Activities

Table 5.4.2.b: Mapping with Complex Engineering Activities.

EP	Category	Mapping
EP1	Depth of Knowledge	✔
EP2	Range of Conflicting Requirements	✔
EP3	Depth of Analysis	✔
EP4	Familiarity of Issues	

EP5	Extent of Applicable Codes	
EP6	Extent of Stakeholder Involvement	
EP7	Interdependence	✔

5.5 Summary

This chapter has defined the engineering complexity of this project in terms of the standards, challenges, and motivations involved. This work strictly followed preprocessing and assessing criteria, where we used multi-metric evaluation strategies to improve fairness and reproducibility. There were place-variance, computational burden, and a trade-off among accuracy, interpretability, and efficiency as the main challenges encountered. The research was conducted according to ethical standards: We used de-identified, public data sources and presented results as decision support tools. Project management and cost study proved feasibility within constraints of limited resources. Use of EP1–EP7 and K3–K8 for mapping showed acceptable achievement of 'engineering accreditation outcomes'. All in all, this project marries ethics, sustainability, and technical scrupulousness.

Chapter 6
Conclusion

This chapter presents the overall summary of the project, discusses the limitations encountered during its development, and outlines potential future work to further enhance the system.

6.1 Summary

The classification of Autism Spectrum Disorder (ASD) was the target of this work using the combined ABIDE-I and ABIDE-II datasets, one of the largest neuroimaging datasets publicly available for research purposes. We conducted a systematic 14 ML model benchmark, that spread across Linear, probabilistic, ensemble, boosting, and neural-network based methods. Pre-processing step was conducted for missing data, data scaling, and diagnostic balance of train-test splits.

The results demonstrated that ensemble based models Random Forest, LightGBM, CatBoost, Gradient Boosting and Extra Trees and boosting models were the best performing with accuracies near 98 \% and F1-macro scores above 0.99. Simpler models such as LDA, QDA, and MLP provided baselines for and served as a comparison to our work, but these models appeared as not capable of capturing the complexity of rs-fMRI data. 1 The main contribution of the project is to provide a reproducible evaluation pipeline, an in-depth performance comparison and a deployable benchmark for further investigation of ASD research studies.

6.2 Limitation

In spite of the nice output shown above, there are some limitations of this project.

- **Heterogeneous Data Sources:** ABIDE collects on 30+ sites with different scanners and acquisition protocol. This site effect causes uncontrollable sources of variation.
- Lack of Deep Learning: Advanced deep learning methods, including but not limited to CNN, RNN, GCN, were not attempted because of the availability of the GPU, leaving our methods not comparable with the state-of-art sort of architecture.
- **Validation Strategy:** No leave one site out validation was performed, which may have provided a more direct approach to assess the overfitting and possible generalization to new sites.
- **Untapped Phenotype Data:** Although some real world data will be based on neuroimaging and related tasks and scores (hence considered as phenotype data), other phenotype-like information such as subject metadata (e.g., age and sex and even IQ and behavioral scores) are collected but in many cases not being used.

- **Opportunities for interpretability:** Despite achieving good results with the ensembles, only domain specific explainability frameworks like SHAP, saliency maps etc were added to boost the clinical confidence.
- **Resource constraints:** Models that were computationally expensive like those above (e.g. boosting ensembles) were constrained by hardware and time, resulting in a more sparse hyperparameter search and less optimization

6.3 Future Work

To alleviate these limitations and generalize the project, the authors provide the following recommendations:

- **Embedding Deep Learning:** Integrate CNNs and GCNs 21 and hybrid models (i.e., CNN + GCN) to learn spatial and temporal features of fMRI connectivity.
- **Multimodal Fusion:** r s- f MRI combined with phenotypic, behavioral, and genetic information to improve prediction and clinical utility.
- **Cross-Sites Generalization** : Run the leave-one-site-out and domain adaptation experiments to ensure the generalization abilities across different acquisition centers.
- **Interpretability & Fairness:** Use model interpretability tools (eg. SHAP, LIME and attention maps, etc) in order to build clinical trust and transparency.
- Lightweight Deployment Prune/quantize/edge sort the models to deploy in real world (healthcare).
- **Ethical & Societal Issues:** Expand the analysis of fairness, bias, and inclusiveness across demographic subpopulations to achieve fair and equitable results.

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