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DEPARTMENT OF COMPUTER ENGINEERING

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"Anomaly Detection Using Artificial Intelligence Methods"

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'Anomaly Detection Using Artificial Intelligence Methods'

Submitted in partial fulfillment of the requirements for Bachelor's Degree in Computer Engineering of Goa University is the bonafide work of

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Project Report

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This project was completed under the guidance and supervision of Prof. Snehanshu Saha at Birla Institute of Technology and Science (BITS), Pilani, Goa, during the academic year 2023-2024.

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ABSTRACT

In today's increasingly complex and data-driven world, anomaly detection is paramount for ensuring the robustness and dependability of industrial systems and various other critical applications. This project utilizes multiple artificial intelligence (AI)-based methods for anomaly detection.AI models like supervised and unsupervised learning, and potentially deep learning algorithms, are deployed to facilitate anomaly detection. A significant emphasis lies in the selection and utilization of performance metrics. Performance metrics such as precision, recall, F1-score, and ROC AUC allow for assessment of the effectiveness of the AI methods in identifying anomalies and provide insights into model performance for optimal results. In the end, the results of this project carry substantial significance for anomaly detection in various sectors, encompassing fields like cybersecurity, finance, and industrial maintenance. Early anomaly detection is crucial for these industries to maintain operational efficiency. Furthermore, to enhance accessibility and user interaction, we have developed a user-friendly web-based interface. The interface enables users to upload their datasets, choose from a selection of anomaly detection algorithms, and visualize the algorithm's performance metrics in an intuitive manner. The user interface serves as a practical tool for data analysts and domain experts seeking efficient anomaly detection solutions tailored to their specific requirements.

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CHAPTER 1:

INTRODUCTION

1.1 INTRODUCTION TO PROJECT

In the era of burgeoning data, anomaly detection is critical in ensuring the integrity and security of various applications. This research project delves into the realm of anomaly detection, using artificial intelligence (AI) to identify deviations from normal patterns within data. The increasing complexity of anomalies and the ever-expanding digital landscape questions the need for robust anomaly detection techniques that can adapt to evolving threats. Through our user platform we aim to help researchers upload their data and perform efficient detection of anomalies using various algorithms and ultimately identify the most suitable one. In statistics and data science, there are 3 main types of anomalies [28]:

1. Global (aka point anomaly):

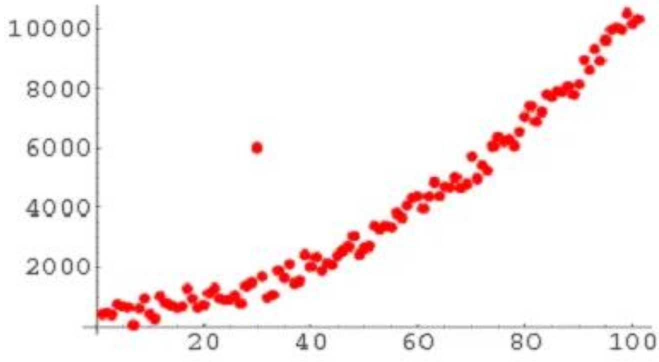


Figure a.1: Global anomalies
Source:https://medium.com

A data point is considered a global outlier if its value is far outside the entirety of the data set in which it is found.

2. Contextual (aka conditional outlier):

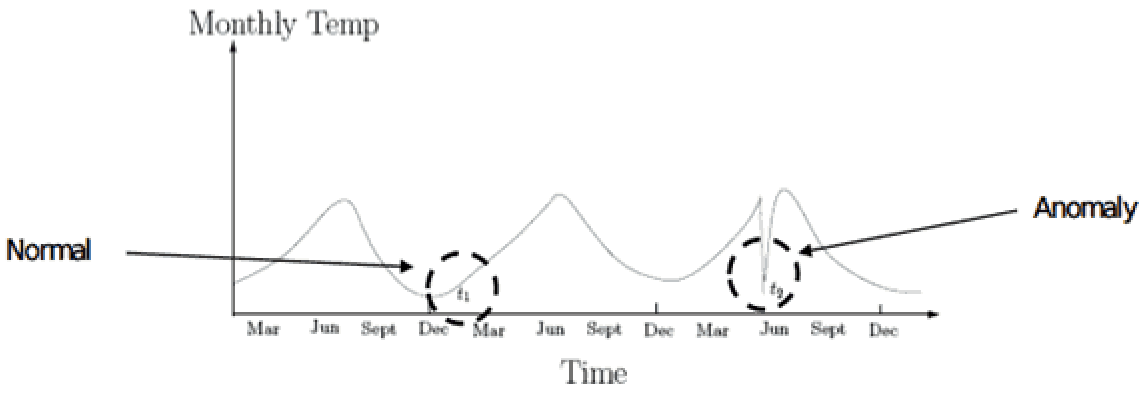


Figure 1.b: Contextual anomalies
Source:https://medium.com

If individual data point is different in a specific context or condition , then it is termed as a contextual outlier. Attributes of data objects should be divided into two groups;1.Contextual attributes - defines the context, e.g., time & location. 2.Behavioural attributes - characteristics of the object, used in outlier evaluation, e.g., temperature.

3. Collective Outliers:

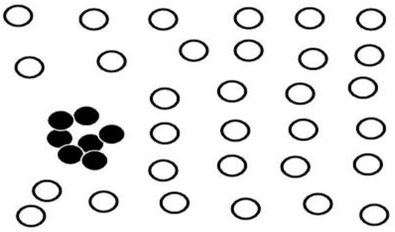


Figure 1.c: Collective anomalies
Source:https://medium.com

If a collection of data points is completely different with respect to the entire data set, it is termed as a collective outlier. A subset of data points in a data set is said to be different if these values as a collection deviate remarkably from the entire data set, However the values of each data points are not different in either a contextual or global sense.

1.1.1 GOALS AND OBJECTIVES

The overarching goal of this research is to advance anomaly detection methodologies using artificial intelligence. Specific objectives include the exploration and evaluation of several state-of-the-art anomaly detection algorithms. Furthermore, the project aims to develop a user-friendly interface, facilitating seamless data upload, result retrieval, and visualization, empowering users to interact with and comprehend the anomaly detection outcomes effortlessly.

1.1.2 MOTIVATION

The motivation behind this research stems from the escalating importance of anomaly detection in safeguarding critical systems and information. As datasets burgeon in size and complexity, traditional methods fall short in effectively identifying anomalies. Artificial intelligence, with its capacity for pattern recognition and adaptability, emerges as a compelling solution to address this challenge.

1.1.3 METHOD

The methodology involves a comprehensive evaluation of state-of-the-art anomaly detection algorithms, including machine learning and deep learning techniques. The performance of these algorithms will be assessed using key metrics like precision, recall, F1 score, and AUC-ROC on over 98 publicly available datasets. Additionally, A user interface will be developed to facilitate user interaction for seamless data uploading, result retrieval, and visualization.

1.1.4 OVERVIEW OF TECHNICAL AREA

The technical landscape of anomaly detection using artificial intelligence encompasses a diverse array of algorithms. From traditional statistical methods to advanced machine learning and deep learning models, the field is dynamic and continually evolving. This project aims to identify the most effective algorithms and methodologies for anomaly detection from the diverse datasets.

1.2 PURPOSE OF PROJECT

The primary purpose of the project is to enhance anomaly detection accuracy. By leveraging the algorithms and developing an intuitive user interface, the project aims to provide a robust solution for detecting anomalies in various domains. The end goal is to empower users with a tool that identifies anomalies effectively allowing for seamless interaction and interpretation of results.

1.3 PROBLEM DEFINITION

In the contemporary digital landscape, the pressing challenge of anomaly detection within datasets necessitates a sophisticated and adaptive solution. This research project aims to address these challenges by evaluating and leveraging state-of-the-art artificial intelligence algorithms, developing a user-friendly interface, and establishing comprehensive evaluation metrics. By doing so, the research aims to significantly enhance the accuracy, adaptability, and user-interactivity of anomaly detection systems, thereby fortifying the security and reliability.

1.3.1 EXISTING SYSTEM

The current landscape of anomaly detection systems often relies on traditional methods that struggle to adapt to the complexities of modern datasets. The limitations of these systems underscore the need for a more sophisticated and adaptable approach. This research project seeks to address these shortcomings by leveraging the capabilities of artificial intelligence in anomaly detection.

1.3.2 PROPOSED SYSTEM

The proposed system will leverage the advancements in artificial intelligence, specifically focusing on implementing and evaluating state-of-the-art anomaly detection algorithms. Additionally, a user interface will be developed to assist users perform anomaly detection, allowing result interpretation and visualisation.

1.4 SCOPE OF PROJECT

- Scope- The project entails the creation of a web application where users can upload pre-processed datasets. The application will then calculate performance metrics and visualize results.
- Out of Scope- The user can upload only one Dataset at a time onto our web application.

1.5 REPORT ORGANIZATION

The current introductory section provides a brief introduction to each chapter.

Chapter 1: Introduction

This section focuses on the purpose and the scope of the proposed system.

Chapter 2: Literature Survey

This section describes the concepts and technologies used to develop the project.

Chapter 3: Software Requirement Specification

This section provides information about specific requirement of the proposed system.

Chapter 4: System Design

This section describes the software life cycle model, which will be used in developing the software. It includes system design and detailed design.

Chapter 5: Implementation

This section describes the implementation of the software and the experimentation carried out.

Chapter 6: Conclusion

This section summarizes the key findings and outcomes of the project and provides insights gained from the project experience.

CHAPTER 2:
LITERATURE SURVEY

2.1 STUDY ON ANOMALY DETECTION

Anomaly detection [4] refers to the process of identifying patterns in data that deviate from expected normal behaviour. It finds extensive use in a wide variety of applications such as fraud detection for credit cards, insurance, healthcare, intrusion detection for cyber-security, fault detection safety critical systems, and military surveillance activities

2.1.1 EXISTING ANOMALY DETECTION SYSTEMS

The research presented in this paper investigates anomaly detection, aiming to establish our work as a benchmark paper in the field. To contextualize this study, it is crucial to introduce the existing system that serves as a foundation for our research.

Existing anomaly detection systems have proven effective through a combination of statistical methods, machine learning algorithms [31][32][41][42][44][57], and domain-specific techniques. These current systems incorporate a range of techniques, including statistical methods like Z-Score [5] and Box Plot [24] for simplicity and interpretability, machine learning methods such as Support Vector Machine [3], Random Forests [16], and clustering for pattern identification. In addition, time series analysis and deep learning approaches, like LSTM (Long Short Term Memory) networks [2] and GANs (Generative Adversarial Networks) [12], excel in scenarios involving sequential data.

Supervised anomaly detection [15] uses labelled data to distinguish normal from anomaly instances, but it faces challenges with scarce anomaly labels, adapting to new machine classes, and complex machinery. Rule-based classifier methods may struggle with novel patterns, and ensemble techniques have limitations in memory and high-dimensional data.

Unsupervised anomaly detection [1] does not rely on training data but can be computationally intensive, especially in high-dimensional datasets. Density-based methods struggle with varying data densities, and profile-based techniques generate excessive false alarms in small datasets. Clustering-based methods like K-Means [14] and isolation Forest [7] may require prior knowledge of cluster numbers. Semi-supervised [1] techniques adapt to unsupervised use and are more widely applicable than fully supervised methods, as they only need labels for the normal class.

2.2 STUDY ON ALGORITHMS DEFINED

2.2.1 DYNAMIC BINARY TREE ANOMALY IDENTIFIER (d-BTAI)

Dynamic-Binary Tree Anomaly Identifier (d-BTAI) [21] is a distributed anomaly detection algorithm designed for large-scale time-series data. It combines Bayesian statistics with distributed computing capabilities to efficiently detect anomalies in extensive time-series datasets. Its distributed architecture and Bayesian approach set it apart from other methods, making it particularly valuable for real-time anomaly detection in industrial systems and other domains. DBTAI uses a unique data structure called BAT to identify anomalies, and it can be integrated with standard clustering algorithms to reduce memory consumption and improve runtime complexity. The Binary Anomaly Tree (BAT) produced by the d-BTAI algorithm clusters data points, with some leaf nodes containing anomalies.

2.2.2 MULTI-GENERATION TREE (MG-TREE)

MGTree-based (Multi-Generation Tree) [21] anomaly detection involves two key algorithms: one for constructing the Anomaly Tree and the other for generating subsequent tree generations to isolate anomalies [22]. MGTree repeatedly invokes the BAT algorithm, typically three times for anomaly detection. It relies on two thresholds: the Tree Generation Threshold to decide if the dataset qualifies for the next generation and the Leaf Level Threshold to identify lower-level leaves as probable anomalies, reducing the need for extensive clustering. The algorithm terminates when the dataset size falls below the tree generation threshold, and it identifies the lowest-level leaf in the last generation as an anomaly.

2.3 STUDY ON EVALUATION METRICS

Evaluation metrics are crucial for benchmarking in sequence-type data as there is no natural definition of a sample, and individual data points lack context. Precision is a measure of the accuracy of positive predictions made by a classification model. Recall (Sensitivity or True Positive Rate) is a measure of the model's ability to identify all relevant instances within a dataset. F1-score [26] metric operates by considering an entire ground truth anomaly segment as correct if one anomaly point within it is detected accurately. It then calculates the F1-score using these adjusted predictions.

There are metrics based on receiver operator characteristic (ROC) curve [8] and the area under the curve (AUC) [19]. The original ROC and AUC are based on point-wise detection. Volume Under the Surface (VUS) [9] metric [60]extends the AUC-based measures to account for range-based anomalies.

2.4 STUDY ON EXISTING BENCHMARK PAPERS

In the field of research, several benchmark papers have paved the way for significant advancements. These following papers serve as crucial reference for understanding the domain.

In the benchmark paper [17] both shallow and deep AD methods are discussed, although the focus is primarily on the theoretical aspects, lacking experimental results. [10] assessed 19 different unsupervised methods on 10 datasets and analysed the characteristics of density-based and clustering-based algorithms. [20] tested 14 unsupervised AD methods on 15 public datasets, emphasizing factors like scalability, memory consumption, and method robustness.[11] proposed a method for generating realistic synthetic data, reconstructing synthetic normal instances from existing real-world benchmark data and modeling synthetic anomalies in a characterizable manner. [6] evaluated eight unsupervised methods on 19 public datasets and created a substantial collection of synthetic anomaly detection datasets, varying across dimensions crucial for real-world applications.

AD Bench [13] examines the performance of 30 detection algorithms across an extensive set of 57 benchmark datasets, adding to the body of research in the field. Doshi et al. in 2022

[39]found surprising results, such as the widely used F1-score with point adjustment metric favoring a basic random guessing method over state-of-the-art detectors. Kim et al. in 2022 [52]highlighted the flaws of F1-score with point adjustment in both theoretical and experimental contexts. Although numerous new TSAD metrics have emerged, even the latest ones are not without their drawbacks.

[60]focused on univariate TSAD and introduced 13,766 time series to enhance the limited public dataset, most of which were synthetic or derived from existing classification datasets. Vincent Jacob and Tatbul in 2021[60]delved into explainable anomaly detection in time series using real-world AIOps data, yet deep learning-based TSAD models were not thoroughly explored in these works.

2.4.1 LIMITATIONS OF EXISTING PAPERS

We highlight several limitations in the existing literature which we attempt to address in our research.

Precision and Recall are both important for evaluation in a certain application. However, most of the existing metrics do not take these points into consideration. Deep learning-based [18] models are data-hungry and may overfit if not properly regularized leading to false-positive detections. The “black-box" nature of deep learning models makes it difficult to interpret and compare different models. Thus, the fair comparison between different deep learning algorithms remains challenging.

There are serious flaws using Time series anomaly detection (TSAD) in public datasets, metrics, and model settings. The flaws become more challenging in Multivariate Time Series Anomaly Detection (MTSAD) as the anomalies in multivariate time series are more complicated and harder to detect

The benchmark relies on static datasets which does not account for changes and evolving patterns over time. Real-world applications often involve streaming data, where anomaly detection algorithms need to adapt to changing conditions. ADBench [13] does not address this dynamic aspect. ADBench primarily employs AUCROC and AUCPR as evaluation metrics but they may not provide a comprehensive view of algorithm performance. There are other metrics that could provide additional information, including F1-score [26], precision [26], and recall [26].

With the rapid expansion of applying various machine learning algorithms for anomaly detection, there has been a surge in the availability of anomaly benchmarking datasets [13][60][67], along with numerous empirical studies evaluating the performance of existing algorithms [45][20][49][23] on these benchmark datasets. The benchmark focuses on generic datasets but does not provide insights into how these algorithms perform in specific real-world applications such as fraud detection, network security or medical diagnosis.

2.5 DISCUSSION

There have been several surveys focusing on domain-specific anomaly detection, including those on deep learning-based algorithms for images and videos [35][55], network traffic [40][66]real-time data [30][34][56], urban traffic [38], and more. A comprehensive survey of anomaly detection techniques was performed, encompassing both supervised and unsupervised methods, including classic machine learning and deep learning approaches. It underscores the challenges associated with supervised methods due to their reliance on the availability of labelled training data and highlights the tendency of unsupervised methods to produce false positives. Deep learning-based techniques require extensive training data and distributional assumptions, while semi-supervised neural networks attempt to mitigate data labelling dependencies but not entirely. This research stands to significantly advance anomaly detection methods across various domains.

CHAPTER 3:
SOFTWARE REQUIREMENT SPECIFICATION

3.1 INTRODUCTION

3.1.1 PURPOSE

The project aims to analyse and evaluate existing anomaly detection methods the goal of conducting comprehensive analysis of existing methods to enhance accuracy, while also providing a web-application for users to upload datasets, select anomaly detection models and view the predicted results along with visualisation of the same.

3.1.2 SCOPE

Alongside this research, we are developing a web application which will enable users to select algorithms, upload datasets and visualize results through intuitive plots. Our project will offer both, theoretical insights and practical tool for experimentation.

3.1.3 OVERVIEW

In line with making this project accessible and practical, a user-centric web application will be developed. Utilizing Python and its associated libraries such as Flask, alongside frontend technologies like HTML, CSS, and JavaScript, this application will enable users to interact with various AD algorithms. Users will have the capability to select algorithms and upload datasets for analysis, with the results visualized through intuitive plots and displays.

3.2 GENERAL DESCRIPTIONS

3.2.1 DATASET DESCRIPTION

In our anomaly detection study, we have meticulously assembled a diverse dataset collection comprising 98 datasets sourced from reputable repositories such as the Very Large Databases (VLDB) [13] and the Singapore University of Technology and Design (SUTD)[58].This comprehensive compilation consists of 67 multivariate datasets obtained from VLDB and SUTD, and 31 univariate datasets acquired from Yahoo Webscope[70]and Numenta [53]encompassing a wide range of domains.

3.2.2 ALGORITHM DESCRIPTION

In our anomaly detection study, we evaluated a diverse set of anomaly detection algorithms. The selected algorithms encompass a range of traditional and contemporary approaches, contributing to a comprehensive assessment of method effectiveness.

Local Outlier Factor (LOF) [33]	Density-based method measuring local density deviation to identify anomalies with significantly lower density.
One-Class Support Vector Machine (OCSVM) [47]	Machine learning algorithm creating a boundary around normal data points, flagging instances outside as anomalies.
Elliptic Envelope[27]	Creates an imaginary elliptical area around a given dataset. Values that fall outside the envelope are outliers.
Isolation Forest (IForest)[12]	Ensemble-based algorithm constructing binary trees to identify anomalies as instances requiring fewer partitions.
Dynamic Binary Anomaly Tree with Anomaly Identification (d-BTAI)	Anomaly detection algorithm using Binary Anomaly Trees, identifies anomalies based on anomaly scores assigned.
Multi-generations Binary Tree For Anomaly Detection (MGBTAI)	Unsupervised tree-based approach addressing false alarms in anomaly detection, effective on both large and small datasets.

Table 3.1: Classical ML algorithms

Deviation Network (DevNet) [59]	Combines Variational Autoencoders with clustering for anomaly detection by identifying data points that are not fitting in the clusters.
Autoencoders [68]	Neural network architecture for unsupervised learning which identify anomalies by high reconstruction error.

Generative Adversarial Network (GAN)	Creates a generative model for normal data distribution, identifying anomalies based on deviations from learned distribution.
Deep Autoencoding Gaussian Mixture Model (DAGMM) [64]	Combines autoencoders with Gaussian mixture models for anomaly detection based on low likelihood under the model.
Long Short Term Memory (LSTM) [48]	LSTM neural networks analyses previous values and predict future behaviour. If the actual value is within a certain standard deviation, then it is not an anomaly. If it is more, it is an anomaly.
Quantile -LSTM [63]	Advanced models that specifically focuses on predicting quantiles, allowing for probabilistic forecasting and capturing uncertainty in predictions.
Deep Quantile Regression [65]	Deep quantile regression anomaly detection is an unsupervised model that does not require any assumption of regular data distribution to identify anomalous data points.

Table 3.2: Deep Learning ML algorithms

Empirical Cumulative Distribution-based Outlier Detection (ECOD) [36]	A Python-based algorithm for anomaly detection that uses data distribution information to identify outliers
Copula-Based Outlier Detection(COPOD) [37]	Outlier detection algorithm inspired by copulas for modeling multivariate data distribution.
GOAD [54]	Anomaly detection algorithm that leverages generative models

Principal Component Analysis (PCA)	A dimensionality reduction technique used to transform high-dimensional data into a lower-dimensional space while preserving most of the variability in the data.
LUNAR [62]	A graph neural network-based anomaly detection method that uses information from a node's nearest neighbors to find anomalies
K-Nearest Neighbors (KNN)	A simple, non-parametric classification algorithm used for both classification and regression tasks. It works by finding the 'k' nearest data points to a given query point and making predictions based on them[43]
Deep Support Vector Data Description (Deep-SVDD) [46]	A network anomaly detection method that combines a convolutional neural network (CNN) with Support Vector Data Description (SVDD).

Table 3.3: Additional algorithms

3.2.3 EVALUATION METRICS DESCRIPTION

The study employs a concise yet comprehensive set of evaluation metrics: precision, recall, F1 score, and AUC-ROC.

Precision	Measures the proportion of correctly identified anomalies out of all anomalies detected.	Precision = TP / (TP + FP)	Higher precision indicates fewer false positives, indicating a low rate of misclassifying normal data as anomalies.
Recall	Measures the proportion of correctly identified anomalies out of all actual anomalies in the dataset.	Recall = TP / (TP + FN)	Higher recall indicates fewer false negatives, indicating a low rate of failing to detect actual anomalies.

F1 Score	Harmonic mean of precision and recall	F1 Score = 2 * (Precision * Recall) / (Precision + Recall)	F1 score considers both false positives and false negatives, providing a comprehensive evaluation of anomaly detection performance.
AUC ROC	Area under the Receiver Operating Characteristic curve	-	Higher AUC-ROC values indicate better overall performance, with a larger area indicating a higher true positive rate and a lower false positive rate.

Table 3.4: Evaluation metrics

3.3 INTERFACE REQUIREMENTS

3.3.1 USER INTERFACES

- Homepage – provides an intuitive interface displaying options to select various anomaly detection algorithms.
- Algorithm Selection – enabling users to choose among various AD algorithms, including established methods and the proposed Multi Generation Binary Tree and Dynamic Tree approaches.
- Dataset upload – an interface allowing users to upload dataset from their local storage.
- Visualization – visualization of results through plots and graphical representation for easy interpretation and evaluation of models using various evaluation metrics.

3.3.2 SOFTWARE INTERFACES

- Flask – Python web framework that provides useful tools and features for building web applications and back-end development.
- NumPy, Pandas – python libraries that provide support for large, multi-dimensional arrays, metrices and data structures, along with large collection of mathematical functions to operate on these arrays.
- Matplotlib – python library for creating static, animated and interactive visualizations.

- Scikit-learn [61]– machine learning library supporting classification, regression and clustering algorithms.
- Tensorflow – machine learning and artificial intelligence library which particularly focuses on training and inference of deep neural networks.
- Keras [24]– high level neural network library that runs on top of tensorflow and is used for developing and evaluating deep learning models.
- HTML, CSS – scripting language used to define structure of a webpage and stylesheet language that controls how elements in a document should be rendered on different media.

3.3.3 HARDWARE INTERFACES

- The application should run on standard computing systems with reasonable processing capabilities.
- Adequate storage for dataset and processing on the server-side ensuring efficient retrieval and analysis.

3.3.4 COMMUNICATION INTERFACES

- HTTP/HTTPS protocols – utilized for communication between web server and user's browser.
- Data upload/download – methods for secure and efficient upload and download of datasets between user's system and application's server.

CHAPTER 4:
DESIGN

4.1 SOFTWARE DEVELOPMENT MODEL

The fundamental life cycle model for software development is the Agile Model. The Agile model is a flexible and iterative approach to software development that emphasizes adaptability, collaboration, and customer feedback. It is particularly well-suited for projects where requirements are expected to evolve and change throughout the development process.

The 7 steps of the agile model are as follows:

1. Project Initiation - Define the research objectives and goals for anomaly detection. Identify key stakeholders, including researchers, domain experts, and potential users. Establish the scope of the research project, specifying the types of anomalies and data sources.
2. Literature Review - Conduct a comprehensive literature review to understand existing approaches to anomaly detection and the performance metrics commonly used in the field. Identify relevant machine learning algorithms for anomaly detection.
3. Data Requirement & Specification - Choose a set of machine learning algorithms suitable for anomaly detection. Consider a diverse range of algorithms, such as isolation forests, one-class SVM, k-nearest neighbors, etc. Gather relevant datasets for anomaly detection.
4. Develop Algorithms & Analyze results - Implement baseline models using selected machine learning algorithms. Train models on a subset of the data to assess their initial performance. Define performance metrics for evaluating the anomaly detection models
5. Iterative Model Development and Evaluation - Break down the project into iterations, each focused on evaluating and improving the performance of a specific algorithm. Conduct iterations to train and evaluate different machine learning algorithms.

6. Feedback and Adjustments Gather - feedback from research collaborators, stakeholders, or domain experts. Adjust the research plan and algorithms based on insights gained during the iterative process.
7. Documentation - Choose the best-performing machine learning algorithm based on the overall evaluation. Document the details of each iteration, including algorithm configurations, parameter settings, and results. Develop a web-based visualization platform to showcase the performance metrics and results of the AI algorithm to present the evaluation metrics.

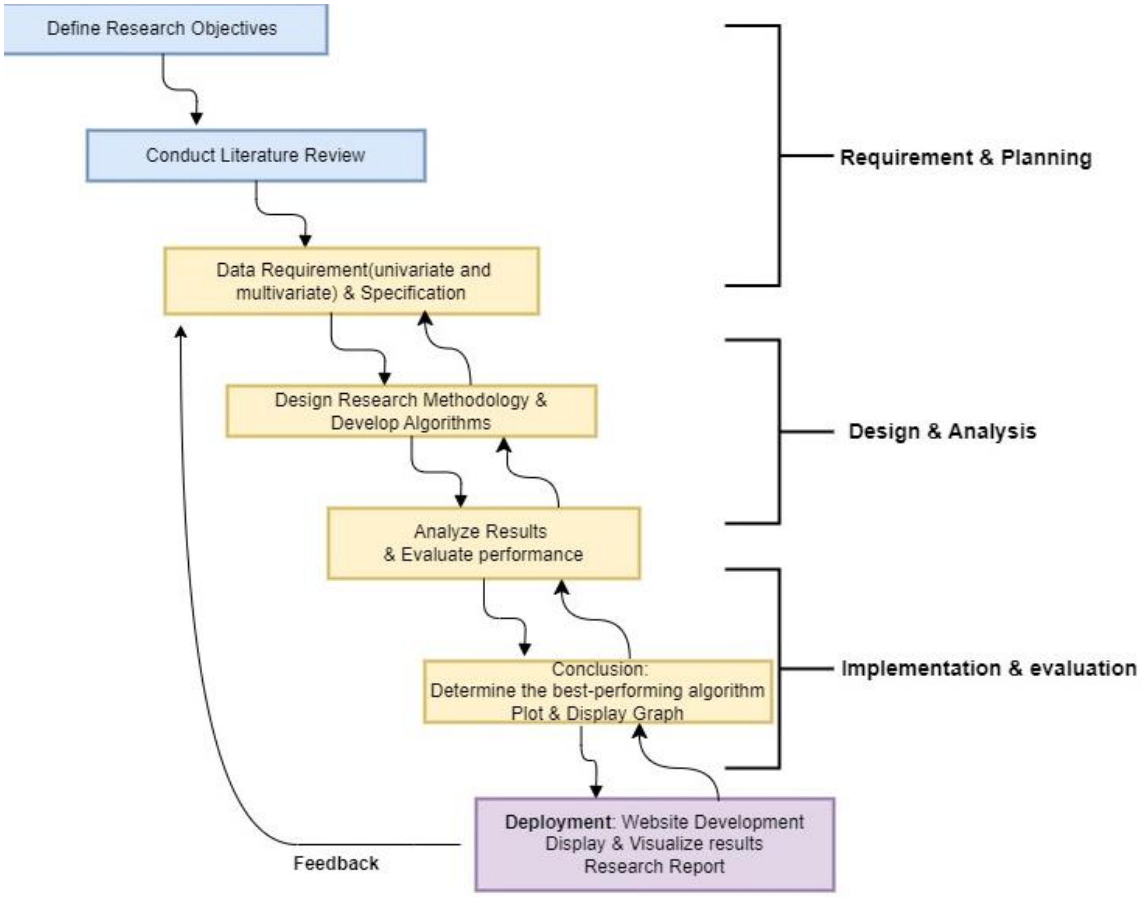


Figure 4.1: Agile Life Cycle Model

4.2 SYSTEM DESIGN

4.2.1 DATA FLOW DIAGRAM

A Data Flow Diagram (DFD) visually represents the flow of data within a system, illustrating how information moves between processes, data stores, and external entities. It provides a clear and concise overview of the data processing and interaction within the system's architecture.

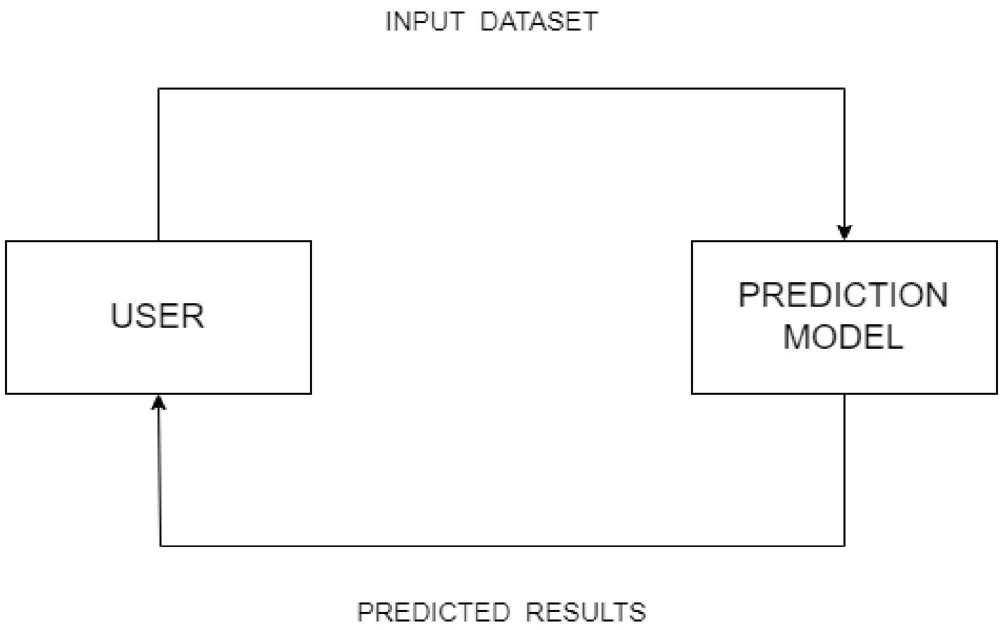


Figure 4.2: Level 0 DFD

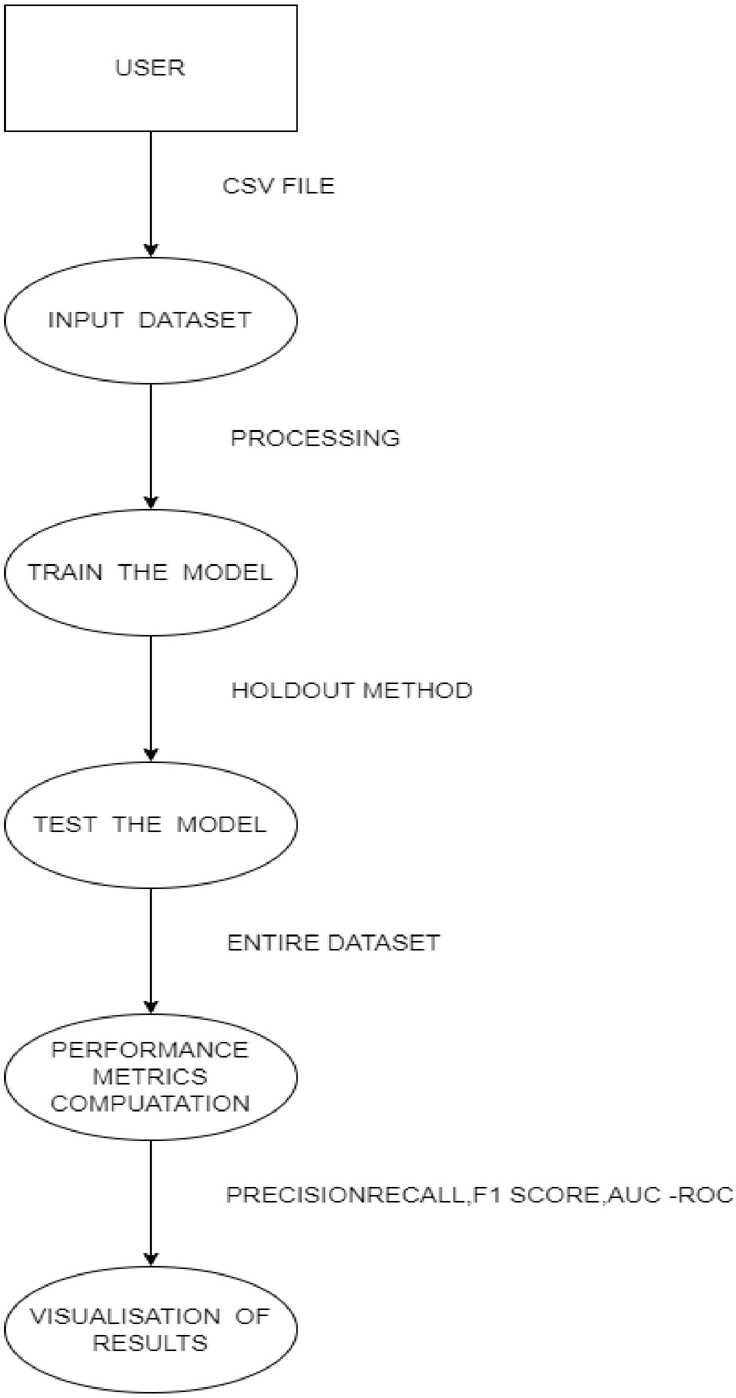


Figure 4.3: Level 1 DFD

4.3 DETAILED DESIGN

4.3.1 USE CASE DIAGRAM

A Use Case Diagram is a visual representation in UML that depicts the interactions between system components and external actors, outlining various scenarios or use cases to illustrate how the system responds to user actions. It serves as a powerful tool for understanding and communicating the functional requirements and user interactions within a software system.

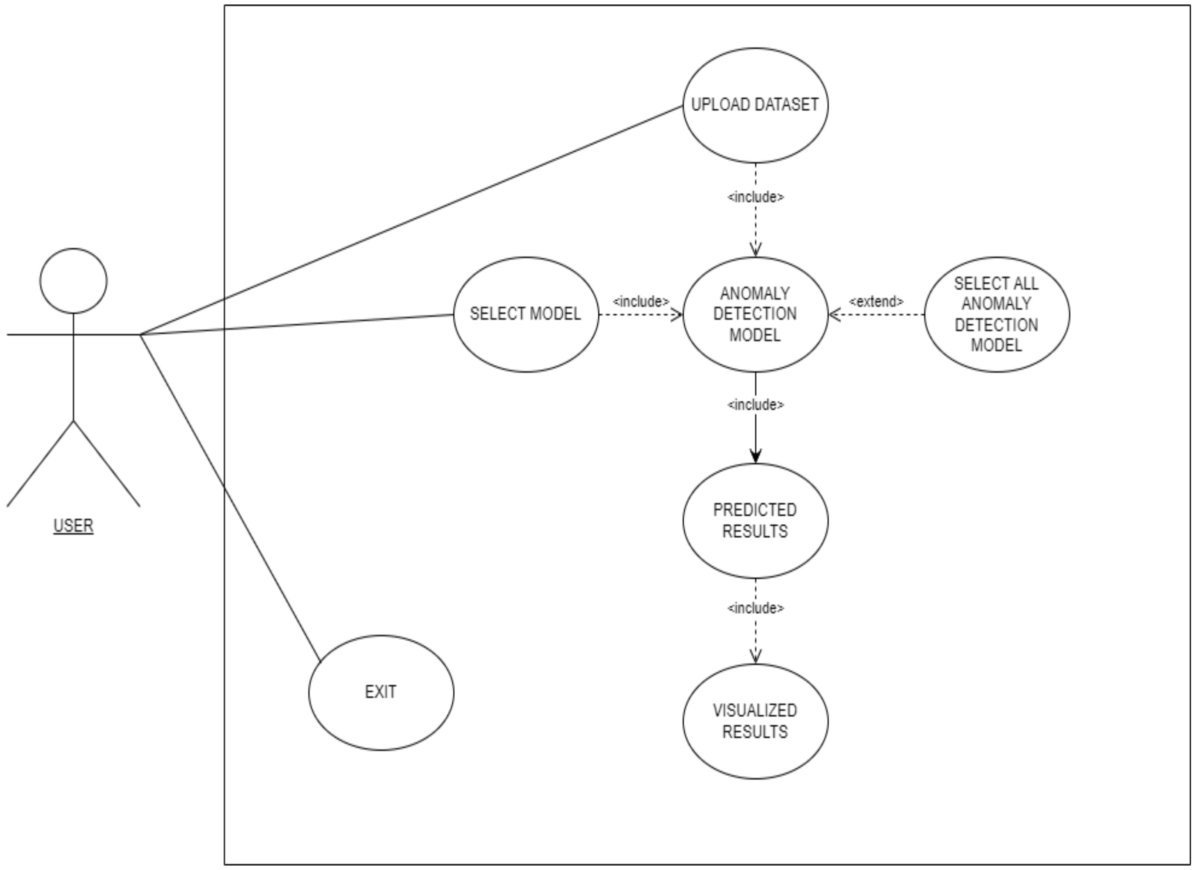


Figure 4.4: Use Case Diagram

4.3.2 ACTIVITY DIAGRAM

Activity diagrams visualize the dynamic aspects of a system's behavior, showcasing the flow of activities and their interactions. Using nodes to represent actions, decision points, and concurrency, activity diagrams provide a clear and intuitive way to model complex processes. Employing symbols like control flows and object nodes. Activity diagram aid in understanding, analyzing, and documenting the sequential and parallel activities within a system.

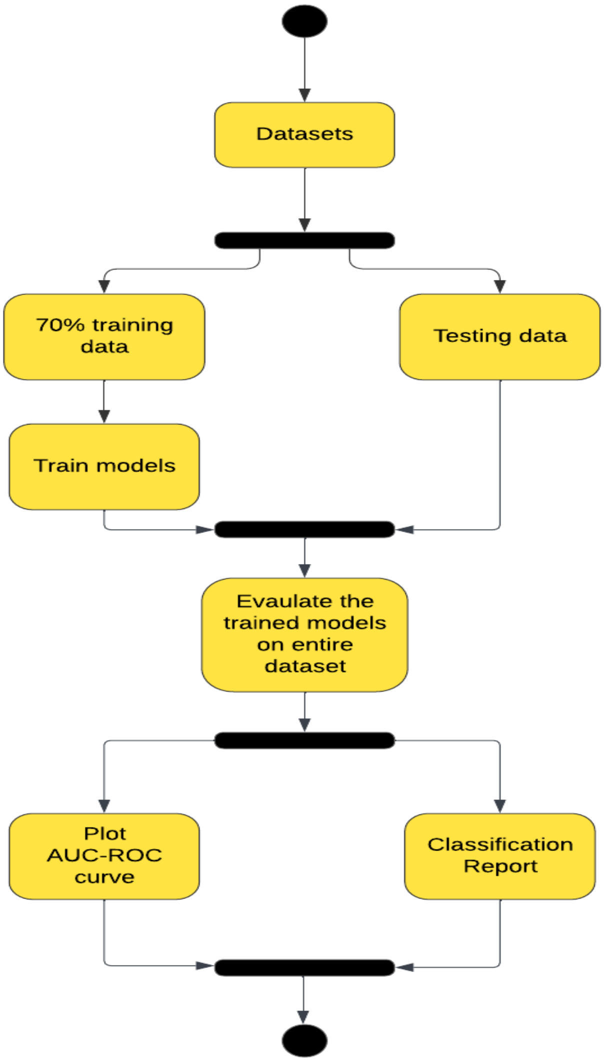


Figure 4.5: Activity Diagram 1 for models trained on mixture of normal and anomalous data

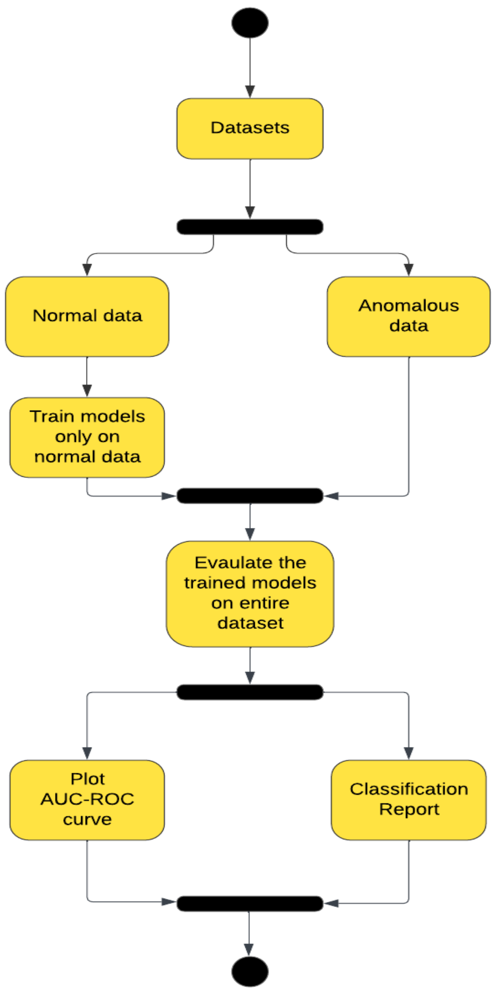


Figure 4.6: Activity Diagram 2 for models trained only on normal data and evaluated on entire data

4.3.3 SEQUENCE DIAGRAM

Sequence diagrams is a key UML diagram type which illustrates the interactions between objects or components in a system over time, showcasing the order of message exchanges between them. Through vertical lifelines representing entities and horizontal arrows depicting messages, sequence diagrams provide a visual representation of the dynamic behavior and collaboration within a software system.

Sequence diagram for training and evaluating models-

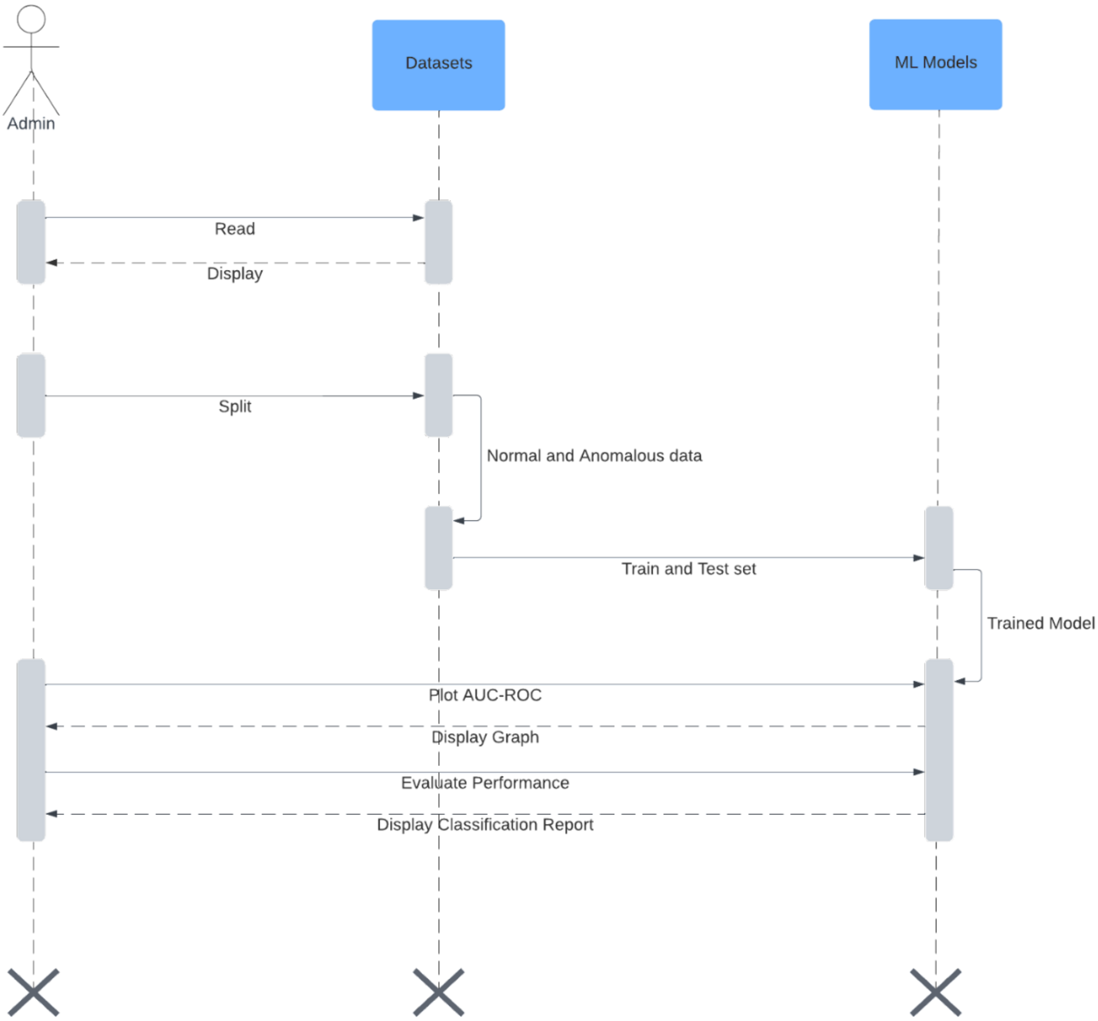


Figure4.7: Sequence Diagram 1

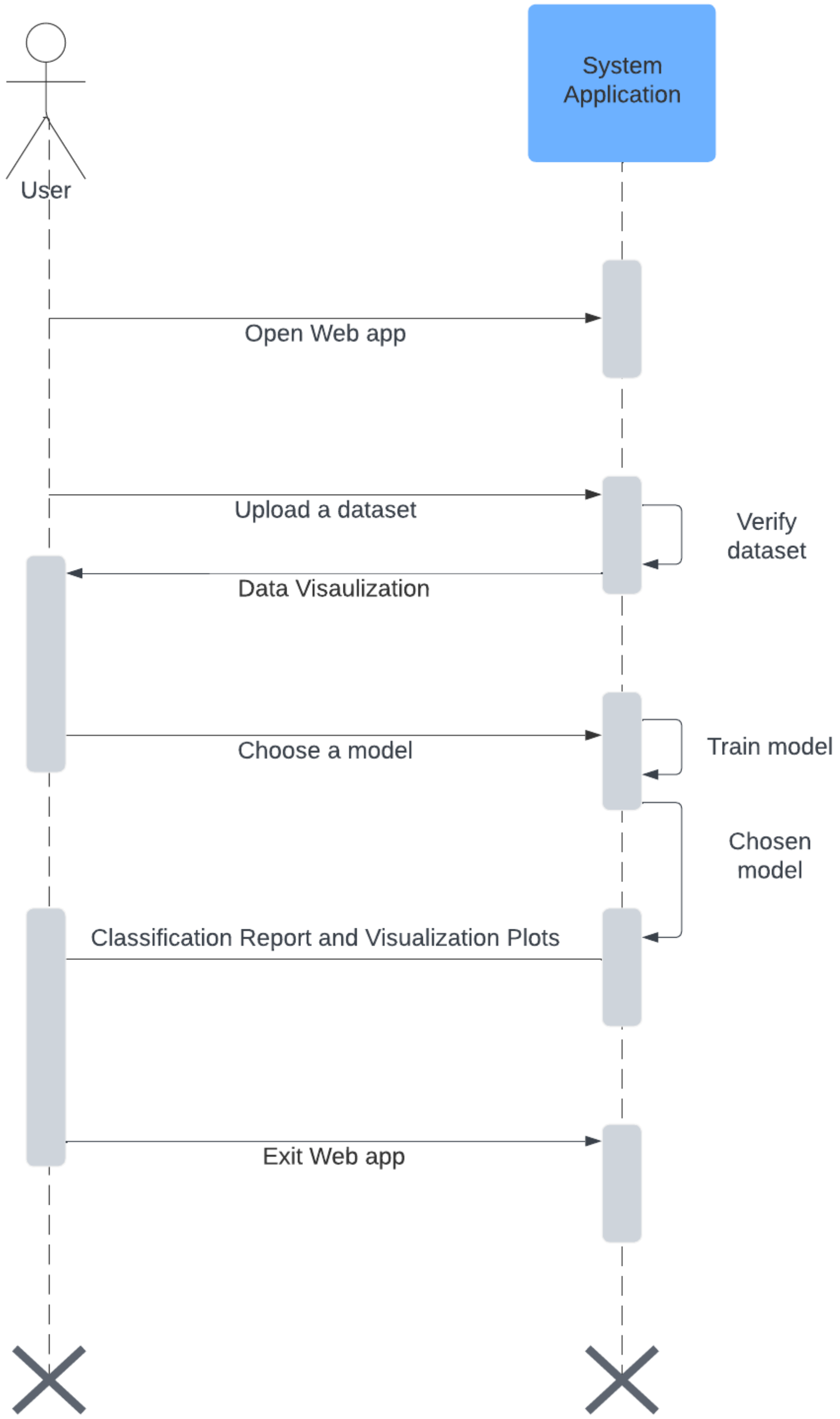


Figure4.8: Sequence Diagram 2

CHAPTER 5:
IMPLEMENTATION

5.1 IMPLEMENTATION

5.1.1 METHODOLOGY

Accurate implementation of anomaly detection algorithms is essential for the benchmarking exercise. We prioritized the use of established implementations, wherever possible. We utilized scikit-learn [40]for Isolation Forest and Elliptic PYOD. LOF was implemented using Python Outlier Detection (PyOD)library [69]. We used Deep Learning based Outlier Detection (DeepOD)library for Devnet[51]. LSTM, GAN and Autoencoders were implemented using Keras . For deep quantile regression we have implemented the code using the algorithm from the paper. All experiments were carried out on Google Colab ensuring consistency and accessibility.

5.1.2 TREE BASED METHODS

Among all the state-of-the-art algorithms used in this benchmark study we would like to delve into the discussion of tree-based approaches MGBTAI and d-BTAI as they have outperformed other algorithms in this benchmark study.

1. Firstly, tree-based approaches are unsupervised and hence do not require training data. This is particularly useful, as training data may not always be available and if available, it may be scarce.
2. Tree based approaches are adaptable, and can be used on both temporal as well as non-temporal data. They are flexible and not limited to a specific domain. They can be applied across various domains from finance to cybersecurity to healthcare.
3. These methods have been successful in detecting anomalies of varying densities, from detecting a singleton to thousands of anomalies as seen in the multivariate data. Unlike

deep learning algorithms that have results that deviate on multiple runs, tree-based approaches produce same results on all runs thus ensuring reliability.

4. Instead of creating an ensemble of binary trees like Iforest, d-BTAI employs a single binary tree making it much more efficient in terms of memory and time required for termination.
5. These approaches not only manage to accurately identify anomalies but also reduce the number of false positives and this is clearly depicted under the evaluation of univariate data as most algorithms mange to achieve a perfect recall in many datasets with tree-based approaches, but when we go a step ahead and compare precision, tree-based methods achieve high precision thereby emerging as clear winners.

5.1.3 EXPERIMENTAL SETTING FOR d-BTAI

Threshold Determination Using the Knee/Elbow Method for multivariate data: We opted to leverage the knee/elbow method for threshold determination due to the intrinsic nature of multivariate data, which often contains a substantial number of anomalies. This method, with its capacity to automatically pinpoint the inflection point in the distribution of anomaly scores, proves to be particularly effective in such scenarios.

Threshold Identification: Employing the knee/elbow method, we discern a key point on the plot known as the knee or elbow point[29]. This specific point on the curve marks the location where there is a significant change in the slope of the plotted scores. The knee/elbow point essentially serves as a potential threshold that distinguishes normal data from anomalies.

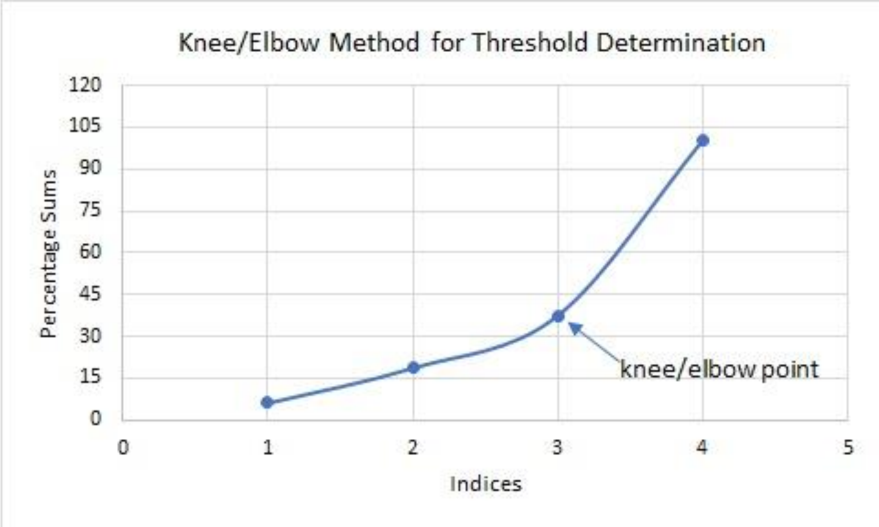


Figure5.1: Knee/Elbow Method

Threshold Setting: Upon the identification of the knee/elbow point, we establish it as the definitive threshold for identifying anomalies within our dataset. Any data point with an ECBLOF score exceeding this threshold is marked as an anomaly.In datasets where anomalies are numerous and complex, the knee/elbow method proves to be an invaluable enhancement. By automatically identifying the optimal threshold, this method greatly simplifies the process and bolsters anomaly detection accuracy.

5.2 RESULTS

5.2.1 MULTIVARIATE DATA RESULTS

In this subsection, we focus on examining the performance of anomaly detection algorithms through Precision, Recall, F1- score and AUC ROC on multivariate datasets of varying sizes and domains. By assessing each of these metrics individually, we demonstrate that even though deep learning algorithms are effective, they may not be sufficient alone. We also underscore the generalizability of binary tree based algorithms (MGBTAI and DBTAI) on datasets having varying numbers of anomalies.

Tree-based methods, specifically MGBTAI and d-BTAI, showcased outstanding performance across diverse multivariate datasets, exhibiting remarkable precision, recall, and F1-score values. They attained the highest precision values across 20 datasets, with perfect precision achieved in 2 datasets. Additionally, they demonstrated exceptional recall, securing perfect recall in 12 datasets and emerging as top performers in 40 datasets. Moreover, these methods excelled in achieving optimal F1-score values across various datasets, emerging as top performers in 20 datasets. Furthermore, they unraveled complex patterns effectively, emerging as top performers in 13 datasets and significantly advancing insights in anomaly detection.

Dataset	Size	Dimension	Number of Anomalies	Percentage of Anomalies	Domain
ALOI	49534	27	1508	3.04	Image
annthyroid	7200	6	534	7.42	Healthcare
backdoor	95329	196	2329	2.44	Network
breastw	683	9	239	34.99	Healthcare
campaign	41188	62	4640	11.27	Finance
cardio	1831	21	176	9.61	Healthcare
Cardiotocography	2114	21	466	22.04	Healthcare
celeba	202599	39	4547	2.24	Image
cover	286048	10	2747	0.96	Botany
donors	619326	10	36710	5.93	Sociology
fault	1941	27	673	34.67	Physical
fraud	284807	29	492	0.17	Finance
glass	214	7	9	4.21	Forensic
Hepatitis	80	19	13	16.25	Healthcare
http	567498	3	2211	0.39	Web
InternetAds	1966	1555	368	18.72	Image
Ionosphere	351	33	126	35.9	Mineralogy
landsat	6435	36	1333	20.71	Astronautics
letter	1600	32	100	6.25	Image
Lymphography	148	18	6	4.05	Healthcare
magic.gamma	19020	6	260	1.37	Physical
mammography	11183	6	260	2.32	Healthcare
mnist	7603	100	700	9.21	Image
musk	3062	166	97	3.17	Chemistry
optdigits	5216	64	150	2.88	Image
PageBlocks	5393	10	510	9.46	Document
pendigits	6870	16	156	2.27	Image
Pima	768	8	268	34.9	Healthcare
satellite	6435	36	2036	31.64	Astronautics
satimage-2	5803	36	71	1.22	Astronautics
shuttle	49097	9	3511	7.15	Astronautics
skin	245057	3	50859	20.75	Image
smtp	95156	3	30	0.03	Web
SpamBase	4207	57	1679	39.91	Document
speech	3686	400	61	1.65	Linguistics
Stamps	340	9	31	9.12	Document

thyroid	3772	6	93	2.47	Healthcare
vertebral	240	6	30	12.5	Biology
vowels	1456	12	50	3.43	Linguistics
Waveform	3443	21	100	2.9	Physics
WBC	223	9	10	4.48	Healthcare
WDBC	367	30	10	2.72	Healthcare
Wilt	4819	5	257	5.33	Botany
wine	129	13	10	7.75	Chemistry
WPBC	198	33	47	23.74	Healthcare
yeast	1484	8	507	34.16	Biology
CIFAR10	5263	512	263	5	Image
FashionMNIST	6315	512	315	5	Image
MNIST-C	10000	512	500	5	Image
MVTec-AD	292	512	63	21.5	Image
SVHN	5208	512	260	5	Image
Agnews	10000	768	500	5	NLP
Amazon	10000	768	500	5	NLP
Imdb	10000	768	500	5	NLP
Yelp	10000	768	500	5	NLP
20newsgroups	3090	768	155	5	NLP
BATADAL 04	4177	43	219	5.24	Industrial
SWaT 1	50400	51	4466	8.86	Industrial
SWaT 2	86400	51	4216	4.88	Industrial
SWaT 3	86400	51	3075	3.56	Industrial
SWaT 4	86319	51	37559	43.51	Industrial
SWaT 5	86400	51	2167	2.51	Industrial
SWaT 6	54000	51	3138	5.81	Industrial
ecoli	336	7	9	2.68	Healthcare
cmc	1473	9	17	1.15	Healthcare
lympho h	148	18	6	4.05	Healthcare
wbc h	378	30	21	5.56	Healthcare

Table 5.1: Multivatriate Datasets Characterisation

Dataset	LOF	IForest	AutoEncoders	DAGMM	Elliptic Envelope	DevNet	GAN	MGBTAI	d-BTAI
ALOI	**0.1**	0.04	0.05	0.03	0.03	0.03	0.04	0.04	0.04
annthyroid	0.26	0.25	0.15	0.24	**0.4**	0.12	0.09	0.07	0.11
backdoor	0.11	0.03	0.2	**0.21**	**0.21**	**0.21**	**0.21**	0.01	0.06
breastw	0.39	0.98	0.27	**1**	**1**	0.86	0	0.85	0.89
campaign	0.07	0.33	0.22	0.3	0.34	**0.42**	0.21	0.17	0.16
cardio	0.17	0.48	0.34	0.13	0.4	**0.5**	0.07	0.48	0.2
Cardiotocography	0.32	0.48	0.31	0.36	0.48	0.4	0.24	**0.8**	0.35
celeba	0.01	0.07	0.02	0.07	0.09	**0.19**	0.03	0.08	0.03
cover	0.02	0.05	0.09	0.02	0.01	**0.1**	0.01	0	0.02
donors	0.21	0.1	0.14	**0.5**	0.2	0.44	0.04	0	0.13
fault	0.32	**0.49**	0.19	0.36	0.24	0.36	0.47	0.42	**0.49**
fraud	0	**0.02**	**0.02**	0.01	**0.02**	**0.02**	NA	0.01	0
glass	**0.18**	0.1	0.09	0	0.12	0	0.06	0.08	0.17
Hepatitis	0.25	0.18	0.13	0.25	**0.33**	0.25	0.2	0	0.14
http	0	0.03	0.04	0.04	0.04	0.04	NA	**0.05**	0.03
InternetAds	0.48	0.64	0.53	0.2	0.63	0.32	0.11	**0.98**	0.28
Ionosphere	0.94	0.96	0.5	0.69	**1**	0.58	0.58	0.44	0.82
landsat	0.31	0.15	0.19	0.18	0.04	0.24	**0.38**	0.01	0.26
letter	**0.36**	0.08	0.05	0.06	0.17	0.07	0.06	0.11	0.12
Lymphography	0.33	0.4	0.13	0.07	0.38	0.11	0.13	**0.43**	0.15
magic.gamma	0.62	0.78	0.55	0.56	**0.91**	0.78	0.76	0.77	0.53
mammography	0.08	0.12	0.05	0.15	0.03	**0.19**	0.01	0	0.07
mnist	0.23	0.32	0.19	0.16	0.16	**0.47**	0.09	0.02	0.17
musk	0.01	0.25	0.17	0.32	0.31	0.29	0.03	0.23	**0.36**
optdigits	0.07	0.05	0.04	0.05	0	0.26	0.03	**0.33**	0.02
PageBlocks	0.39	0.41	0.29	0.27	0.56	0.17	0.31	**0.67**	0.17
pendigits	0.04	0.16	0.13	0	0.06	**0.23**	0.06	0	0.04
Pima	0.32	0.59	0.35	0.45	0.51	**0.68**	0.15	0.28	0.44
satellite	0.48	0.93	0.39	0.77	0.96	0.59	0.32	**1**	0.54
satimage-2	0.03	0.1	0	0.08	0.12	0.12	0.01	**0.14**	0.04
shuttle	0	0.98	0.47	0.51	**1**	0.48	0.07	0.49	0.44
skin	0.24	0.06	0.08	0.57	0.3	**0.76**	0.1	0.62	0.27
smtp	0.002	0.002	0.002	**0.003**	0.002	0.002	**0.003**	**0.003**	0.001
SpamBase	0.32	0.41	0.41	0.63	0.31	**0.76**	0.08	0.73	0.66
speech	0.02	0.02	0.03	0.01	0.02	**0.13**	0.08	0.01	0.02
Stamps	0.15	0.23	0.14	0.03	0.11	0.15	**0.45**	0.13	0.15
thyroid	0.1	0.19	0.15	0.17	**0.23**	0.18	0.17	0.13	0.08
vertebral	0.04	0.03	0	0.08	0	**0.1**	0.04	0	0.05
vowels	0.26	0.09	0.11	0.01	0.05	0.19	0.03	**0.67**	0.08
Waveform	0.09	0.06	0.11	0.09	0.04	0.07	**0.21**	0	0.05
WBC	0.09	0.32	0.38	0.35	0.38	0.31	0.06	**0.42**	0.19
WDBC	**0.27**	0.21	0.26	0.24	0.26	0.26	0.01	0.21	0.19
Wilt	**0.1**	0.01	0.05	**0.1**	**0.1**	0	0.05	0	0.05
wine	**0.77**	0.18	0.5	0.31	0.36	0.45	0.51	0.53	0.26
WPBC	0.1	0.14	**0.25**	0.15	0.15	0.18	0.2	0.12	**0.25**
yeast	0.27	0.3	0.35	0.36	0.26	0.35	**0.49**	0.1	0.3
CIFAR10	0.14	0.13	0.07	0.05	0.13	0.17	**0.18**	0.04	0.08
FashionMNIST	0.15	0.19	0.12	0.11	0.18	**0.29**	0.21	0.06	0.1
MNIST-C	0.13	0.08	0.04	0.08	0.08	**0.38**	0.09	0.05	0.17
MVTec-AD	0.87	**1**	0.5	0.4	0.12	0.26	0.97	**1**	0.9

SVHN	0.11	0.06	0.04	0.05	0.09	**0.38**	0.1	0.06	0.1
Agnews	**0.11**	0.06	0.05	0.06	0.07	0.07	0.1	0.05	0.06
Amazon	**0.06**	**0.06**	0.05	0.05	**0.06**	**0.06**	**0.06**	0.05	0.05
Imdb	0.04	0.04	0.05	0.05	0.03	**0.07**	0	0.02	0.05
Yelp	**0.1**	0.09	0.03	0.06	0.07	0.06	0.04	0.04	0.06
20newsgroups	**0.18**	0.07	0.05	0.06	0.1	0.05	0.04	0	0.04
BATADAL 04	0.2	0.1	0.09	0.19	**0.26**	0.05	0.1	0.1	0.09
SWaT 1	0.08	**0.63**	0.13	0.5	0.19	0.22	0.09	**0.63**	0.19
SWaT 2	0.06	**0.71**	0.1	0.11	0.13	0.12	0.05	**0.71**	0.08
SWaT 3	0.04	0.02	0.13	**0.23**	0.09	0.15	0.04	0.02	0.07
SWaT 4	0.45	0.34	0.08	**0.99**	0.27	0.88	0.44	0.34	0.18
SWaT 5	0.02	**0.22**	0.09	0.1	0.12	0.12	0.03	**0.22**	0.06
SWaT 6	0.07	**0.97**	0.37	0.26	0.26	0.17	0.06	**0.97**	0.13
ecoli	0.21	0.19	0.2	**0.22**	0.21	0.06	0	0.14	0.06
cmc	0.01	0	0.03	0.01	0.01	0	**0.05**	0	0.02
lympho h	**0.33**	0.32	0.12	0	0.21	0.06	0.05	0	0.11
wbc h	0.37	0.34	0.27	0.32	0.35	0.4	0.04	**0.61**	0.17

Table 5.2: Precision values of the 9 algorithms on the 67 multivariate datasets. The highest value(s) is marked in bold. The notation (NA) denotes that the algorithm exceeded a runtime of three hours without successfully generating results.

Dataset	LOF	Iforest	AutoEncoders	DAGMM	Elliptic Envelope	DevNet	GAN	MGBTAI	d-BTAI
ALOI	0.34	0.15	0.12	0.11	0.09	0.08	0.14	0.13	**0.4**
annthyroid	0.35	0.41	0.2	0.32	**0.52**	0.17	0.12	0.18	0.51
backdoor	0.45	0.16	0.19	0.87	0.84	**0.91**	0.86	0.02	0.87
breastw	**1**	0.41	0.13	0.29	0.32	**1**	0	0.33	0.87
campaign	0.06	0.35	0.19	0.27	0.31	0.52	0.19	0.16	**0.66**
cardio	0.18	0.61	0.36	0.14	0.42	**0.79**	0.07	0.32	0.76
Cardiotocography	0.15	0.26	0.13	0.16	0.21	0.23	0.32	0.2	**0.47**
celeba	0.05	0.38	0.1	0.29	0.38	**0.88**	0.15	0.7	0.38
cover	0.22	0.57	0.37	0.24	0.13	0.97	**1**	0	0.7
donors	0.33	0.2	0.24	0.86	0.33	**1**	0.1	0	0.47
fault	0.09	0.18	0.24	0.1	0.07	0.11	0.14	0.07	**0.6**
fraud	0.11	0.89	0.88	0.62	0.85	0.92	NA	0.62	**0.96**
glass	0.44	0.33	0.22	0	0.33	0	0.13	0.11	**1**
Hepatitis	0.15	0.15	0.08	0.15	**0.31**	0.15	0.12	0	0.23
http	0.03	**1**	**1**	**1**	**1**	**1**	NA	**1**	**1**
InternetAds	0.26	0.42	0.29	0.11	0.36	0.17	0.04	0.23	**0.6**
Ionosphere	0.26	0.35	0.14	0.2	0.25	0.25	0.16	0.03	**0.84**
landsat	0.15	0.09	0.09	0.09	0.02	0.12	0.19	0	**0.46**
letter	0.57	0.16	0.08	0.09	0.28	0.12	0.1	0.18	**0.86**
Lymphography	0.83	**1**	0.33	0.17	0.83	0.33	0.33	**1**	**1**
magic.gamma	0.18	0.26	0.16	0.16	0.26	0.57	0.22	0.21	**0.59**
mammography	0.37	0.64	0.42	0.64	0.13	0.8	0.04	0	**0.84**
mnist	0.25	0.42	0.21	0.18	0.18	0.71	**1**	0.02	0.85
musk	0.04	**1**	0.53	**1**	**1**	**1**	**1**	0.79	**1**
optdigits	0.26	0.21	0.15	0.16	0.01	**0.99**	0.12	0.81	0.27
PageBlocks	0.41	0.52	0.3	0.29	**0.61**	0.2	0.33	0.06	0.21
pendigits	0.17	0.88	0.56	0.01	0.28	**0.98**	0.25	0.03	0.72
Pima	0.09	0.23	0.1	0.13	0.16	0.36	0.04	0.05	**0.43**
satellite	0.15	0.34	0.12	0.24	0.29	0.31	**1**	0.3	0.59
satimage-2	0.28	0.99	0.01	0.65	**1**	0.97	**1**	**1**	**1**
shuttle	0	0.41	0.65	0.72	0.31	0.98	**1**	0.01	0.88
skin	0.12	0.03	0.04	0.28	0.14	**1**	0.05	0.15	0.22
smtp	0.7	0.77	0.7	0.87	0.77	0.7	**1**	0.33	0.87
SpamBase	0.08	0.12	0.1	0.16	0.07	**0.45**	0.02	0.18	0.26
speech	0.15	0.15	0.18	0.03	0.11	0.75	0.12	0.11	**0.8**
Stamps	0.16	0.32	0.15	0.03	0.13	0.16	0.49	0.06	**0.61**
thyroid	0.39	0.97	0.62	0.71	0.96	0.72	0.71	0.25	**1**
vertebral	0.03	0.03	0	0.07	0	0.07	0.03	0	**0.13**
vowels	0.76	0.3	0.33	0.02	0.14	0.62	0.08	0.16	**1**
Waveform	0.31	0.25	0.37	0.32	0.16	0.24	0.72	0	**0.76**
WBC	0.2	**1**	0.9	0.8	**1**	**1**	0.13	**1**	**1**
WDBC	**1**	**1**	**1**	0.9	0.9	**1**	0.33	**1**	**1**
Wilt	0.19	0.02	0.1	0.18	0.2	0	**1**	0	0.18
wine	**1**	0.3	0.7	0.4	0.4	**1**	0.67	**1**	**1**
WPBC	0.04	0.09	0.11	0.06	0.06	0.06	0.09	0.04	**0.4**
yeast	0.08	0.1	0.1	0.11	0.08	0.1	0.14	0	**0.27**
CIFAR10	0.27	0.31	0.14	0.1	0.26	0.37	0.37	0.07	**0.71**
FashionMNIST	0.3	0.47	0.24	0.22	0.36	0.71	0.42	0.12	**0.93**
MNIST-C	0.27	0.18	0.08	0.15	0.15	**0.97**	0.18	0.12	0.85
MVTec-AD	0.41	0.51	0.24	0.19	0.21	0.13	0.46	0.22	**0.87**
SVHN	0.22	0.13	0.08	0.1	0.2	**0.96**	0.2	0.06	0.88
Agnews	0.22	0.15	0.09	0.12	0.14	0.14	0.21	0.02	**0.47**

Amazon	0.12	0.14	0.1	0.11	0.12	0.12	0.11	0.12	**0.47**
Imdb	0.08	0.08	0.1	0.1	0.06	0.13	0	0.02	**0.43**
Yelp	0.2	0.21	0.07	0.11	0.14	0.11	0.08	0.04	**0.54**
20newsgroups	**0.37**	0.17	0.11	0.13	0.19	0.1	0.08	0	0.29
BATADAL 04	0.38	0.1	0.17	0.36	0.5	0.10	0.23	0.1	**0.75**
SWaT 1	0.09	0.15	0.15	0.57	0.21	0.23	**1**	0.15	0.81
SWaT 2	0.13	0.08	0.2	0.23	0.27	0.26	**1**	0.08	0.53
SWaT 3	0.12	0.03	0.38	0.65	0.24	0.42	**1**	0.03	0.69
SWaT 4	0.1	0.12	0.02	0.23	0.06	0.89	**1**	0.12	0.15
SWaT 5	0.08	0.22	0.36	0.38	0.51	0.5	**1**	0.22	0.83
SWaT 6	0.12	0.4	0.63	0.44	0.44	0.30	**1**	0.4	0.81
ecoli	**0.78**	**0.78**	**0.78**	**0.78**	**0.78**	0.22	0	**0.78**	**0.78**
cmc	0.06	0	0.24	0.06	0.12	0	**0.47**	0	**0.47**
lympho h	0.83	**1**	0.33	0	0.67	0.17	0.11	0	**1**
wbc h	0.67	0.71	0.48	0.57	0.67	**1**	0.08	0.52	**1**

*Table 5.3: **Recall** values of the 9 algorithms on the 68 multivariate datasets. The highest value(s) is marked in bold.*

Dataset	LOF	Iforest	AutoEncoders	DAGMM	Elliptic Envelope	DevNet	GAN	MGBTAI	d-BTAI
ALOI	**0.16**	0.06	0.06	0.05	0.04	0.04	0.06	0.07	0.06
annthyroid	0.3	0.31	0.17	0.28	**0.45**	0.14	0.1	0.1	0.19
backdoor	0.18	0.05	0.26	0.34	0.33	**0.35**	0.34	0.02	0.11
breastw	0.56	0.57	0.26	0.45	0.49	**0.92**	0	0.48	0.88
campaign	0.06	0.34	0.2	0.28	0.32	**0.47**	0.2	0.16	0.26
cardio	0.18	0.54	0.35	0.13	0.41	**0.61**	0.07	0.38	0.32
Cardiotocography	0.2	0.34	0.19	0.22	0.29	0.29	0.22	0.32	**0.4**
celeba	0.02	0.12	0.04	0.11	0.14	**0.32**	0.05	0.14	0.06
cover	0.04	0.09	**0.17**	0.04	0.02	**0.17**	0.02	0	0.04
donors	0.26	0.13	0.19	**0.63**	0.25	0.61	0.06	0	0.2
fault	0.15	0.26	0.38	0.16	0.11	0.16	0.21	0.12	**0.54**
fraud	0	0.03	0.03	0.02	**0.04**	0.03	NA	0.02	0.01
glass	0.26	0.16	0.13	0	0.18	0	0.08	0.09	**0.29**
Hepatitis	0.19	0.17	0.1	0.19	**0.32**	0.19	0.15	0	0.18
http	0	0.06	0.07	0.07	0.07	**0.08**	NA	**0.08**	0.06
InternetAds	0.33	0.42	0.37	0.14	**0.46**	0.22	0.16	0.38	0.39
Ionosphere	0.41	0.51	0.22	0.31	0.39	0.35	0.25	0.06	**0.83**
landsat	0.2	0.11	0.13	0.12	0.02	0.16	0.25	0	**0.33**
letter	**0.57**	0.11	0.06	0.07	0.22	0.09	0.07	0.13	0.21
Lymphography	0.48	0.57	0.18	0.1	0.53	0.17	0.19	**0.6**	0.26
magic.gamma	0.27	0.39	0.24	0.25	0.4	**0.66**	0.34	0.33	0.56
mammography	0.14	0.21	0.09	0.24	0.05	**0.3**	0.02	0	0.13
mnist	0.24	0.37	0.2	0.17	0.17	**0.56**	0.17	0.02	0.28
musk	0.02	0.39	0.25	0.48	0.47	0.45	0.06	0.35	**0.53**
optdigits	0.12	0.08	0.07	0.07	0	0.42	0.05	**0.47**	0.03
PageBlocks	0.4	0.46	0.3	0.28	**0.58**	0.18	0.32	0.11	0.19
pendigits	0.06	0.28	0.21	0	0.11	**0.37**	0.09	0	0.08
Pima	0.14	0.33	0.16	0.2	0.24	**0.47**	0.07	0.09	0.43
satellite	0.23	0.5	0.19	0.37	0.45	0.41	0.48	0.46	**0.57**
satimage-2	**0.28**	0.18	0	0.14	0.21	0.22	0.02	0.25	0.07
shuttle	0	0.57	0.54	0.6	0.48	**0.64**	0.13	0.01	0.59
skin	0.16	0.04	0.05	0.37	0.19	**0.86**	0.07	0.24	0.24
smtp	0.004	0.004	0.004	**0.005**	**0.005**	0.004	0.001	0.004	0.002
SpamBase	0.13	0.18	0.16	0.25	0.12	**0.57**	0.03	0.29	0.37
speech	0.04	0.04	0.05	0.01	0.03	**0.23**	0.03	0.03	0.03
Stamps	0.15	0.27	0.14	0.03	0.12	0.15	**0.47**	0.09	0.24
thyroid	0.15	0.32	0.24	0.28	**0.37**	0.29	0.28	0.17	0.14
vertebral	0.04	0.03	0	0.07	0	**0.08**	0.04	0	0.07
vowels	**0.39**	0.14	0.17	0.01	0.07	0.3	0.0408	0.26	0.14
Waveform	0.14	0.09	0.17	0.14	0.07	0.11	**0.32**	0	0.09
WBC	0.12	0.49	0.53	0.48	0.56	0.48	0.08	**0.57**	0.31
WDBC	**0.43**	0.35	0.42	0.38	0.4	0.41	0.02	0.34	0.32
Wilt	**0.14**	0.01	0.07	0.12	0.13	0	0.1	0	0.07
wine	**0.87**	0.22	0.58	0.35	0.38	0.55	0.58	0.69	0.42
WPBC	0.06	0.11	0.15	0.09	0.09	0.09	0.12	0.06	**0.31**
yeast	0.12	0.16	0.16	0.16	0.12	0.16	0.22	0.01	**0.28**
CIFAR10	0.18	0.18	0.09	0.07	0.18	0.23	**0.25**	0.05	0.14
FashionMNIST	0.2	0.27	0.16	0.15	0.24	**0.41**	0.28	0.08	0.18
MNIST-C	0.18	0.11	0.06	0.1	0.1	**0.55**	0.12	0.07	0.28
MVTec-AD	0.56	0.67	0.32	0.26	0.15	0.17	0.62	0.36	**0.89**

SVHN	0.15	0.08	0.06	0.06	0.13	**0.55**	0.12	0.06	0.18
Agnews	**0.15**	0.09	0.06	0.08	0.09	0.09	0.14	0.03	0.11
Amazon	0.08	0.08	0.07	0.07	0.08	0.08	0.07	0.07	**0.1**
Imdb	0.06	0.05	0.07	0.07	0.04	0.09	0	0.02	**0.5**
Yelp	0.13	0.12	0.06	0.07	0.1	0.07	0.06	0.04	**0.56**
20newsgroups	0.25	0.1	0.09	0.09	0.13	0.06	0.06	0	**0.47**
BATADAL 04	0.26	0.1	0.12	0.25	**0.34**	0.07	0.14	0.1	0.17
SWaT 1	0.09	0.24	0.14	**0.53**	0.2	0.22	0.16	0.24	0.31
SWaT 2	0.08	0.15	0.13	0.15	**0.18**	0.16	0.04	0.15	0.14
SWaT 3	0.06	0.02	0.2	**0.34**	0.13	0.23	0.04	0.02	0.13
SWaT 4	0.17	0.18	0.03	0.37	0.1	**0.89**	0.44	0.18	0.16
SWaT 5	0.03	**0.22**	0.15	0.15	0.2	0.17	0.02	**0.22**	0.12
SWaT 6	0.09	**0.57**	0.46	0.33	0.32	0.20	0.06	**0.57**	0.22
ecoli	**0.33**	0.3	0.31	**0.33**	0.21	0.1	0	0.23	0.1
cmc	0.01	0	0.06	0.01	0.03	0	**0.1**	0	0.03
lympho h	**0.48**	**0.48**	0.18	0	0.32	0.09	0.07	0	0.2
wbc h	0.47	0.46	0.35	0.41	0.46	**0.57**	0.06	0.56	0.29

Table 5.4: : F1 Score values of the 9 algorithms on the 67 multivariate datasets. The highest value(s) is marked in bold.

Dataset	LOF	Iforest	AutoEncoders	DAGMM	Elliptic Envelope	DevNet	GAN	MGBTAI	d-BTAI
ALOI	**0.63**	0.51	0.51	0.51	0.49	0.49	0.52	0.52	0.53
annthyroid	0.63	0.66	0.55	0.62	**0.73**	0.54	0.51	0.5	0.6
backdoor	0.68	0.52	0.53	0.89	0.88	**0.91**	0.89	0.49	0.76
breastw	0.57	0.7	0.63	0.64	0.66	**0.95**	0.41	0.65	0.91
campaign	0.48	0.63	0.55	0.59	0.62	**0.72**	0.55	0.53	0.61
cardio	0.55	0.77	0.64	0.52	0.68	**0.85**	0.4	0.64	0.72
Cardiotocography	0.53	0.59	0.55	0.54	0.57	**0.67**	0.5	0.59	0.61
celeba	0.47	0.63	0.5	0.6	0.64	**0.9**	0.52	0.75	0.55
cover	0.56	0.73	0.91	0.57	0.52	**0.94**	0.5	0.5	0.68
donors	0.63	0.54	0.6	0.9	0.62	**0.96**	0.47	0.5	0.63
fault	0.5	0.54	**0.68**	0.5	0.48	0.5	0.53	0.51	0.63
fraud	0.51	0.88	0.89	0.77	0.88	**0.91**	NA	0.75	0.78
glass	0.68	0.6	0.56	0.50	0.61	0.50	0.52	0.53	**0.89**
Hepatitis	0.53	0.51	0.49	0.53	**0.59**	0.53	0.51	0.44	0.48
http	0.47	0.94	**0.95**	**0.95**	**0.95**	**0.95**	NA	**0.95**	0.94
InternetAds	0.6	**0.68**	0.61	0.5	0.66	0.54	0.47	0.62	0.63
Ionosphere	0.63	0.67	0.53	0.57	0.62	0.57	0.55	0.5	**0.87**
landsat	0.53	0.48	0.5	0.49	0.45	0.51	0.55	0.44	**0.56**
letter	**0.75**	0.52	0.49	0.49	0.6	0.51	0.5	0.54	0.72
Lymphography	0.88	**0.97**	0.62	0.53	0.89	0.61	0.62	**0.97**	0.88
magic.gamma	0.56	0.61	0.54	0.55	0.62	**0.74**	0.59	0.59	0.65
mammography	0.64	0.77	0.58	0.78	0.52	**0.86**	0.47	0.5	0.8
mnist	0.58	0.67	0.56	0.54	0.54	**0.82**	0.5	0.46	0.71
musk	0.47	0.95	0.72	**0.96**	**0.96**	**0.96**	0.5	0.85	0.82
optdigits	0.58	0.55	0.52	0.53	0.45	**0.96**	0.51	0.88	0.42
PageBlocks	0.67	0.72	0.61	0.6	**0.78**	0.55	0.62	0.53	0.55
pendigits	0.53	0.89	0.74	0.46	0.59	**0.95**	0.58	0.41	0.67
Pima	0.49	0.57	0.5	0.52	0.54	**0.64**	0.46	0.49	0.57
satellite	0.54	0.66	0.52	0.6	0.64	0.61	0.5	0.65	**0.68**
satimage-2	0.59	0.94	0.46	0.78	**0.95**	0.94	0.5	0.92	0.83
shuttle	0.43	0.7	0.8	0.83	0.66	**0.95**	0.5	0.5	0.9
skin	0.51	0.45	0.46	0.61	0.53	**0.96**	0.47	0.56	0.53
smtp	0.8	0.82	0.8	**0.88**	0.83	0.8	0.5	0.64	0.81
SpamBase	0.48	0.5	0.5	0.55	0.48	**0.68**	0.43	0.57	0.58
speech	0.52	0.51	0.54	0.47	0.51	**0.84**	0.51	0.49	0.48
Stamps	0.53	0.61	0.53	0.46	0.51	0.53	**0.72**	0.51	0.63
thyroid	0.65	0.93	0.76	0.81	**0.94**	0.82	0.81	0.6	0.84
vertebral	0.46	0.44	0.44	0.48	0.44	**0.49**	0.31	**0.49**	0.39
vowels	**0.84**	0.6	0.62	0.46	0.52	0.76	0.49	0.58	0.79
Waveform	0.61	0.56	0.64	0.61	0.53	0.57	**0.82**	0.5	0.64
WBC	0.55	0.95	0.91	0.86	0.96	0.95	0.52	**0.97**	0.9
WDBC	**0.96**	0.95	**0.96**	0.91	0.91	**0.96**	0.46	0.95	0.94
Wilt	**0.55**	0.44	0.5	0.54	**0.55**	0.45	0.5	0.48	0.48
wine	**0.99**	0.59	0.82	0.66	0.67	0.95	0.81	0.96	0.88
WPBC	0.46	0.46	0.5	0.48	0.48	0.49	0.49	0.47	**0.51**
yeast	0.48	0.49	0.5	0.5	0.48	0.5	**0.53**	0.49	0.47
CIFAR10	0.59	0.6	0.52	0.5	0.59	**0.68**	0.64	0.49	0.64
FashionMNIST	0.6	0.68	0.58	0.56	0.64	**0.81**	0.67	0.51	0.76
MNIST-C	0.59	0.53	0.49	0.53	0.53	**0.94**	0.54	0.5	0.71
MVTec-AD	0.7	0.75	0.59	0.56	0.39	0.51	0.73	0.61	**0.92**
SVHN	0.56	0.51	0.49	0.5	0.55	**0.94**	0.58	0.51	0.73
Agnews	**0.56**	0.51	0.5	0.51	0.52	0.51	**0.56**	0.5	0.55

Amazon	**0.51**	**0.51**	0.5	0.5	**0.51**	**0.51**	**0.51**	0.5	0.5
Imdb	0.49	0.48	0.5	0.5	0.48	**0.52**	0.5	0.48	0.5
Yelp	0.55	0.55	0.48	0.51	0.52	0.51	0.49	0.5	**0.56**
20newsgroups	**0.64**	0.53	0.51	0.52	0.55	0.5	0.49	0.5	0.47
BATADAL 04	0.65	0.52	0.54	0.64	**0.71**	0.50	0.55	0.52	0.68
SWaT 1	0.5	0.57	0.53	**0.76**	0.56	0.57	0.5	0.57	0.74
SWaT 2	0.51	0.54	0.55	0.57	0.59	0.58	0.5	0.54	**0.61**
SWaT 3	0.51	0.48	0.64	**0.79**	0.57	0.66	0.5	0.48	0.68
SWaT 4	0.5	0.47	0.43	0.61	0.47	**0.9**	0.5	0.47	0.31
SWaT 5	0.49	0.6	0.63	0.65	0.71	0.70	0.5	0.6	**0.75**
SWaT 6	0.51	0.7	**0.78**	0.68	0.68	0.60	0.5	0.7	0.74
ecoli	**0.85**	0.84	0.83	**0.85**	**0.85**	0.57	0.5	0.82	0.71
cmc	0.48	0.44	0.59	0.48	0.51	0.45	**0.69**	0.46	0.57
lympho h	0.88	**0.95**	0.62	0.45	0.78	0.53	0.5	0.44	0.83
wbc h	0.8	0.82	0.71	0.75	0.8	**0.96**	0.49	0.75	0.86

Table 5.5: AUC-ROC values of the 9 algorithms on the 67 multivariate datasets. The highest value(s) is marked in bold.

5.2.2 ANALYSING OF GAN

In our study, GAN achieved the highest recall across 15 datasets, achieving a perfect recall in 14 of them. However, a closer examination revealed an interesting nuance: for 13 datasets, GAN classified all data points as anomalies in all 3 runs(We ran GAN 3 times on each dataset and recorded the mean and standard deviation). This is observed for all 6 SWaT datasets. This peculiar outcome stemmed from the uniform discriminator score assigned to all the datapoints by the algorithm in the prediction of anomalies, emphasizing the need for a nuanced understanding of the algorithm's output. Furthermore, a crucial aspect of GANs' performance lies in its unstability, as revealed through a comparative analysis of standard deviation values. The consistently high standard deviation[0-0.5774] on multiple runs highlights the algorithm's susceptibility to fluctuations, raising concerns about its stability and robustness in practical applications. This instability is further emphasized by comparing GAN with Autoencoders which prove to be a more stable alternative. Standard deviation obtained from running GAN 3 times on all datasets went as high as 0.5774 whereas that obtained from running Autoencoders had a maximum value of 0.1985.

Dataset	AUTOENCODERS				GAN			
	Precision($\mu \pm \sigma$)	Recall($\mu \pm \sigma$)	F1 Score($\mu \pm \sigma$)	AUC-ROC($\mu \pm \sigma$)	Precision($\mu \pm \sigma$)	Recall($\mu \pm \sigma$)	F1 Score($\mu \pm \sigma$)	AUC-ROC($\mu \pm \sigma$)
ALOI	0.05±0.0267	0.12±0.0063	0.06±0.003	0.51±0.0032	0.04±0.0006	0.14±0.0021	0.06±0.0012	0.52±0
annthyroid	0.15±0.004	0.2±0.0056	0.17±0.0045	0.55±0.0029	0.09±0	0.12±0	0.1±0	0.51±0
backdoor	0.2±0.0247	0.19±0.0443	0.26±0.0699	0.53±0.0473	0.21±0.0014	0.86±0.0056	0.34±0.0022	0.89±0.0028
breastw	0.27±0.0587	0.13±0.064	0.26±0.0623	0.63±0.083	0±0	0±0	0±0	0.41±0.0089
campaign	0.22±0.0233	0.19±0.0207	0.2±0.0219	0.55±0.0116	0.21±0.0755	0.19±0.0758	0.2±0.0758	0.55±0.0412
cardio	0.34±0.0137	0.36±0.0143	0.35±0.0142	0.64±0.0079	0.07±0.051	0.07±0.0589	0.07±0.0589	0.4±0.2081
Cardiotocography	0.31±0.0485	0.13±0.0026	0.19±0.0197	0.55±0.0577	0.24±0.0575	0.32±0.3818	0.22±0.0861	0.5±0.0207
celeba	0.02±0.0044	0.1±0.0195	0.04±0.0072	0.5±0.0101	0.03±0.028	0.15±0.125	0.05±0.0458	0.52±0.0639
cover	0.09±0.0014	0.37±0.1985	0.17±0.014	0.91±0.0173	0.01±0	1±0	0.02±0	0.5±0
donors	0.14±0.0058	0.24±0.0062	0.19±0.0373	0.6±0.0618	0.04±0.0413	0.1±0.0869	0.06±0.0546	0.47±0.0442
fault	0.19±0	0.24±0.0006	0.38±0	0.68±0	0.47±0.245	0.14±0.245	0.21±0.0283	0.53±0.0134
fraud	0.02±0.0001	0.88±0	0.03±0	0.89±0.0001	NA	NA	NA	0±NA
glass	0.09±0.0787	0.22±0.1924	0.13±0.1118	0.56±0.1005	0.06±0.0539	0.13±0.1434	0.08±0.0832	0.52±0.0737
Hepatitis	0.13±0	0.08±0	0.1±0	0.49±0	0.2±0.1	0.12±0.0671	0.15±0.085	0.51±0.0402
http	0.04±0	1±0	0.07±0.0001	0.95±0	NA	NA	NA	0±NA
InternetAds	0.53±0	0.29±0	0.37±0	0.61±0	0.11±0.0467	0.04±0.0207	0.16±0.1934	0.47±0.0187
Ionosphere	0.5±0	0.14±0	0.22±0	0.53±0	0.58±0.2589	0.16±0.0829	0.25±0.1286	0.55±0.0644
landsat	0.19±0.0614	0.09±0.0296	0.13±0.04	0.5±0.0187	0.38±0.0376	0.19±0.0195	0.25±0.0259	0.55±0.0114
letter	0.05±0	0.08±0	0.06±0	0.49±0	0.06±0.0172	0.1±0.0321	0.07±0.0241	0.5±0.0192
Lymphography	0.13±0	0.33±0	0.18±0	0.62±0	0.13±0.1254	0.33±0.3524	0.19±0.2039	0.62±0.1827
magic.gamma	0.55±0.013	0.16±0.0037	0.24±0.0058	0.54±0.0029	0.76±0.1388	0.22±0.0432	0.34±0.0671	0.59±0.0339
mammography	0.05±0.0381	0.42±0.0077	0.09±0.0578	0.58±0.068	0.01±0.004	0.04±0.0182	0.02±0.0055	0.47±0.0071
mnist	0.19±0.0013	0.21±0.0015	0.2±0.0014	0.56±0.0008	0.09±0	1±0	0.17±0	0.5±0
musk	0.17±0	0.53±0	0.25±0	0.72±0	0.03±0	1±0	0.06±0	0.5±0
optdigits	0.04±0	0.15±0	0.07±0	0.52±0	0.03±0.0136	0.12±0.054	0.05±0.0249	0.51±0.0279
PageBlocks	0.29±0	0.3±0	0.3±0	0.61±0	0.31±0.0264	0.33±0.0295	0.32±0.0295	0.62±0.0167
pendigits	0.13±0.0077	0.56±0.0339	0.21±0.0125	0.74±0.0173	0.06±0.0354	0.25±0.1716	0.09±0.0666	0.58±0.0872

Pima	0.35±0	0.1±0	0.16±0	0.5±0	0.15±0.0942	0.04±0.0303	0.07±0.0493	0.46±0.0219
satellite	0.39±0	0.12±0	0.19±0	0.52±0	0.32±0	1±0	0.48±0	0.5±0
satimage-2	0±0	0.01±0	0±0	0.46±0	0.01±0	1±0	0.02±0	0.5±0
shuttle	0.47±0	0.65±0	0.54±0	0.8±0	0.07±0	1±0	0.13±0	0.5±0
skin	0.08±0.1367	0.04±0.0659	0.05±0.0889	0.46±0.0417	0.1±0	0.05±0	0.07±0	0.47±0
smtp	0±0	0.7±0	0±0	0.8±0	0±0	1±0	0±0	0.5±0
SpamBase	0.41±0	0.1±0	0.16±0	0.5±0	0.08±0	0.02±0	0.03±0	0.43±0
speech	0.03±0	0.18±0	0.05±0	0.54±0	0.08±0.1143	0.12±0.0095	0.03±0.0027	0.51±0.0048
Stamps	0.14±0.017	0.15±0.0186	0.14±0.0177	0.53±0.0102	0.45±0.1797	0.49±0.1971	0.47±0.188	0.72±0.1085
thyroid	0.15±0.0237	0.62±0.0964	0.24±0.038	0.76±0.0494	0.17±0.0573	0.71±0.2329	0.28±0.092	0.81±0.1193
vertebral	0±0	0±0	0±0	0.44±0	0.04±0.0415	0.03±0.0333	0.04±0.037	0.31±0.0191
vowels	0.11±0.0209	0.33±0.0611	0.17±0.0312	0.62±0.0316	0.03±0.0069	0.08±0.02	0.04±0.0102	0.49±0.0104
Waveform	0.11±0.005	0.37±0.0173	0.17±0.0078	0.64±0.0089	0.21±0.0117	0.72±0.0404	0.32±0.0181	0.82±0.0208
WBC	0.38±0	0.9±0	0.53±0	0.91±0	0.06±0.1004	0.13±0.2309	0.08±0.1399	0.52±0.1208
WDBC	0.26±0	1±0	0.42±0	0.96±0	0.01±0.0157	0.33±0.5774	0.02±0.0306	0.46±0.0308
Wilt	0.05±0	0.1±0	0.07±0	0.5±0	0.05±0	1±0	0.1±0	0.5±0
wine	0.5±0	0.7±0	0.58±0	0.82±0	0.51±0.4441	0.67±0.5774	0.58±0.502	0.81±0.3129
WPBC	0.25±0.05	0.11±0.0213	0.15±0.0299	0.5±0.014	0.2±0.2291	0.09±0.0975	0.12±0.1368	0.49±0.0639
yeast	0.35±0.0444	0.1±0.0137	0.16±0.0199	0.5±0.0098	0.49±0.0303	0.14±0.0089	0.22±0.0137	0.53±0.0067
CIFAR10	0.07±0.0019	0.14±0.0073	0.09±0.0033	0.52±0.0021	0.18±0.0113	0.37±0.0256	0.25±0.0161	0.64±0.0129
FashionMNIST	0.12±0.0009	0.24±0.0016	0.16±0.0011	0.58±0.0039	0.21±0.0211	0.42±0.0421	0.28±0.028	0.67±0.0221
MNIST-C	0.04±0.0015	0.08±0.0031	0.06±0.004	0.49±0.0016	0.09±0.0085	0.18±0.0171	0.12±0.011	0.54±0.0087
MVTec-AD	0.5±0	0.24±0.0011	0.32±0.0015	0.59±0.0021	0.97±0.0335	0.46±0.0161	0.62±0.0216	0.73±0.0102
SVHN	0.04±0.0021	0.08±0.0061	0.06±0.0041	0.49±0.0021	0.1±0.012	0.2±0.0239	0.12±0.0171	0.58±0.0473
Agnews	0.05±0.0036	0.09±0.0072	0.06±0.0064	0.5±0.0038	0.1±0.0122	0.21±0.024	0.14±0.0159	0.56±0.0127
Amazon	0.05±0.005	0.1±0.0122	0.07±0.0072	0.5±0.0053	0.06±0.0042	0.11±0.006	0.07±0.0044	0.51±0.0042
Imdb	0.05±0.0023	0.1±0.0046	0.07±0.0027	0.5±0.0024	0.05±0.01	0.09±0.02	0.06±0.0134	0.5±0.0106
Yelp	0.03±0.0046	0.07±0.0035	0.06±0.0273	0.48±0.0006	0.04±0.0016	0.08±0.0031	0.06±0.0021	0.49±0.0016
20newsgroups	0.05±0.0082	0.11±0.0201	0.09±0.042	0.51±0.0127	0.04±0.0035	0.08±0.0065	0.06±0.0043	0.49±0.0034
BATADAL04	0.09±0.0005	0.17±0.002	0.12±0.0004	0.54±0.0007	0.1±0.003	0.23±0.0253	0.14±0.005	0.55±0.0153
SWaT 1	0.13±0.0018	0.15±0.00	0.14±0.000	0.53±0.0014	0.09±0.0012	1±0	0.16±0	0.5±0

SWaT 2	0.1±0.0006	0.2±0.0016	0.13±0.0017	0.55±0.0023	0.05±0	1±0	0.04±0	0.5±0
SWaT 3	0.13±0.0021	0.38±0.0027	0.2±0.0017	0.64±0.0016	0.04±0	1±0	0.04±0	0.5±0
SWaT 4	0.08±0.0024	0.02±0.0015	0.03±0.0009	0.43±0.0018	0.44±0	1±0	0.44±0	0.5±0
SWaT 5	0.09±0.0005	0.36±0.0013	0.15±0.0027	0.63±0.0026	0.03±0	1±0	0.02±0	0.5±0
SWaT 6	0.37±0.002	0.63±0.0004	0.46±0.0021	0.78±0.001	0.06±0	1±0	0.06±0	0.5±0
ecoli	0.2±0.0183	0.78±0.0648	0.31±0.0282	0.83±0.0337	0±0	0±0	0±0	0.5±0.0011
cmc	0.03±0.0022	0.24±0.0312	0.06±0.0061	0.59±0.0162	0.05±0.0022	0.47±0.0003	0.1±0.0019	0.69±0.0017
lympho h	0.12±0.0029	0.33±0.0017	0.18±0.001	0.62±0.0015	0.05±0.0393	0.11±0.0972	0.07±0.0564	0.5±0.0491
wbc h	0.27±0.0406	0.48±0.0455	0.35±0.0517	0.71±0.0384	0.04±0.0399	0.08±0.0733	0.06±0.052	0.49±0.0387

Table 5.6: Comparison of mean and standard deviation on 3 runs on Autoencoders and GAN

5.2.3 HIGH ANOMALY PERCENTAGE IN MULTIVARIATE DATA

Traditional anomaly detection assumes a small proportion of anomalies, typically between 2% and 10% of the dataset. However, with datasets containing higher percentages of outliers, exceeding the 10% threshold, a shift towards classification may be warranted. Among the 67 multivariate datasets used, 17 have more than 10% anomalies, making classification more suitable. Training a Linear Support Vector Machine (SVM) on these datasets yielded promising results, outperforming other anomaly detection algorithms in 7 cases. This suggests that these datasets are better suited for classification. Our research investigates the performance of established anomaly detection methods, d-BTAI and MGBTAI, on datasets with a significantly higher anomaly prevalence, ranging from 10% to 40%.

Dataset	% Anomaly	Precision	Recall	F1 Score	AUC-ROC
breastw	34.99	0.95	0.96	0.96	0.97
campaign	11.27	0.65	0.31	0.42	0.65
Cardiotocography	22.04	0.82	0.77	0.8	0.86
fault	34.67	0.75	0.35	0.47	0.64
Hepatitis	16.25	0.91	0.77	0.83	0.88
InternetAds	18.72	0.98	0.91	0.94	0.95
Ionosphere	35.9	0.92	0.74	0.82	0.85
landsat	20.71	0	0	0	0.5
Pima	34.9	0.7	0.59	0.64	0.73
satellite	31.64	0.94	0.66	0.77	0.82
skin	20.75	0	0	0	0.5
SpamBase	39.91	0.92	0.89	0.91	0.92
vertebral	12.5	0.82	0.47	0.6	0.73
WPBC	23.74	0.78	0.15	0.25	0.57
yeast	34.16	0	0	0	0.5
MVTec-AD	21.5	0.98	0.89	0.93	0.94
SWaT4	43.51	0.99	0.97	0.98	0.98

Table 5.8: Evaluation Metrics for Linear SVM on datasets with more than 10% Anomalies

5.2.4 ANALYSING OCSVM

OCSVM is popular for anomaly detection due to its effective modeling of normal data and ability to identify deviations. However, a challenge arises when it exhibits high recall but low precision. High recall means it captures many actual anomalies, but low precision means many normal instances are incorrectly classified as anomalies. This imbalance suggests OCSVM is overly sensitive, marking many instances as anomalies, ensuring genuine anomalies aren't overlooked but compromising precision with false positives.

Dataset	Precision	Recall	F1 Score	AUC-ROC
ALOI	0.03	0.49	0.06	0.5
annthyroid	0.09	0.61	0.15	0.55
backdoor	0.04	0.92	0.08	0.71
breastw	0.55	1	0.71	0.78
campaign	0.16	0.73	0.26	0.62
cardio	0.16	1	0.28	0.73
Cardiotocography	0.34	0.91	0.49	0.7
celeba	0.03	0.76	0.06	0.63
cover	0.02	0.94	0.04	0.72
donors	NA	NA	NA	NA
fault	0.39	0.6	0.47	0.55
fraud	NA	NA	NA	NA
glass	0.05	0.56	0.09	0.55
Hepatitis	0.19	0.62	0.29	0.55
http	NA	NA	NA	NA
InternetAds	0.25	0.74	0.37	0.61
Ionosphere	0.52	0.98	0.68	0.74
landsat	0.2	0.45	0.28	0.49
letter	0.07	0.69	0.13	0.54
Lymphography	0.08	1	0.14	0.75
magic.gamma	0.46	0.8	0.59	0.65
mammography	0.05	0.94	0.1	0.77
mnist	0.16	0.96	0.28	0.73
musk	0.07	1	0.13	0.78
optdigits	0.05	0.83	0.09	0.67
PageBlocks	0.15	0.86	0.25	0.67
pendigits	0.04	1	0.69	0.75
Pima	0.45	0.76	0.57	0.63
satellite	0.39	0.7	0.51	0.6
satimage-2	0.02	1	0.05	0.75
shuttle	0.13	1	0.24	0.75
skin	0.34	1	0.51	0.75
smtp	0	0.7	0	0.6
SpamBase	0.44	0.59	0.5	0.54
speech	0.02	0.61	0.03	0.5
Stamps	0.17	1	0.3	0.76
thyroid	0.05	0.98	0.09	0.74
vertebral	0.13	0.57	0.22	0.52

vowels	0.05	0.94	0.1	0.68
Waveform	0.05	0.81	0.09	0.65
WBC	0.09	1	0.16	0.75
WDBC	0.05	1	0.09	0.73
Wilt	0.04	0.42	0.08	0.46
wine	0.14	1	0.25	0.74
WPBC	0.25	0.55	0.34	0.52
yeast	0.3	0.41	0.34	0.45
CIFAR10	0.08	0.79	0.14	0.64
FashionMNIST	0.35	0.98	0.51	0.74
MNIST-C	0.09	0.93	0.16	0.71
MVTec-AD	0.08	0.76	0.14	0.63
SVHN	0.07	0.73	0.13	0.62
Agnews	0.07	0.67	0.12	0.58
Amazon	0.05	0.52	0.09	0.51
Imdb	0.06	0.56	0.1	0.53
Yelp	0.05	0.46	0.08	0.48
20newsgroups	0.06	0.61	0.11	0.55
BATADAL 04	0.09	0.84	0.16	0.67
SWaT 1	0.13	0.74	0.22	0.63
SWaT 2	0.05	0.48	0.08	0.48
SWaT 3	0.05	0.78	0.1	0.64
SWaT 4	0.59	0.95	0.73	0.72
SWaT 5	0.04	0.72	0.07	0.61
SWaT 6	0.1	0.92	0.19	0.71
BATADAL 04	0.09	0.84	0.16	0.67
ecoli	0.05	0.89	0.09	0.69
cmc	0.01	0.47	0.02	0.49
lympho h	0.08	1	0.14	0.74
wbc h	0.1	1	0.19	0.75

Table 5.10: OCSVM Results on multivariate data

5.2.5 UNIVARIATE DATA RESULTS

MGBTAI stood out with perfect precision in 16 datasets, emerging as the top performer overall in 19 datasets. Following closely, d-BTAI achieved the highest precision in 18 datasets, with perfect precision in 11, highlighting its robust anomaly identification. Quantile-based algorithms (tanh, sigmoid, PEF) collectively excelled in 7 univariate datasets, showcasing their effectiveness. Notably, among quantile-based algorithms, sigmoid achieved the highest precision in 5 Univariate datasets. However, other algorithms showed low performance, with only Autoencoders achieving the highest precision in one dataset, and other deep learning algorithms failing to achieve the highest precision for even one dataset.

d-BTAI achieves perfect recall in 15 datasets, followed by MGBTAI with 12. Quantile-based algorithms collectively achieve perfect recall in 16 datasets, with PEF excelling in 20 univariate datasets. d-BTAI emerges as the top performer among 13 algorithms, achieving the highest F1-score overall and excelling in 19 univariate datasets, including 7 perfect scores. MGBTAI follows closely, leading in 9 datasets. Together, d-BTAI and MGBTAI jointly provide the highest F1-score across the entire univariate dataset collection. Conversely, other algorithms show lower performance, with only Autoencoders achieving the highest F1 score in one dataset. Quantile-based algorithms excel in 8 univariate datasets, with PEF leading in 5. For AUC-ROC, d-BTAI leads overall with perfect scores in 15 datasets, followed by MGBTAI with 12. Quantile algorithms collectively excel in 10 univariate datasets, emphasizing their effectiveness, while other algorithms show lower performance, collectively leading in 4 datasets.

DATASET	SIZE	ANOMALIES	%ANOMALIES	DOMAIN
yahoo1	1420	2	0.14	Industrial
yahoo2	1461	8	0.55	Industrial
yahoo3	1439	8	0.56	Industrial
yahoo5	1421	9	0.63	Industrial
yahoo6	1421	4	0.28	Industrial
yahoo7	1680	11	0.65	Industrial
yahoo8	1680	10	0.60	Industrial
yahoo9	1680	8	0.48	Industrial
Speed 6005	2500	1	0.04	Non-Industrial
Speed 7578	1127	4	0.35	Non-Industrial
Speed t4013	2495	2	0.08	Non-Industrial
TravelTime 387	2500	3	0.12	Non-Industrial
TravelTime 451	2162	1	0.05	Non-Industrial
Occupancy 6005	2380	1	0.04	Non-Industrial
Occupancy t4013	2500	2	0.08	Non-Industrial
yahoo syn1	1420	12	0.85	Industrial
yahoo syn2	1461	18	1.23	Industrial
yahoo syn3	1449	18	1.24	Industrial
yahoo syn5	1431	19	1.33	Industrial
yahoo syn6	1431	14	0.98	Industrial
yahoo syn7	1690	21	1.24	Industrial
yahoo syn8	1690	20	1.18	Industrial
yahoo syn9	1690	18	1.07	Industrial
aws1	1049	1	0.10	Industrial
aws2	2486	2	0.08	Industrial
aws3	1499	1	0.07	Industrial
aws syn1	1049	10	1.05	Industrial
aws syn2	2486	20	0.88	Industrial
aws syn3	1499	10	0.73	Industrial
Industrial 1	544	8	1.47	Industrial
Industrial 2	1609	3	0.19	Industrial

Table 5.12: Univariate Datasets Characterisation

Dataset	LOF	Iforest	Autoencoders	DAGMM	Envelope	DevNet	GAN	MGBTAI	d-BTAI	q-LSTM (tanh)	q-LSTM (sigmoid)	QReg	q-LSTM (PEF)
yahoo1	0.01	0.01	0.01	0.01	0.01	0.01	0.01	**1**	**1**	0.08	0.022	0	0.0465
yahoo2	0.06	0.04	0.05	0.05	0.05	0.06	0	**1**	0.89	0.015	0.22	0.1786	**1**
yahoo3	0.06	0.04	0.05	0.05	0.05	0.06	0	0.5	**0.88**	0.25	0.7778	0.1538	0.28
yahoo5	0.02	0.03	0.04	0.04	0.04	0	0	**1**	**1**	0.019	0.0092	0	0.022
yahoo6	0.03	0.02	0.03	0.03	0.03	0.03	0	**1**	**1**	0.027	0.0139	0.0028	0.0275
yahoo7	0.02	0.03	0	0.03	0.03	0.01	0.01	0.5	**0.57**	0.069	0.0732	0	0.066
yahoo8	0.01	0.01	0.01	0.01	0.01	0.01	0.01	**1**	**1**	0.029	0.0268	0	0.028
yahoo9	0.01	0.01	0.05	0.05	0.01	0.02	0	**1**	**1**	0.019	**1**	0.0049	0.0208
Speed 6005	0.01	0.004	0.004	0.004	0.004	NA	0.004	0.2	**0.5**	0.0138	0.0123	0	0.014
Speed 7578	0.03	0.03	0.03	0.04	0.03	0	0.04	0.09	0.25	**0.5**	**0.5**	**0.5**	0.086
Speed t4013	0.02	0.01	0.01	0	0.01	0	0.01	0.29	**0.67**	0.0078	0.0344	0.0392	0.053
TravelTime 387	0.01	0.01	0.01	0.01	0.01	0.01	0	0.05	**0.33**	0.0069	0.0041	0.0011	0.011
TravelTime 451	0.005	0.004	0.005	0.005	0.005	NA	0	0.04	**0.09**	0	0.007	0	0.006
Occupancy 6005	0.004	0.004	0.004	0.004	0.004	NA	0	0.06	**1**	0.0116	0.0109	0	0.03
Occupancy t4013	0.01	0.01	0.01	0	0.01	NA	0	0.33	**1**	0.0869	0.0076	0.0038	0.06
yahoo syn1	0.08	0.06	0.08	0.08	0.08	0.08	0	**1**	**1**	0.087	0.0816	0.0303	0.375
yahoo syn2	0.13	0.1	0.12	0.12	0.13	0.14	0	**1**	0.94	**1**	0.0243	0	**1**
yahoo syn3	0.1	0.1	0.11	0.11	0.11	0.14	0	0.81	0.89	0.061	**1**	0.0805	0.6
yahoo syn5	0.08	0.09	0.11	0.11	0.11	0	0.01	**1**	0.48	0.055	0.0394	0	0.0625
yahoo syn6	0.03	0.08	0.03	0.03	0.03	0.03	0.01	**1**	0.25	0.043	0.0606	0.0098	0.764
yahoo syn7	0.04	0.07	0.05	0.07	0.08	0.1	0.01	**0.56**	0.24	0.2	0.26	0.0092	0.411
yahoo syn8	0.03	0.02	0.02	0	0.02	0.02	0.01	**1**	0.1	0.07	0.0714	0.2	0.197
yahoo syn9	0.11	0.08	0.11	0.03	0.1	0.11	0	**1**	**1**	0.116	**1**	0.0102	**1**
aws1	0.01	0.01	0.01	0.01	0.01	NA	0	**1**	0.1	0.036	0.0278	0.0204	0.041
aws2	0.09	0.01	0	0	0.04	0.01	0	**1**	0.18	0.005	0.0147	0	0.0042

aws3	0.01	0.01	0.01	0.01	0.01	NA	0	**0.5**	0.07	0.006	0.0083	0.0116	0.0181
aws syn1	0.0952	0.0324	0	0.08	0.0599	0.0283	0	0.9	**0.91**	0.224	0.0843	0.0204	0.0843
aws syn2	0.0241	0.0694	0	0.08	0.0797	0.004	0.008	**0.67**	0.52	0.049	0.0424	0	0.0042
aws syn3	0.0667	0.0526	0.0133	0.07	0.0617	0.0213	0	0.9	0.9	**1**	0.0603	0.0116	0.0603
Industrial 1	0.1538	0.0167	0.014	0	0.0099	0.0203	0	**1**	**1**	0.019	0.028	0	0.357
Industrial 2	0.0341	0.0167	**1**	0.0148	0.0099	0.0203	0	**1**	**1**	**1**	**1**	0.0148	**1**

Table 5.13: Precision values of the 13 algorithms on the 31 univariate datasets. The highest value(s) is marked in bold. NA implies that DevNet cannot be run on those datasets since they have less than 2 anomalies.

Dataset	LOF	Iforest	Autoencoders	DAGMM	Envelope	DevNet	GAN	MGBTAI	d-BTAI	q-LSTM (tanh)	q-LSTM (sigmoid)	QReg	q-LSTM (PEF)
yahoo1	**1**	**1**	**1**	**1**	**1**	**1**	0.5	**1**	**1**	**1**	**1**	0	**1**
yahoo2	**1**	**1**	**1**	**1**	**1**	**1**	0	0.25	**1**	0.25	0.625	0.625	0.375
yahoo3	**1**	**1**	**1**	0.88	0.88	**1**	0	0.88	0.88	**1**	0.875	0.75	**1**
yahoo5	0.33	**0.67**	**0.67**	**0.67**	**0.67**	0	0	0.33	0.33	**0.67**	0.333	0	0.66
yahoo6	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
yahoo7	0.36	0.55	0	0.45	0.45	0.09	**1**	0.36	0.36	0.3636	0.545	0	0.54
yahoo8	0.2	0.2	0.1	0.2	0.2	0.2	**1**	0.01	0.1	0.3	0.3	0	0.3
yahoo9	0.2	0.2	**1**	**1**	0.2	0.38	0	0.62	**1**	0.625	0.75	0.875	0.75
Speed 6005	**1**	**1**	**1**	**1**	**1**	NA	**1**	**1**	**1**	**1**	**1**	0	**1**
Speed 7578	0.75	**1**	**1**	**1**	**1**	0	**1**	0.75	0.5	0.25	0.25	0.24	**1**
Speed t4013	**1**	**1**	**1**	**1**	**1**	0	**1**	**1**	**1**	**1**	**1**	**1**	**1**
TravelTime 387	**0.67**	**0.67**	**0.67**	**0.67**	**0.67**	**0.67**	0	**0.67**	0.33	0.33	0.33	0.33	**0.67**
TravelTime 451	**1**	**1**	**1**	**1**	**1**	NA	0	**1**	**1**	0	**1**	0	**1**
Occupancy 6005	**1**	**1**	**1**	**1**	**1**	**1**	0	**1**	**1**	**1**	**1**	0	**1**
Occupancy t4013	**1**	**1**	**1**	0	**1**	NA	0	**1**	**1**	**1**	**1**	**1**	**1**
yahoo syn1	**1**	**1**	**1**	**1**	**1**	**1**	0	0.17	**1**	**1**	**1**	0.0833	**1**
yahoo syn2	**1**	**1**	**1**	**1**	**1**	**1**	0	0.28	0.94	0.5	0.611	0	0.611
yahoo syn3	0.83	**1**	0.94	0.94	**1**	**1**	0	0.72	0.94	0.6111	0.444	0.3889	**1**
yahoo syn5	0.58	0.84	0.84	0.84	0.84	0	**1**	0.42	0.53	0.7368	0.737	0	0.578
yahoo syn6	0.29	**1**	0.29	0.29	0.29	0.29	**1**	0.29	0.29	0.8571	0.857	**1**	0.928
yahoo syn7	0.33	0.71	0.43	0.52	0.67	0.71	**1**	0.24	0.24	0.619	0.619	0.1905	0.66
yahoo syn8	0.25	0.2	0.15	0	0.15	0.2	**1**	0.05	0.1	0.4	0.4	**1**	0.7
yahoo syn9	**1**	**1**	**1**	0.25	**1**	**1**	0	0.06	**1**	0.2778	0.722	0.8889	0.94
aws1	**1**	**1**	**1**	**1**	**1**	NA	0	**1**	**1**	**1**	**1**	**1**	**1**
aws2	**1**	**1**	**1**	**1**	**1**	**1**	0	0.5	**1**	**1**	**1**	0	**1**
aws3	**1**	**1**	**1**	**1**	**1**	NA	0	**1**	**1**	**1**	**1**	**1**	**1**
aws syn1	0.045	**1**	0	0.82	**1**	0.3	0	0.9	**1**	**1**	0.636	**1**	**1**
aws	0.02	**1**	0	**1**	**1**	0.05	**1**	**1**	0.55	**1**	0.86	0	**1**

syn2	41										4		
aws syn3	0.06 7	**1**	0.2	**1**	**1**	0.3	0	0.9	0.9	**1**	0.63 6	**1**	**1**
Industri al 1	0.15 38	**1**	**1**	0	**1**	**1**	0	**1**	0.23	0.6 6	0.66	0	**1**
Industri al 2	0.03 41	**1**	**1**	**1**	**1**	**1**	0	**1**	0.88	**1**	**1**	**1**	**1**

Table 5.14: Recall values of the 13 algorithms on the 31 univariate datasets. The highest value(s) is marked in bold.

Dataset	LOF	Iforest	Autoencoders	DAGMM	Envelope	DevNet	GAN	MGBTAI	d-BTAI	q-LSTM (tanh)	q-LSTM (sigmoid)	QReg	q-LSTM (PEF)
yahoo1	0.03	0.02	0.01	0.03	0.03	0.03	0.01	**1**	**1**	0.1481	0.043	0	0.0889
yahoo2	0.11	0.08	0.1	0.1	0.1	0.12	0	0.4	**0.94**	0.0282	0.325	0.2778	0.5455
yahoo3	0.11	0.09	0.1	0.09	0.09	0.11	0	0.64	**0.88**	0.4000	0.8235	0.2553	0.4375
yahoo5	0.04	0.06	0.08	0.08	0.08	0	0	**0.5**	**0.5**	0.0374	0.0179	0	0.0426
yahoo6	0.05	0.04	0.05	0.05	0.06	0.05	0.01	**1**	**1**	0.0526	0.0275	0.0056	0.0535
yahoo7	0.04	0.05	0	0.06	0.05	0.01	0.01	0.42	**0.44**	0.1159	0.129	0	0.1176
yahoo8	0.02	0.02	0.01	0.02	0.02	0.02	0.01	0.01	**0.18**	0.0526	0.0492	0	0.0512
yahoo9	0.02	0.02	0.09	0.09	0.02	0.03	0	0.77	**1**	0.0362	0.8571	0.0098	0.0405
Speed 6005	0.03	0.01	0.01	0.01	0.01	0	0.01	0.33	**0.67**	0.0273	0.0243	0	0.0276
Speed 7578	0.06	0.06	0.06	0.07	0.06	0	0.07	0.16	**0.33**	**0.33**	**0.33**	0.32	0.1584
Speed t4013	0.04	0.01	0.01	0.01	0.02	0	0.01	0.44	**0.8**	0.0155	0.0666	0.0755	0.1007
TravelTime 387	0.02	0.01	0.02	0.02	0.02	0.02	0	0.09	**0.33**	0.0135	0.0089	0.0021	0.0216
TravelTime 451	0.01	0.01	0.01	0.01	0.01	0	0	0.08	**0.17**	0	0.0139	0	0.0119
Occupancy 6005	0.01	0.01	0.01	0.01	0.01	0.01	0	0.12	**1**	0.0229	0.0217	0	0.0583
Occupancy t4013	0.02	0.01	0.02	0	0.02	0.02	0	0.5	**1**	0.16	0.0152	0.0076	0.1132
yahoo syn1	0.16	0.12	0.16	0.16	0.14	0.16	0	0.29	**1**	0.1600	0.1509	0.0444	0.5455
yahoo syn2	0.23	0.18	0.21	0.22	0.23	0.24	0	0.43	**0.94**	0.6667	0.0467	0	0.7585
yahoo syn3	0.18	0.18	0.2	0.2	0.2	0.24	0	0.76	**0.92**	0.1111	0.6154	0.1333	0.75
yahoo syn5	0.14	0.17	0.2	0.2	0.2	0	0.03	**0.59**	0.5	0.1022	0.0749	0	0.1128
yahoo syn6	0.05	0.15	0.05	0.05	0.05	0.05	0.02	0.44	0.27	0.0825	0.1132	0.0194	**0.8381**
yahoo syn7	0.07	0.13	0.09	0.012	0.15	0.17	0.02	0.33	0.24	0.3023	0.3662	0.0176	**0.5066**
yahoo syn8	0.05	0.04	0.03	0	0.03	0.04	0.02	0.1	0.1	0.1194	0.1212	**0.34**	0.3075
yahoo syn9	0.19	0.15	0.19	0.05	0.18	0.19	0	0.11	**1**	0.1639	0.8387	0.0202	0.9691
aws1	0.02	0.02	0.02	0.02	0.02	0.02	0	**1**	0.18	0.0690	0.0541	0.04	0.0788
aws2	0.17	0.02	0	0.01	0.08	0.02	0	**0.67**	0.31	0.0092	0.029	0	0.0084

aws3	0.01	0.01	0.01	0.01	0.01	0.01	0	**0.67**	0.13	0.0123	0.0164	0.023	0.0356
aws syn1	0.1739	0.0627	0	0.14	0.113	0.0517	0	0.9	0.95	0.3667	0.1489	0.04	**0.9888**
aws syn2	0.0496	0.1299	0	0.15	0.1476	0.0074	0.0159	0.8	0.54	0.0934	0.0809	0	**0.9045**
aws syn3	0.125	0.1	0.025	0.12	0.1163	0.0397	0	0.9	0.9	**1**	0.1102	0.023	0.9818
Industrial 1	0.2667	0.0328	0.0276	0	0.0195	0.0397	0	**1**	0.375	0.038	0.054	0	0.0689
Industrial 2	0.0659	0.0328	**1**	0.0291	0.0195	0.0397	0	**1**	0.94	**1**	**1**	0.029	**1**

Table 5.15: F1 Score values of the 13 algorithms on the 31 univariate datasets. The highest value(s) is marked in bold.

Dataset	LOF	Iforest	Autoencoders	DAGMM	Envelope	DevNet	GAN	MGBTAI	d-BTAI	q-LSTM (tanh)	q-LSTM (sigmoid)	QReg	q-LSTM (PEF)
yahoo1	0.95	0.94	0.9	0.95	0.95	0.95	0.7	**1**	**1**	0.992	0.9686	0.4908	0.9855
yahoo2	0.95	0.94	0.95	0.95	0.95	0.96	0.45	0.62	**1**	0.58	0.84	0.8046	0.6875
yahoo3	0.95	0.94	0.95	0.89	0.89	0.95	0.45	0.94	0.94	0.992	0.9367	0.8634	**0.994**
yahoo5	0.62	0.77	**0.78**	**0.78**	**0.78**	0.45	0.45	0.67	0.67	0.725	0.5496	0.4865	0.7364
yahoo6	0.95	0.94	0.95	0.95	0.95	0.95	0.5	**1**	**1**	0.949	0.8998	0.5	0.95
yahoo7	0.63	0.71	0.45	0.68	0.68	0.5	0.5	0.68	0.68	0.666	**0.7499**	0.4889	0.7448
yahoo8	0.55	0.54	0.5	0.55	0.55	0.55	0.5	0.5	0.55	0.62	0.6172	0.4892	**0.6188**
yahoo9	0.55	0.54	0.95	0.95	0.55	0.63	0.45	0.81	**1**	0.734	0.875	0.5139	0.7905
Speed 6005	0.99	0.95	0.95	0.93	0.95	NA	0.94	**1**	**1**	0.9857	0.9839	0.4577	0.9718
Speed 7578	0.83	0.94	0.95	0.95	0.95	0.45	0.95	0.86	0.75	0.6240	0.62400	0.6121	**0.981**
Speed t4013	0.98	0.94	0.93	0.91	0.95	0.46	0.94	**1**	**1**	0.9492	0.989	0.9902	0.9928
TravelTime 387	0.78	0.77	0.78	0.78	0.79	0.78	0.45	**0.83**	0.67	0.638	0.618	0.4782	0.7988
TravelTime 451	0.95	0.94	0.95	0.95	0.95	NA	0.45	0.99	**1**	0.496	0.967	0.4903	0.9616
Occupancy 6005	0.95	0.94	0.95	0.95	0.95	0.95	0.45	**1**	**1**	0.9821	0.9810	0.4891	0.9932
Occupancy t4013	0.95	0.94	0.95	0.5	0.95	NA	0.45	**1**	**1**	0.9957	0.9480	0.895	0.9937
yahoo syn1	0.95	0.94	0.95	0.95	0.95	0.95	0.45	0.58	**1**	0.955	0.952	0.5303	0.9928
yahoo syn2	0.96	0.94	0.95	0.95	0.96	0.96	0.45	0.64	**0.97**	0.75	0.652	0.4903	0.8055
yahoo syn3	0.87	0.94	0.93	0.93	0.95	0.96	0.45	0.86	0.97	0.747	0.722	0.6664	**0.9958**
yahoo syn5	0.74	0.87	**0.88**	**0.88**	**0.88**	0.45	0.5	0.71	0.76	0.783	0.748	0.4908	0.7306
yahoo syn6	0.59	0.94	0.59	0.59	0.6	0.59	0.5	0.64	0.64	0.835	0.863	0.5	**0.9625**
yahoo syn7	0.62	0.8	0.67	0.71	0.79	0.82	0.5	0.62	0.61	0.794	0.798	0.4662	**0.824**
yahoo syn8	0.58	0.54	0.52	0.5	0.52	0.55	0.5	0.53	0.54	0.668	0.669	0.65	**0.8329**
yahoo syn9	0.95	0.94	0.95	0.58	0.95	0.95	0.45	0.53	**1**	0.628	0.861	0.4789	0.97
aws1	0.95	0.94	0.95	0.95	0.95	NA	0.45	**1**	**1**	0.987	0.9832	0.977	0.9888
aws2	**1**	0.96	0.75	0.86	0.99	0.96	0.41	0.75	**1**	0.91	0.97	0.48	0.90

										3	3	95	45
aws3	0.95	0.94	0.95	0.95	0.95	NA	0.45	**1**	**1**	0.946	0.9596	0.9716	0.9818
aws syn1	0.9543	0.8788	0.449	0.85	0.9363	0.85	0.4494	0.95	**1**	0.983	0.785	0.977	0.9833
aws syn2	0.6007	0.9457	0.449	0.95	0.9532	0.95	0.5	**1**	0.77	0.921	0.853	0.489	0.9211
aws syn3	0.953	0.9396	0.55	0.95	0.949	0.95	0.4492	0.95	0.95	**1**	0.785	0.9716	**1**
Industrial 1	0.9589	0.5605	0.93	0.45	0.553	0.45	0.41	**1**	0.975	0.5803	0.6604	0.48	0.9865
Industrial 2	0.995	0.945	**1**	0.0148	0.9065	0.9378	0.41	**1**	0.9998	**1**	**1**	0.9378	**1**

Table 5.16: AUC-ROC values of the 13 algorithms on the 31 univariate datasets. The highest value(s) is marked in bold.

5.2.6 COMPARISON WITHIN QUANTILE-BASED ALGORITHMS

In this section we assessed the performance of q-LSTM with tanh, sigmoid and PEF activation functions, alongside deep quantile regression, across 31 univariate datasets. As seen in table 17 Quantile LSTM(PEF) emerged as the top performer for 16 datasets. Quantile LSTM with tanh and sigmoid activation excelled in 5 datasets and the traditional Deep Quantile Regression on only 3 datasets.

Dataset	q-LSTM(tanh)				q-LSTM(sigmoid)				Deep Quantile Regression				Quantile LSTM(PEF)			
	Precision	Recall	F1 Score	AUC-ROC	Precision	Recall	F1 Score	AUC-ROC	Precision	Recall	F1 Score	AUC-ROC	Precision	Recall	F1 Score	AUC-ROC
yahoo1	**0.08**	1	0.1481	0.992	0.022	1	0.043	0.9686	0	0	0	0.4908	0.0465	1	0.0889	0.9855
yahoo2	0.015	0.25	0.0282	0.58	**0.22**	0.625	0.325	0.84	0.1786	0.625	0.2778	0.8046	1	0.375	0.5455	0.6875
yahoo3	0.25	1	0.4	0.992	0.7778	0.875	0.8235	0.9367	0.1538	0.75	0.2553	0.8634	**0.28**	1	0.4375	0.994
yahoo5	0.019	**0.67**	0.0374	0.725	0.0092	0.333	0.0179	0.5496	0	0	0	0.4865	0.022	0.66	0.0426	0.7364
yahoo6	0.027	1	0.0526	0.949	0.0139	1	0.0275	0.8998	0.0028	1	0.0056	0.5	**0.0275**	1	0.0535	0.95
yahoo7	0.069	0.3636	0.1159	0.666	0.0732	**0.545**	0.129	0.7499	0	0	0	0.4889	0.066	0.54	0.1176	0.7448
yahoo8	**0.029**	0.3	0.0526	0.62	0.0268	0.3	0.0492	0.6172	0	0	0	0.4892	0.028	0.3	0.0512	0.6188
yahoo9	0.019	0.625	0.0362	0.734	1	0.75	0.8571	0.875	0.0049	**0.875**	0.0098	0.5139	0.0208	0.75	0.0405	0.7905
Speed 6005	0.0138	1	0.0273	0.9857	0.0123	1	0.0243	0.9839	0	0	0	0.4577	**0.014**	1	0.0276	0.9718
Speed 7578	0.5	0.25	0.33	0.624	0.5	0.25	0.33	0.624	0.5	0.24	0.32	0.6121	0.086	**1**	0.1584	0.981
Speed t4013	0.0078	1	0.0155	0.9492	0.0344	1	0.0666	0.989	0.0392	1	0.0755	0.9902	**0.053**	1	0.1007	0.9928
TravelTime 387	0.0069	0.33	0.0135	0.638	0.0041	0.33	0.0089	0.618	0.0011	0.3333	0.0021	0.4782	0.011	**0.67**	0.0216	0.7988
TravelTime 451	0	0	0	0.496	**0.007**	1	0.0139	0.967	0	0	0	0.4903	0.006	1	0.0119	0.9616
Occupancy 6005	0.0116	1	0.0229	0.9821	0.0109	1	0.0217	0.981	0	0	0	0.4891	**0.03**	1	0.0583	0.9932
Occupancy t4013	**0.0869**	1	0.16	0.9957	0.0076	1	0.0152	0.948	0.0038	1	0.0076	0.895	0.06	1	0.1132	0.9937
yahoo syn1	0.087	1	0.16	0.955	0.0816	1	0.1509	0.952	0.0303	0.0833	0.0444	0.5303	**0.375**	1	0.5455	0.9928
yahoo syn2	1	0.5	0.6667	0.75	0.0243	0.611	0.0467	0.652	0	0	0	0.4903	**1**	0.611	0.7585	0.8055
yahoo syn3	0.061	0.6111	0.1111	0.747	1	0.444	0.6154	0.722	0.0805	0.3889	0.1333	0.6664	0.6	**1**	0.75	0.9958
yahoo syn5	0.055	0.7368	0.1022	0.783	0.0394	**0.737**	0.0749	0.748	0	0	0	0.4908	0.0625	0.578	0.1128	0.7306
yahoo syn6	0.043	0.8571	0.0825	0.835	0.0606	0.857	0.1132	0.863	0.0098	**1**	0.0194	0.5	0.764	0.928	0.8381	0.9625
yahoo syn7	0.2	0.619	0.3023	0.794	0.26	0.619	0.3662	0.798	0.0092	0.1905	0.0176	0.4662	0.411	**0.66**	0.5066	0.824
yahoo syn8	0.07	0.4	0.1194	0.668	0.0714	0.4	0.1212	0.669	0.2	**1**	0.34	0.65	0.197	0.7	0.3075	0.8329
yahoo syn9	0.116	0.2778	0.1639	0.628	1	0.722	0.8387	0.861	0.0102	0.8889	0.0202	0.4789	1	**0.94**	0.9691	0.97
aws1	0.036	1	0.069	0.987	0.0278	1	0.0541	0.9832	0.0204	1	0.04	0.977	**0.041**	1	0.0788	0.9888
aws2	0.005	1	0.0092	0.913	**0.0147**	1	0.029	0.973	0	0	0	0.4895	0.0042	1	0.0084	0.9045
aws3	0.006	1	0.0123	0.946	0.0083	1	0.0164	0.9596	0.0116	1	0.023	0.9716	**0.0181**	1	0.0356	0.9818

aws syn1	0.224	1	0.3667	0.983	0.0843	0.636	0.1489	0.785	0.0204	1	0.04	0.977	0.224	1	0.366	0.9833
aws syn2	**0.049**	1	0.0934	0.921	0.0424	0.864	0.0809	0.853	0	0	0	0.4895	0.0489	1	0.0932	0.9211
aws syn3	1	**1**	1	1	0.0603	0.636	0.1102	0.785	0.0116	1	0.023	0.9716	1	**1**	1	1
Industrial 1	0.019	0.66	0.038	0.5803	0.028	0.66	0.054	0.6604	0	0	0	0.48	0.357	**1**	0.0689	0.9865
Industrial 2	1	**1**	1	1	1	**1**	1	1	0.0148	1	0.029	0.9378	1	**1**	1	1

Table 5.17: performance of quantile LSTM with activation functions tanh, sigmoid and PEF activation function along with Deep Quantile Regression on 31 univariate datasets.

5.2.7 EXPERIMENTING WITH PARAMETERISED ELIOT FUNCTION

LSTM with standard activation functions tanh and sigmoid achieved excelled for 11 datasets whereas LSTM with PEF activation function achieved the highest recall for 10 datasets. Identical results observed for 10 datasets as displayed in 18.

Dataset	LSTM				LSTM(PEF)			
	Precision	Recall	F1 Score	AUC-ROC	Precision	Recall	F1 Score	AUC-ROC
yahoo1	0.007	0.5	0.0139	0.7002	0.007	0.5	0.0139	0.7002
yahoo2	0.0411	0.75	0.0779	0.8267	0.0411	0.75	0.0779	0.8267
yahoo3	0.0417	0.75	0.0789	0.8267	0.0486	**0.875**	0.0921	0.8895
yahoo5	0.0141	0.2222	0.0265	0.5614	0.0352	**0.5556**	0.0662	0.7292
yahoo6	0.0141	0.5	0.0274	0.7005	0.0211	**0.75**	0.0411	0.8258
yahoo7	0.0119	**0.1818**	0.0223	0.5411	0.006	0.0909	0.0112	0.4953
yahoo8	0.0119	**0.2**	0.0225	0.5502	0.006	0.1	0.0112	0.4999
yahoo9	0.0119	**0.25**	0.0227	0.5753	0	0	0	0.4497
Speed 6005	0.004	**1**	0.0079	0.9497	0	0	0	0.4499
Speed 7578	0.0254	0.75	0.0492	0.8237	**0.0263**	0.75	0.0508	0.8254
Speed t4013	**0.0079**	1	0.0156	0.9494	0.0078	1	0.0156	0.9492
TravelTime 387	0	0	0	0.4499	0.004	**0.3333**	0.0079	0.6167
TravelTime 451	0	0	0	0.45	0	0	0	0.45
Occupancy 6005	0.0042	1	0.0084	0.9501	0.0042	1	0.0084	0.9501
Occupancy t4013	0.008	1	0.0159	0.9503	0.008	1	0.0159	0.9503
yahoo syn1	0.0211	0.25	0.039	0.5755	0.0282	**0.3333**	0.0519	0.6176
yahoo syn2	0.0411	0.3333	0.0732	0.6181	0.0479	**0.3889**	0.0854	0.6462
yahoo syn3	0.0479	0.3889	0.0854	0.6458	0.0548	**0.4444**	0.0976	0.6739
yahoo syn5	0.0208	0.1579	0.0368	0.5289	0.0278	**0.2105**	0.0491	0.5556
yahoo syn6	0.0278	0.2857	0.0506	0.5934	0.0278	0.2857	0.0506	0.5934
yahoo syn7	0.0118	0.0118	0.0209	0.4972	0.0059	**0.0476**	0.0105	0.4731
yahoo syn8	0.0118	**0.1**	0.0211	0.4996	0.0059	0.05	0.0105	0.4743
yahoo syn9	0.0176	**0.1667**	0.0319	0.5333	0.0059	0.0556	0.0106	0.4771
aws1	0.0094	1	0.0187	0.9498	0.0094	1	0.0187	0.9498
aws2	0.0032	0.5	0.0063	0.6865	0.0032	0.5	0.0076	0.6978
aws3	0.0067	**1**	0.0132	0.9502	0	0	0	0.4498
aws syn1	0.0935	1	0.1709	0.9533	0.0935	1	0.1709	0.9533
aws syn2	**0.0249**	1	0.0486	0.8412	0.0176	1	0.0345	0.7733
aws syn3	0.0667	1	0.125	0.953	0.0667	1	0.125	0.953
Industrial 1	0.014	**1**	0.0276	0.9343	0	0	0	0.42
Industrial 2	0.0976	**1**	0.1778	0.931	0.11	0.75	0.19	0.83

Table 5.18: A comparative study of LSTM vs LSTM using PEF activation function on 31 univariate datasets

Dataset	Deep Quantile Regression				Deep Quantile Regression(PEF)			
	Precision	Recall	F1 Score	AUC-ROC	Precision	Recall	F1 Score	AUC-ROC
yahoo1	0	0	0	0.4908	0.0014	**1**	0.0028	0.5
yahoo2	0.1786	0.625	0.2778	0.8046	0.0055	**1**	0.0109	0.5
yahoo3	0.1538	**0.75**	0.2553	0.8634	0.0169	0.125	0.0299	0.5422
yahoo5	0	0	0	0.4865	0.0143	**0.444**	0.0278	0.6246
yahoo6	0.0028	**1**	0.0056	0.5	0.0032	0.75	0.0063	0.5423
yahoo7	0	0	0	0.4889	0.0104	**0.1818**	0.0196	0.5336
yahoo8	0	0	0	0.4892	0.008	**0.8**	0.0158	0.6022
yahoo9	0.0049	**0.875**	0.0098	0.5139	0	0	0	0.4892
Speed 6005	0	0	0	**0.4577**	0	0	0	0.3684
Speed 7578	**0.5**	0.25	0.32	0.6121	0.0022	0.25	0.0044	0.4241
Speed t4013	0.0392	**1**	0.0755	0.9902	0.0009	0.5	0.0018	0.5275
TravelTime 387	0.0011	0.3333	0.0021	0.4782	**0.0037**	0.3333	0.0073	0.6123
TravelTime 451	0	0	0	**0.4903**	0	0	0	0.4541
Occupancy 6005	0	0	0	0.4891	0	0	0	**0.4901**
Occupancy t4013	0.0038	**1**	0.0076	0.895	0.0208	0.5	0.04	0.7406
yahoo syn1	0.0303	0.0833	0.0444	0.5303	0.0085	**1**	0.0168	0.5
yahoo syn2	0	0	0	0.4903	0.0123	**1**	0.0244	0.5
yahoo syn3	0.0805	**0.3889**	0.1333	0.664	0.0521	0.2778	0.0877	0.607
yahoo syn5	0	0	0	0.4908	0.0269	**0.2632**	0.0488	0.5673
yahoo syn6	0.0098	**1**	0.0194	0.5	0.0117	0.2143	0.0222	0.5177
yahoo syn7	0.0092	**0.1905**	0.0176	0.4662	0.023	0.0952	0.037	0.5221
yahoo syn8	0.2	**1**	0.34	0.65	0.0147	0.05	0.0227	0.5049
yahoo syn9	0.0102	**0.8889**	0.0202	0.4789	0	0	0	0.4901
aws1	0.0204	**1**	0.04	0.977	0	0	0	0.4167
aws2	0	0	0	0.4895	0.0008	**1**	0.0016	0.5
aws3	**0.0116**	1	0.023	0.9716	0.0027	1	0.0054	0.8776
aws syn1	0.0204	0.1	0.0339	0.5268	**0.0238**	0.1	0.0385	0.5302
aws syn2	0.0217	0.05	0.0303	0.5159	0.0081	**1**	0.016	0.5
aws syn3	0	0	0	0.4872	0.0116	**0.1**	0.0208	0.5214
Industrial 1	0	0	0	**0.4832**	0	0	0	0.4454
Industrial 2	0.0148	1	0.029	**0.9378**	0.0148	1	0.0291	0.5

Table 5.19: A comparative study of quantile regression using standard activation functions vs PEF activation function on 31 univariate datasets.

Deep Quantile Regression employing the PEF activation function achieved the highest recall for 14. Quantile Regression with tanh and sigmoid activations also emerged as a top-performing model achieving superior performance for 17 datasets as observed in Table 19.

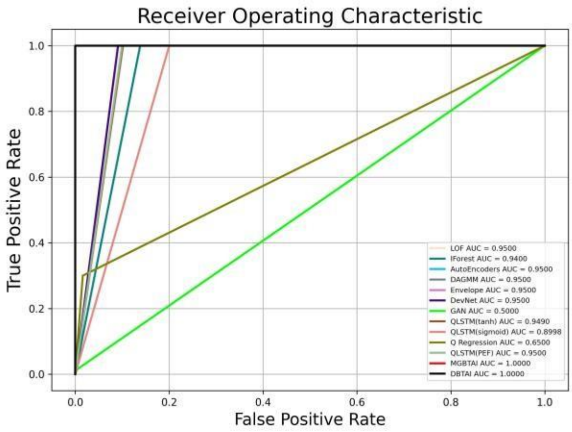
Dataset	GAN				GAN(PEF)			
	Precision	Recall	F1 Score	AUC-ROC	Precision	Recall	F1 Score	AUC-ROC
yahoo1	0.01	**0.5**	0.01	0.7	0	0	0	0.45
yahoo2	0	0	0	0.45	0	0	0	0.45
yahoo3	0	0	0	0.45	0	0	0	0.45
yahoo5	0	0	0	0.45	0	0	0	0.45
yahoo6	0	**1**	0.01	0.5	0	0	0	0.45
yahoo7	0.01	**1**	0.01	0.5	0.04	0.64	0.08	0.77
yahoo8	0.01	**1**	0.01	0.5	0	0	0	0.45
yahoo9	0	0	0	0.45	0.03	**0.63**	0.06	0.76
Speed 6005	0	1	0.01	0.94	0.00	1	0.01	0.94
Speed 7578	0.04	1	0.07	0.95	0.04	1	0.07	0.95
Speed t4013	0.01	**1**	0.01	0.94	0	0	0	0.45
TravelTime 387	0	0	0	0.45	0	0	0	0.45
TravelTime 451	0	0	0	0.45	0	0	0	0.45
Occupancy 6005	0	0	0	0.45	0	0	0	0.45
Occupancy t4013	0	0	0	0.45	0	0	0	0.45
yahoo syn1	0	0	0	0.45	0	0	0	0.45
yahoo syn2	0	0	0	0.45	0	0	0	0.45
yahoo syn3	0	0	0	0.45	0	0	0	0.45
yahoo syn5	0.01	**1**	0.03	0.5	0	0	0	0.45
yahoo syn6	0.01	**1**	0.02	0.5	0	0	0	0.45
yahoo syn7	0.01	**1**	0.02	0.5	0.04	0.33	0.07	0.62
yahoo syn8	0.01	**1**	0.02	0.5	0	0	0	0.45
yahoo syn9	0	0	0	0.45	0.02	**0.17**	0.03	0.53
aws1	0	0	0	0.45	0	0	0	0.45
aws2	0	0	0	0.41	0	0	0	0.41
aws3	0	0	0	0.45	0	0	0	0.45
aws syn1	0	0	0	0.45	0	0	0	0.45
aws syn2	0	0	0	0.41	0	0	0	0.41
aws syn3	0	0	0	0.45	0	0	0	0.45
Industrial 1	0	0	0	0.41	0	0	0	0.41
Industrial 2	0	0	0	0.41	0.13	**1**	0.23	0.95

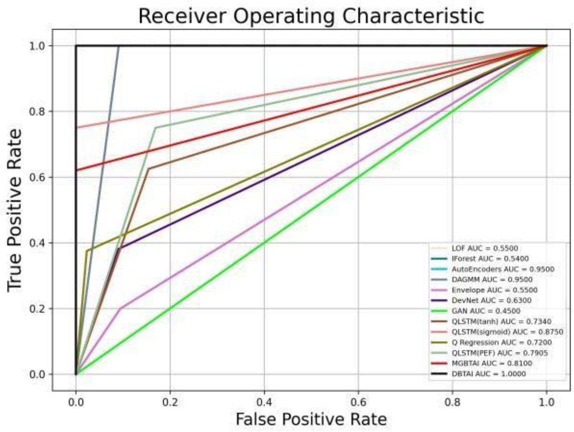
Table 5.20: A comparative study of GAN using standard activation functions vs PEF activation function on 31 univariate datasets.

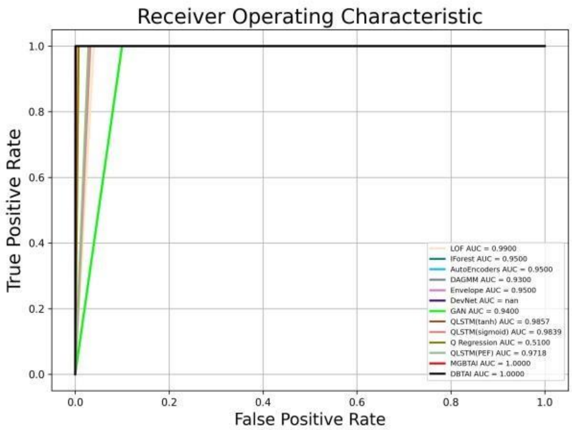
GAN with standard activation functions like tanh and sigmoid achieved outperformed in 9 datasets whereas GAN with PEF activation function demonstrated superiority in only 3 datasets. GAN with PEF and GAN with standard activation functions generated identical results for 19 datasets as displayed in Table 20.

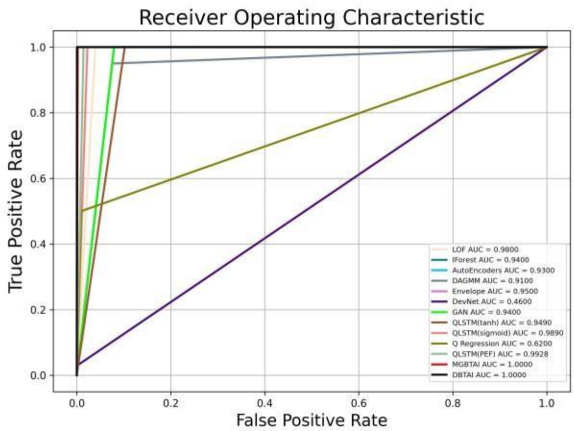
Evaluation of Autoencoders using standard activation functions versus PEF activation function produced same results.

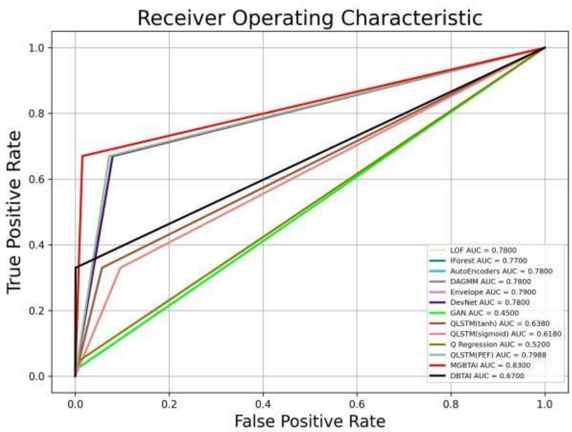
5.2.8 AUC-ROC DIAGRAMS

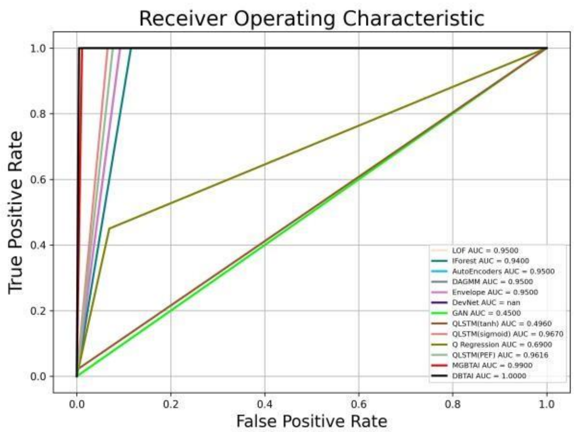


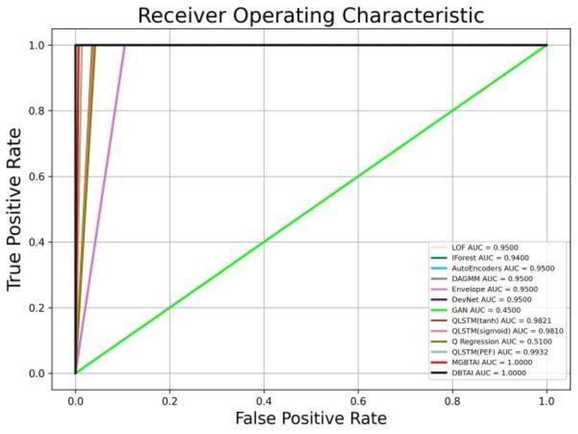


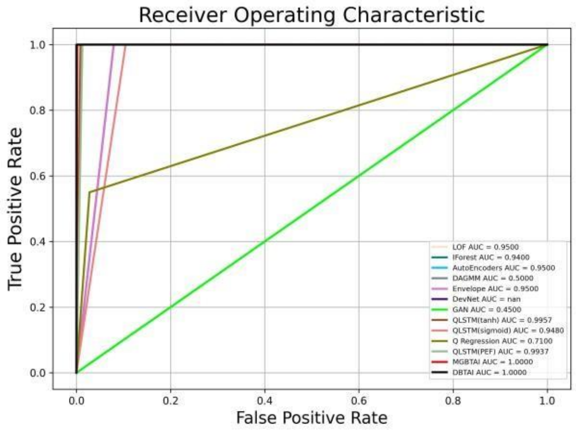


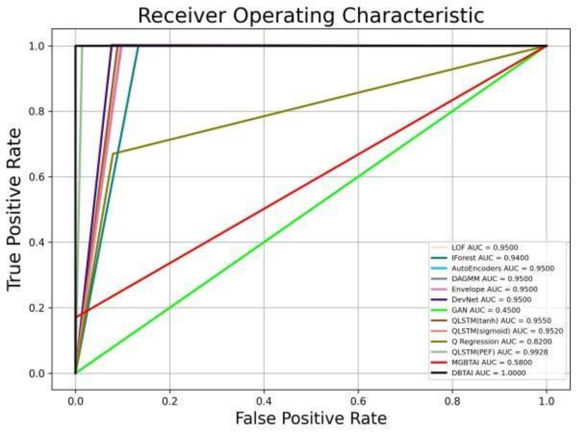


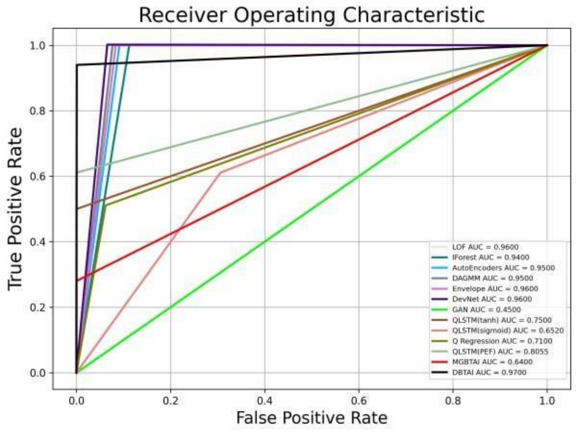


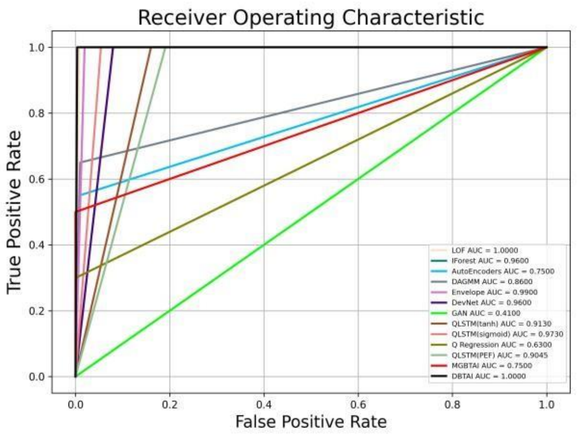


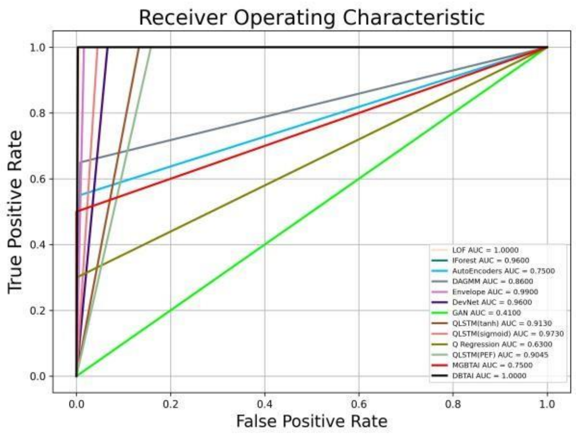

Receiver Operating Characteristic
True Positive Rate
False Positive Rate
LOF AUC = 0.9500
IForest AUC = 0.9400
AutoEncoders AUC = 0.9500
DAGMM AUC = 0.9500
Envelope AUC = 0.9500
DevNet AUC = 0.9500
GAN AUC = 0.4500
QLSTM(tanh) AUC = 0.9821
QLSTM(sigmoid) AUC = 0.9810
Q Regression AUC = 0.5100
QLSTM(PEF) AUC = 0.9932
MGBTAI AUC = 1.0000
DBTAI AUC = 1.0000

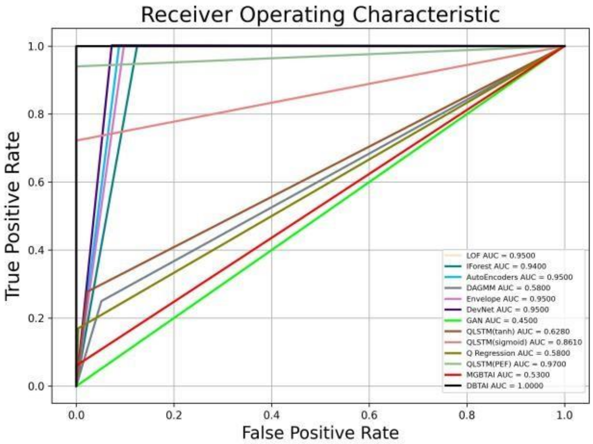

Receiver Operating Characteristic
True Positive Rate
False Positive Rate
LOF AUC = 0.9500
IForest AUC = 0.9400
AutoEncoders AUC = 0.9500
DAGMM AUC = 0.5000
Envelope AUC = 0.9500
DevNet AUC = nan
GAN AUC = 0.4500
QLSTM(tanh) AUC = 0.9957
QLSTM(sigmoid) AUC = 0.9480
Q Regression AUC = 0.7100
QLSTM(PEF) AUC = 0.9937
MGBTAI AUC = 1.0000
DBTAI AUC = 1.0000

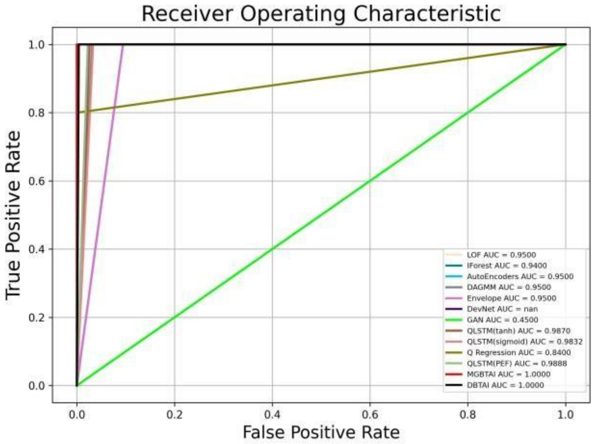

Receiver Operating Characteristic
True Positive Rate
False Positive Rate
LOF AUC = 0.9500
IForest AUC = 0.9400
AutoEncoders AUC = 0.9500
DAGMM AUC = 0.9500
Envelope AUC = 0.9500
DevNet AUC = 0.9500
GAN AUC = 0.4500
QLSTM(tanh) AUC = 0.9550
QLSTM(sigmoid) AUC = 0.9520
Q Regression AUC = 0.8200
QLSTM(PEF) AUC = 0.9928
MGBTAI AUC = 0.5800
DBTAI AUC = 1.0000

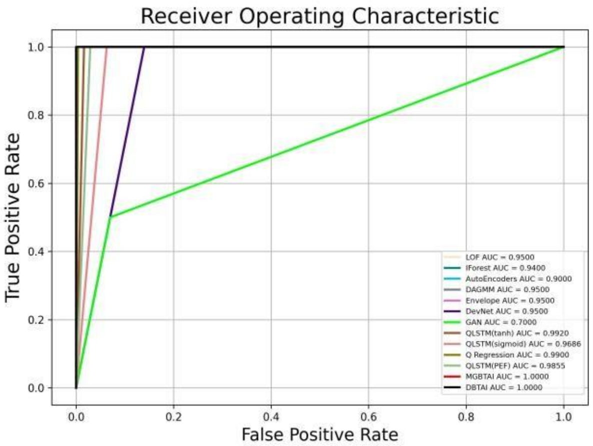

Receiver Operating Characteristic
True Positive Rate
False Positive Rate
LOF AUC = 0.9600
IForest AUC = 0.9400
AutoEncoders AUC = 0.9500
DAGMM AUC = 0.9500
Envelope AUC = 0.9600
DevNet AUC = 0.9600
GAN AUC = 0.4500
QLSTM(tanh) AUC = 0.7500
QLSTM(sigmoid) AUC = 0.6520
Q Regression AUC = 0.7100
QLSTM(PEF) AUC = 0.8055
MGBTAI AUC = 0.6400
DBTAI AUC = 0.9700

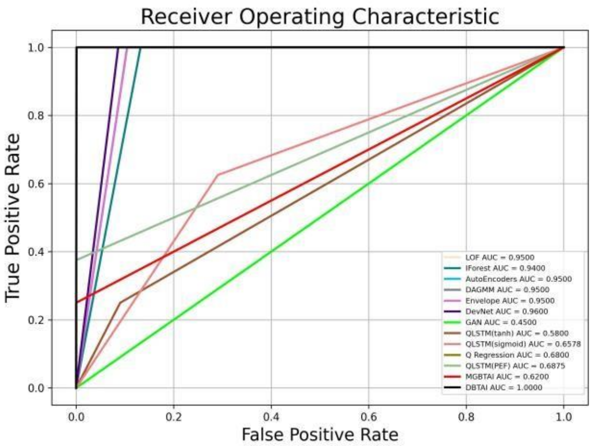

Receiver Operating Characteristic
True Positive Rate
False Positive Rate
LOF AUC = 1.0000
IForest AUC = 0.9600
AutoEncoders AUC = 0.7500
DAGMM AUC = 0.8600
Envelope AUC = 0.9900
DevNet AUC = 0.9600
GAN AUC = 0.4100
QLSTM(tanh) AUC = 0.9130
QLSTM(sigmoid) AUC = 0.9730
Q Regression AUC = 0.6300
QLSTM(PEF) AUC = 0.9045
MGBTAI AUC = 0.7500
DBTAI AUC = 1.0000

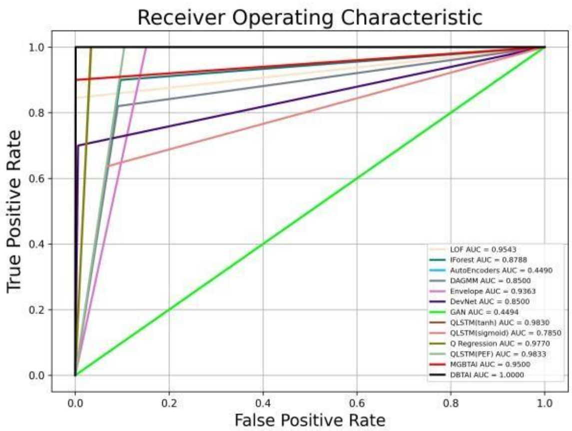

Receiver Operating Characteristic
True Positive Rate
False Positive Rate
LOF AUC = 1.0000
IForest AUC = 0.9600
AutoEncoders AUC = 0.7500
DAGMM AUC = 0.8600
Envelope AUC = 0.9900
DevNet AUC = 0.9600
GAN AUC = 0.4100
QLSTM(tanh) AUC = 0.9130
QLSTM(sigmoid) AUC = 0.9730
Q Regression AUC = 0.6300
QLSTM(PEF) AUC = 0.9045
MGBTAI AUC = 0.7500
DBTAI AUC = 1.0000

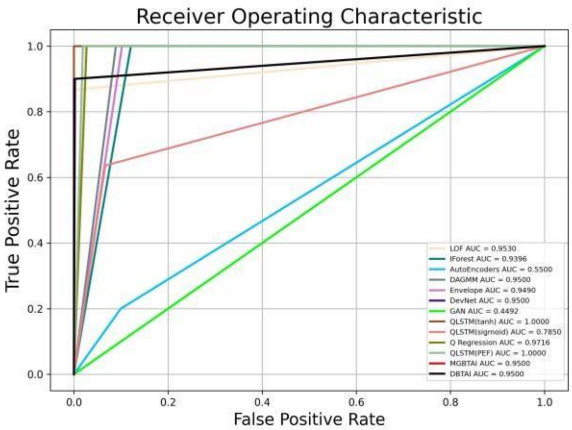

Receiver Operating Characteristic
True Positive Rate
False Positive Rate
LOF AUC = 0.9500
IForest AUC = 0.9400
AutoEncoders AUC = 0.9500
DAGMM AUC = 0.5800
Envelope AUC = 0.9500
DevNet AUC = 0.9500
GAN AUC = 0.4500
QLSTM(tanh) AUC = 0.6280
QLSTM(sigmoid) AUC = 0.8610
Q Regression AUC = 0.5800
QLSTM(PEF) AUC = 0.9700
MGBTAI AUC = 0.5300
DBTAI AUC = 1.0000

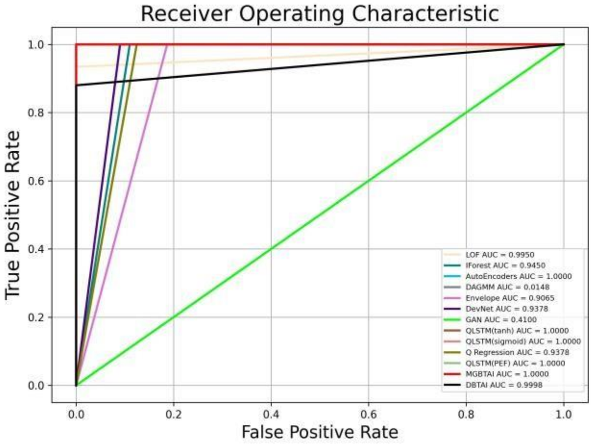

Receiver Operating Characteristic
True Positive Rate
False Positive Rate
LOF AUC = 0.9500
IForest AUC = 0.9400
AutoEncoders AUC = 0.9500
DAGMM AUC = 0.9500
Envelope AUC = 0.9500
DevNet AUC = nan
GAN AUC = 0.4500
QLSTM(tanh) AUC = 0.9870
QLSTM(sigmoid) AUC = 0.9832
Q Regression AUC = 0.8400
QLSTM(PEF) AUC = 0.9888
MGBTAI AUC = 1.0000
DBTAI AUC = 1.0000


Receiver Operating Characteristic
True Positive Rate
False Positive Rate
LOF AUC = 0.9500
IForest AUC = 0.9400
AutoEncoders AUC = 0.9000
DAGMM AUC = 0.9500
Envelope AUC = 0.9500
DevNet AUC = 0.9500
GAN AUC = 0.7000
QLSTM(tanh) AUC = 0.9920
QLSTM(sigmoid) AUC = 0.9686
Q Regression AUC = 0.9900
QLSTM(PEF) AUC = 0.9855
MGBTAI AUC = 1.0000
DBTAI AUC = 1.0000


Receiver Operating Characteristic
True Positive Rate
False Positive Rate
LOF AUC = 0.9500
IForest AUC = 0.9400
AutoEncoders AUC = 0.9500
DAGMM AUC = 0.9500
Envelope AUC = 0.9500
DevNet AUC = 0.9600
GAN AUC = 0.4500
QLSTM(tanh) AUC = 0.5800
QLSTM(sigmoid) AUC = 0.6578
Q Regression AUC = 0.6800
QLSTM(PEF) AUC = 0.6875
MGBTAI AUC = 0.6200
DBTAI AUC = 1.0000


Receiver Operating Characteristic
True Positive Rate
False Positive Rate
LOF AUC = 0.9543
IForest AUC = 0.8788
AutoEncoders AUC = 0.4490
DAGMM AUC = 0.8500
Envelope AUC = 0.9363
DevNet AUC = 0.8500
GAN AUC = 0.4494
QLSTM(tanh) AUC = 0.9830
QLSTM(sigmoid) AUC = 0.7850
Q Regression AUC = 0.9770
QLSTM(PEF) AUC = 0.9833
MGBTAI AUC = 0.9500
DBTAI AUC = 1.0000


Receiver Operating Characteristic
True Positive Rate
False Positive Rate
LOF AUC = 0.9530
IForest AUC = 0.9396
AutoEncoders AUC = 0.5500
DAGMM AUC = 0.9500
Envelope AUC = 0.9490
DevNet AUC = 0.9500
GAN AUC = 0.4492
QLSTM(tanh) AUC = 1.0000
QLSTM(sigmoid) AUC = 0.7850
Q Regression AUC = 0.9716
QLSTM(PEF) AUC = 1.0000
MGBTAI AUC = 0.9500
DBTAI AUC = 0.9500


Receiver Operating Characteristic
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
LOF AUC = 0.9950
IForest AUC = 0.9450
AutoEncoders AUC = 1.0000
DAGMM AUC = 0.0148
Envelope AUC = 0.9065
DevNet AUC = 0.9378
GAN AUC = 0.4100
QLSTM(tanh) AUC = 1.0000
QLSTM(sigmoid) AUC = 1.0000
Q Regression AUC = 0.9378
QLSTM(PEF) AUC = 1.0000
MGBTAI AUC = 1.0000
DBTAI AUC = 0.9998

5.2.9 ADDITIONAL RESULTS AND BENCHMARKING

In our comparison of anomaly detection algorithms, several trends emerge across various performance metrics. Tree-based approaches, KNN, and PCA consistently demonstrate strong performance.In Table 5.21, tree-based approaches, KNN, and PCA show the highest precision values in multiple datasets. LUNAR, ECOD, and GOAD also exhibit notable precision in specific datasets.

Moving to Table 5.22, tree-based algorithms, particularly d-BTAI and MGBTAI, dominate in precision across the entire dataset collection, outperforming other methods.In terms of recall, as shown in Table 5.23, tree-based approaches MGBTAI and d-BTAI achieve the highest recall in numerous datasets, followed by LUNAR and KNN.

Table 5.24 highlights the impressive recall of several algorithms, with LUNAR leading in numerous datasets, closely followed by COPOD and ECOD.KNN emerges as a top performer in F1 score, as depicted in Table 5.25, with tree-based methods close behind. LUNAR also demonstrates effectiveness in achieving high F1 scores.

In Table 5.26, tree-based approaches consistently achieve the highest F1 scores across the entire dataset collection, indicating exceptional performance.Moving to AUC ROC values, as seen in Table 5.27, KNN stands out with exceptional performance in many datasets, followed by LUNAR and PCA.

In Table 5.28, tree-based algorithms MGBTAI and d-BTAI demonstrate outstanding performance, achieving the highest AUC ROC values for numerous datasets, with perfect scores in many cases. Other algorithms like ECOD, GOAD, and PCA show lower performance in terms of AUC ROC.

Dataset	ECOD	COPOD	KNN	LUNAR	GOAD	PCA	DSVDD	MGBTAI	dBTAI
ALOI	0.0308	0.030474	**0.065813**	0.059108	0.0431	0.04	0.0351	0.04	0.04
annthyroid	0.2649	0.218905	0.252955	**0.333793**	0.1199	0.2063	0.1271	0.07	0.11
backdoor	0.0897	0.107135	0.1962	0.125095		**0.2092**	0.0959	0.01	0.06
breastw	**1**	0.933071	0.853571	0.840989	0.8399	**1**	0.8364	0.85	0.89
campaign	**0.417**	0.38463	0.330381	0.329897	0.3204	0.3613	0.2371	0.17	0.16
cardio	0.5185	0.528889	0.439169	0.40048	0.165	**0.6096**	0.2787	0.48	0.2
Cardiotocography	0.5792	0.547619	0.591981	0.538462	0.5865	0.5567	0.3640	**0.8**	0.35
celeba	0.0975	0.094133	0.0526	0.045133		**0.1113**	0.0083	0.08	0.03
cover	0.0653	0.052908	**0.1428**	0.0316		0.0735	0.0049	0	0.02
donors	**0.2902**	0.278359				0.1505	0.2218	0	0.13
fault	0.3383	0.293103	**0.7435**	0.738683		0.3789	0.4686	0.42	0.49
fraud	0.0153	0.015491	0.0147	0.0078		**0.0264**	0.0104	0.01	0
glass	0.0909	0.130435	0.1429	0.125	0.12	0.0909	**0.1935**	0.08	0.17
Hepatitis	0.25	**0.5**	0.2	0.222222	0.125	0.3333	0.4333	0	0.14
http	0.0389	0.037072	0.036934			0.0388	0.0008	**0.05**	0.03
InternetAds	0.6634	0.484848	0.726644	0.602941	0.2796	0.4574	0.5720	**0.98**	0.28
Ionosphere	0.8889	**1**	0.863636	0.82963	0.7767	**1**	0.8380	0.44	0.82
landsat	0.1611	0.202643	**0.588717**	0.511535	0.2161	0.0989	0.4570	0.01	0.26
letter	0.0755	0.0474	0.1962	**0.2788**	0.0741	0.0795	0.1708	0.11	0.12
Lymphography	0.4286	0.3	0.2857	0.1875	0.2727	**0.4615**	0.1765	0.43	0.15
magic.gamma	0.702	0.748404	0.790922	0.758181		**0.8217**	0.6479	0.77	0.53
mammography	0.1776	0.173725	0.15324	0.133459	**0.4286**	0.1346	0.1145	0	0.07
mnist	0.1812	0.266819	**0.484211**	0.458438	0.438	0.3831	0.2513	0.02	0.17
musk	0.2492	0.21164	0.164129	0.143068	0.1219	0.3089	0.2343	0.23	**0.36**
optdigits	0.0222	0.027174	0.253378	**0.259965**	0.0333	0.0019	0.0038	0.33	0.02
PageBlocks	0.4328	0.350291	0.21709	0.312119	0.3411	0.476	0.3004	**0.67**	0.17
pendigits	0.1484	0.127507	0.208278	**0.219718**	0.1581	0.148	0.0750	0	0.04
Pima	0.5517	0.69	0.666667	0.80315	0.4949	**0.8311**	0.3827	0.28	0.44
satellite	0.8152	0.831579	0.785133	0.753225	0.7538	0.8421	0.7187	**1**	0.54
satimage-2	0.1098	0.135699	0.117162	0.124561	0.1056	0.1121	0.0889	**0.14**	0.04
shuttle	**0.7001**	0.657735	0.484276	0.389938	0.4336	0.6788	0.4185	0.49	0.44
skin	0.0719	0.051742	**0.724642**	0.693724		0.0004	0.3841	0.62	0.27
smtp	0.0022	0.002209	0.00251	0.001578		0.0023	0.0029	**0.003**	0.001
SpamBase	0.5465	0.660266	**0.752242**	0.739979	0.4144	0.4103	0.7186	0.73	0.66
speech	0.0183	0.01766	0.0199	**0.033403**	0.0261	0.019	0.0305	0.01	0.02
Stamps	0.2941	**0.55102**	0.491525	0.454545	0.4561	0.2703	0.2429	0.13	0.15
thyroid	**0.2348**	0.191344	0.201422	0.203271	0.1636	0.1969	0.1547	0.13	0.08
vertebral	**0.1333**	0	0.04	0.041667	0.0769	0	0.0455	0	0.05
vowels	0.0839	0.033557	**0.1**	0.092764	0.0928	0.0556	0.0686	0.67	0.08
Waveform	0.0368	0.045627	0.145511	0.11244	0.0587	0.0409	**0.0833**	0	0.05
WBC	0.3846	0.37037	0.344828	0.3125	0.3226	0.3704	0.2941	**0.42**	0.19
WDBC	0.2439	0.227273	0.217391	0.185185	0.2174	**0.2564**	0.1493	0.21	0.19
Wilt	0.0305	0.01004	0.156347	0.013208	**0.0616**	0.0081	0.0165	0	0.05
wine	0.1875	0.363636	0.5	0.428571	**0.5882**	0.1818	0.2632	0.53	0.26
WPBC	0.1304	0.210526	0.263158	0.117647	0.1667	0.1667	**0.4167**	0.12	0.25
yeast	0.3581	0.322368	0.356061	0.216	**0.5248**	0.368	0.2899	0.1	0.3
CIFAR10	0.1338	0.130275	0.166038	0.136015	**0.1918**	0.1477	0.1034	0.04	0.08
FashionMNIST	0.1884	0.174298	**0.32732**	0.303797	0.2043	0.2274	0.1823	0.06	0.1
MNIST-C	0.0788	0.077375	**0.306224**	0.290671	0.0944	0.0999	0.1298	0.05	0.17
MVTec-AD	0.9375	0.943396	0.776316	0.725	0.6905	**1**	0.6237	**1**	0.9
SVHN	0.0569	0.055028	0.131115	0.082645	0.0722	0.0806	**0.0848**	0.06	0.1
Agnews	0.048	0.053785	**0.09889**	0.07841	0.0466	0.05	0.0506	0.05	0.06
Amazon	0.0499	0.062992	0.062967	**0.101427**	0.0654	0.0588	0.0364	0.05	0.05

Imdb	0.0279	0.033697	0.028169	**0.107234**	0.0367	0.0297	0.0333	0.02	0.05
Yelp	0.0729	0.088235	**0.098712**	0.076327	0.0856	0.0855	0.0481	0.04	0.06
20newsgroups	0.0721	0.064103	**0.146497**	0.116041	0.0737	0.0741	0.0601	0	0.04
BATADAL 04	0.2151	0.2021	0.253259	0.2314	0.1779	**0.2891**	0.1526	0.1	0.09
SWaT 1	0.3334	0.2426	0.283324	0.2293		0.0844	0.2962	**0.63**	0.19
SWaT 2	0.0905	0.078379	**0.144328**	0.1295		0.0463	0.1491	0.71	0.08
SWaT 3	0.1752	0.1041	0.107	0.0949		**1**	0.1736	0.02	0.07
SWaT 4	0.1888	**0.965384**	0.946762	0.8851		0.4938	0.8727	0.34	0.18
SWaT 5	0.0122	0.019811	0.073599	0.0669		0.029	0.0288	**0.22**	0.06
SWaT 6	0.2071	0.225972	0.17775	0.1579		0.2599	0.2200	**0.97**	0.13
ecoli	0.1111	0.111111	0	0	0.0946	**0.2333**	0.1321	0.14	0.06
cmc	0.0068	0.006579	0.090909	**0.111111**	0.0194	0	0.0068	0	0.02
lympho h	**0.375**	0.26087	0.285714	0.25	0.25	0.3529	0.1613	0	0.11
wbc h	0.3684	0.34	0.3	0.253012	0.2881	0.4054	0.2286	**0.61**	0.17

Table 5.21: Precision values of the 9 algorithms on the 67 multivariate datasets. The highest value(s) is marked in bold. The empty spaces denote that the algorithm exceeded a runtime of three hours without successfully generating results.

Dataset	ECOD	COPOD	KNN	LUNAR	GOAD	PCA	DSVDD	MGBTAI	d-BTAI
yahoo1	0.014	0.011628	0.010753	0.007519	0.01	0.017	0.0119	**1**	**1**
yahoo2	0.0548	0.057143	0.121212	0.044444	0.0533	0.0205	0.0465	**1**	0.89
yahoo3	0.0548	0.058824	0.189189	0.029412	0.0282	0.0455	0.0648	0.5	**0.88**
yahoo5	0.0414	0.022727	0.046154	0.017544	0.0204	0	0.0214	**1**	**1**
yahoo6	0.0278	0.017094	0.009926	0.008386	0.0201	0.0076	0.0192	**1**	**1**
yahoo7	0.0289	0.024896	0.019231	0.018717	0.049	0.0172	0.0201	0.5	**0.57**
yahoo8	0.0058	0.010909	0.009579	0.013356	0.0079	0	0.0058	**1**	**1**
yahoo9	0.0473	0.046512	0.072072	0.034043	0.0449	0.0395	0.0440	**1**	**1**
Speed 6005	0.0042	0.004082	0.025641	0.028571	0.0035	0.005	0.0038	0.2	**0.5**
Speed 7578	0.0367	0.032787	0.051282	0.061538	0.0219	0.04	0.1143	0.09	**0.25**
Speed t4013	0.0081	0.008299	0.034483	0.04	0.0089	0.0135	0.0417	0.29	**0.67**
TravelTime 387	0.008	0.008772	0.011696	0.008621	0.0027	0.0085	0.0051	0.05	**0.33**
TravelTime 451	0.0047	0.005181	0.006757	0.004484	0.0057	0.0047	0.0000	0.04	**0.09**
Occupancy 6005	0.0039	0.004525	0.005682	0.006803	0.003	0.0046	0.0051	0.06	**1**
Occupancy t4013	0.0079	0.007663	0.011494	0.006494	0.0072	0.0078	0.0075	0.33	**1**
yahoo syn1	0.0816	0.068966	0.063158	0.041667	0.0571	0.48	0.0698	**1**	**1**
yahoo syn2	0.1208	0.12766	0.236842	0.097297	0.1132	0.0728	0.0994	**1**	0.94
yahoo syn3	0.1141	0.133333	0.361702	0.072034	0.0656	0.1074	0.1393	0.81	**0.89**
yahoo syn5	0.1111	0.082707	0.112676	0.036398	0.0645	0	0.0685	**1**	0.48
yahoo syn6	0.0286	0.017021	0.023873	0.021322	0.019	0	0.0122	**1**	0.25
yahoo syn7	0.0819	0.061728	0.04908	0.0401	0.0515	0.0667	0.0532	**0.56**	0.24
yahoo syn8	0.0175	0.025271	0.025145	0.032051	0.0159	0	0.0144	**1**	0.1
yahoo syn9	0.1011	0.102273	0.15	0.068702	0.0942	0.0747	0.0933	**1**	**1**
aws1	0.0095	0.009804	0.014925	0.006993	0.0088	0.0097	0.0097	**1**	0.1
aws2	0.0099	0.00304	0.090909	0.090909	0.125	0.1818	0.0769	**1**	0.18
aws3	0.0065	0.006711	0.010638	0.0025	0.0068	0.0062	0.0072	**0.5**	0.07
aws syn1	0.0926	0.093458	0.12987	0.034247	0.0833	0.0849	0.0394	0.9	**0.91**
aws syn2	0.0922	0.025413	0.47619	0.47619	0.5556	0.6452	0.0127	**0.67**	0.52
aws syn3	0.0671	0.066667	0.097087	0.024938	0.0629	0.06	0.0264	**0.9**	**0.9**
Industrial 1	0.013	0.0283	0.0385	0.0385	0.0349	0.0089	0.0132	**1**	**1**
Industrial 2	0.16	0.1739	0.3636	0.4444	0.509	0.1509	0.129	**1**	**1**

Table 5.22: Precision values of the 9 algorithms on the 31 univariate datasets. The highest value(s) is marked in bold.

Dataset	ECOD	COPOD	KNN	LUNAR	PCA	DSVDD	GOAD	MGBTAI	d-BTAI
ALOI	0.1028	0.096817	0.31366	0.291777	0.1313	0.1154	0.132	0.13	**0.4**
annthyroid	0.3502	0.329588	0.400749	**0.906367**	0.2715	0.1854	0.1704	0.18	0.51
backdoor	0.3658	0.424216	0.9128	**0.923572**	0.8385	0.9057		0.02	0.87
breastw	0.3013	0.991632	**1**	0.995816	0.3974	0.9414	0.9874	0.33	0.87
campaign	0.3705	0.441164	0.34569	0.551724	0.3211	0.2446	0.3709	0.16	**0.66**
cardio	0.5568	0.676136	0.840909	**0.948864**	0.6477	0.3864	0.1875	0.32	0.76
Cardiotocography	0.2511	0.296137	0.538627	**0.540773**	0.2425	0.2124	0.5021	0.2	0.47
celeba	0.433	0.439631	0.1746	0.207829	0.4935	0.0363		**0.7**	0.38
cover	0.6826	0.553695	0.3333	**0.9731**	0.7659	0.0626		0	0.7
donors	0.4886	**0.505884**			0.2518	0.4531		0	0.47
fault	0.101	0.10104	0.4264	0.533432	0.2998	0.1664		0.07	**0.6**
fraud	0.8862	0.876016	0.9085	**0.9736**	0.9592	0.6687		0.62	0.96
glass	0.2222	0.333333	0.3333	0.333333	0.2222	0.6667	0.3333	0.11	**1**
Hepatitis	0.1538	0.461538	0.076923	0.153846	0.2308	**1.0000**	0.0769	0	0.23
http	**1**	**1**	0.999548		**1**	0.0199		**1**	**1**
InternetAds	0.3641	0.478261	0.570652	0.668478	0.2772	**0.7446**	0.1603	0.23	0.6
Ionosphere	0.254	0.103175	0.904762	0.888889	0.2821	**0.9444**	0.6349	0.03	0.84
landsat	0.0765	0.069017	**0.485371**	0.382596	0.0465	0.3631	0.1185	0	0.46
letter		0.09	**0.72**	0.58	0.12	0.4100	0.12	0.18	0.86
Lymphography	**1**	**1**	**1**	**1**	**1**	**1.0000**	**1**	**1**	**1**
magic.gamma	0.2001	0.262859	**0.601824**	0.578499	0.2304	0.3396		0.21	0.59
mammography	0.75	0.773077	0.673077	0.546154	0.5923	0.5500	**1**	0	0.84
mnist	0.1957	0.334286	0.788571	0.78	0.4143	0.3471	0.7571	0.02	**0.85**
musk	0.7938	0.824742	**1**	**1**	**1**	**1.0000**	0.3505	0.79	**1**
optdigits	0.08	0.1	**1**	**1**	0.0067	0.0133	0.12	0.81	0.27
PageBlocks	0.4608	0.472549	0.368627	**0.903922**	0.5059	0.5784	0.5765	0.06	0.21
pendigits	0.6603	0.570513	**1**	**1**	0.6603	0.3590	0.8077	0.03	0.72
Pima	0.1791	0.257463	0.30597	**0.761194**	0.6219	0.1157	0.1828	0.05	0.43
satellite	0.2534	0.349214	**0.710707**	0.659627	0.3921	0.5521	0.6616	0.3	0.59
satimage-2	0.9014	0.915493	**1**	**1**	0.9296	0.9577	0.9859	**1**	**1**
shuttle	0.9806	0.985759	**1**	**1**	0.9644	0.9274	0.9983	0.01	0.88
skin	0.0347	0.021058	**1**	**1**	0.0002	0.2340		0.15	0.22
smtp	0.7	0.7	0.733333	**1**	0.7333	0.8667		0.33	0.87
SpamBase	0.1364	0.26623	0.399643	**0.428827**	0.0904	0.3848	0.1269	0.18	0.26
speech	0.1148	0.131148	0.196721	0.262295	0.1148	0.3607	0.2951	0.11	**0.8**
Stamps	0.3226	0.870968	**0.935484**	0.806452	0.3226	0.5484	0.8387	0.06	0.61
thyroid	0.957	0.903226	0.913978	0.935484	0.828	0.7849	0.7742	0.25	**1**
vertebral	**0.1333**	0	0.033333	0.033333	0	0.0333	0.0667	0	**0.13**
vowels	0.24	0.1	0.98	**1**	0.111	0.4200	0.98	0.16	**1**
Waveform	0.13	0.12	0.47	0.47	0.15	0.3400	0.21	0	**0.76**
WBC	**1**	**1**	**1**	**1**	**1**	**1.0000**	**1**	**1**	**1**
WDBC	**1**	**1**	**1**	**1**	**1**	**1.0000**	**1**	**1**	**1**
Wilt	0.0584	0.019455	0.392996	0.027237	0.0156	0.0389	0.1595	0	0.18
wine	0.3	0.8	**1**	0.9	0.2	**1.0000**	**1**	**1**	**1**
WPBC	0.0638	0.085106	0.106383	0.042553	0.0851	0.3191	0.0638	0.04	**0.4**
yeast	0.1045	0.096647	0.092702	0.053254	0.09167	0.0789	0.2091	0	**0.27**
CIFAR10	0.2738	0.269962	0.334601	0.269962	0.3004	0.2319	0.4449	0.07	**0.71**
FashionMNIST	0.381	0.374603	0.806349	0.761905	0.4635	0.4825	0.4794	0.12	**0.93**
MNIST-C	0.16	0.158	0.738	0.754	0.202	0.3000	0.202	0.12	**0.85**
MVTec-AD	0.4762	0.793651	**0.936508**	0.920635	0.3968	0.9206	0.9206	0.22	0.87

SVHN	0.1154	0.111538	0.257692	0.153846	0.1692	0.1885	0.1462	0.06	**0.88**
Agnews	0.096	0.108	0.196	0.146	0.102	0.1020	0.094	0.02	**0.47**
Amazon	0.1	0.128	0.118	0.27	0.118	0.0720	0.134	0.12	**0.47**
Imdb	0.056	0.068	0.052	0.418	0.06	0.0660	0.074	0.02	**0.43**
Yelp	0.144	0.18	0.184	0.138	0.168	0.0940	0.174	0.04	**0.54**
20newsgroups	0.1429	0.12987	**0.298701**	0.220779	0.1429	0.1429	0.1494	0	0.29
BATADAL 04	0.4155	0.4384	0.621005	0.4977	0.5441	0.3562	0.411	0.1	**0.75**
SWaT 1	0.3793	0.3381	**0.98567**	0.9447	0.0071	0.3439		0.15	0.81
SWaT 2	0.185	0.167932	0.974146	0.9779	0.0052	0.5164		0.08	0.53
SWaT 3	0.4997	0.2976	**0.9997**	0.9974	0.099	0.4743		0.03	0.69
SWaT 4	0.0437	0.84129	**1**	**1**	0.0532	0.8901		0.12	0.15
SWaT 5	0.0489	0.06276	0.945547	**0.9857**	0.0033	0.1154		0.22	0.83
SWaT 6	0.3579	0.364882	**1**	**1**	0.41	0.4363		0.4	0.81
ecoli	0.4444	0.555556	0	0	0.7778	0.7778	0.7778	**0.78**	**0.78**
cmc	0.0588	0.058824	**0.888889**	**0.888889**	0	0.0588	0.1765	0	0.47
lympho h	**1**	**1**	**1**	0.666667	**1**	0.8333	0.8333	0	**1**
wbc h	0.6667	0.809524	0.857143	**1**	0.7143	0.7619	0.8095	0.52	**1**

Table 5.23: Recall values of the 9 algorithms on the 67 multivariate datasets. The highest value(s) is marked in bold. The empty spaces denote that the algorithm exceeded a runtime of three hours without successfully generating results.

Dataset	ECOD	COPOD	KNN	LUNAR	PCA	DSVDD	GOAD	MGBTAI	d-BTAI
yahoo1	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
yahoo2	**1**	**1**	**1**	**1**	0.375	**1**	**1**	0.25	**1**
yahoo3	**1**	**1**	0.875	0.875	0.875	0.8750	0.875	0.88	0.88
yahoo5	0.6667	0.333333	0.666667	**1**	0	0.3333	0.3333	0.33	0.33
yahoo6	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
yahoo7	0.4545	0.545455	0.545455	**0.636364**	0.2727	0.3636	0.4545	0.36	0.36
yahoo8	0.1	0.3	0.5	**0.8**	0	0.2000	0.1	0.01	0.1
yahoo9	**1**	**1**	**1**	**1**	0.875	**1**	**1**	0.62	**1**
Speed 6005	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
Speed 7578	**1**	**1**	**1**	**1**	**1**	**1**	**1**	0.75	0.5
Speed t4013	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
TravelTime 387	0.6667	0.666667	0.666667	0.666667	0.6667	0.3333	0.3333	**0.67**	0.33
TravelTime 451	**1**	**1**	**1**	**1**	**1**	0.0000	**1**	**1**	**1**
Occupancy 6005	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
Occupancy t4013	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
yahoo syn1	**1**	**1**	**1**	**1**	**1**	**1**	**1**	0.17	**1**
yahoo syn2	**1**	**1**	**1**	**1**	0.6111	**1**	**1**	0.28	0.94
yahoo syn3	0.9444	**1**	0.944444	0.944444	0.8889	0.9444	0.8889	0.72	0.94
yahoo syn5	0.8421	0.578947	0.842105	**1**	0	0.5263	0.5263	0.42	0.53
yahoo syn6	0.2857	0.285714	0.642857	**0.714286**	0	0.2857	0.2857	0.29	0.29
yahoo syn7	0.6667	0.714286	**0.761905**	**0.761905**	0.5238	0.4762	0.3333	0.24	0.24
yahoo syn8	0.15	0.35	0.65	**1**	0	0.2500	0.1	0.05	0.1
yahoo syn9	**1**	**1**	**1**	**1**	0.7222	**1**	**1**	0.06	**1**
aws1	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
aws2	**1**	**1**	**1**	**1**	**1**	0.5000	**1**	0.5	**1**
aws3	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
aws syn1	**1**	**1**	**1**	**1**	0.9	**1**	**1**	0.9	**1**
aws syn2	**1**	**1**	**1**	**1**	**1**	0.3500	**1**	**1**	0.55
aws syn3	**1**	**1**	**1**	**1**	0.9	**1**	**1**	0.9	0.9
$Industrial_1$	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
$Industrial_2$	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**

Table 5.24: Recall values of the 9 algorithms on the 31 univariate datasets. The highest value(s) is marked in bold.

Dataset	ECOD	COPOD	KNN	LUNAR	GOAD	PCA	DSVDD	MGBTAI	d-BTAI
ALOI	0.0474	0.046357	**0.108798**	0.098302	0.0649	0.0613	0.0538	0.07	0.06
annthyroid	0.3016	0.263079	0.310145	**0.487903**	0.1408	0.2344	0.1508	0.1	0.19
backdoor	0.144	0.171067	0.323	0.220344		**0.3348**	0.1735	0.02	0.11
breastw	0.463	**0.96146**	0.921002	0.911877	0.9077	0.5688	0.8858	0.48	0.88
campaign	0.3924	0.410962	0.337862	**0.412903**	0.3438	0.34	0.2408	0.16	0.26
cardio	0.537	0.593516	0.576998	0.563238	0.1755	**0.6281**	0.3238	0.38	0.32
Cardiotocography	0.3503	0.384401	**0.564045**	0.539615	0.541	0.3378	0.2683	0.32	0.4
celeba	0.1592	0.155063	0.0808	0.074161		**0.1816**	0.0135	0.14	0.06
cover	**0.1193**	0.096587	0.2	0.0612		0.1341	0.0091	0	0.04
donors	**0.3642**	0.359117				0.1884	0.2978	0	0.2
fault	0.1556	0.150276	0.542	**0.6195**		0.2567	0.2456	0.12	0.54
fraud	0.0301	0.030444	0.0289	0.0154		**0.0513**	0.0205	0.02	0.01
glass	0.129	0.1875	0.2	0.181818	0.1765	0.129	**0.3000**	0.09	0.29
Hepatitis	0.1905	0.48	0.111111	0.181818	0.0952	0.2727	**0.6047**	0	0.18
http	0.0749	0.071494	0.071236			0.0748	0.0015	**0.08**	0.06
InternetAds	0.4702	0.481532	0.639269	0.634021	0.2038	0.3452	**0.6470**	0.38	0.39
Ionosphere	0.3951	0.18705	**0.883721**	0.858238	0.6987	0.44	0.8881	0.06	0.83
landsat	0.1038	0.102966	**0.532072**	0.437768	0.1531	0.0633	0.4047	0	0.33
letter	0.0927	0.0621	0.3084	**0.3766**	0.0916	0.0956	0.2412	0.13	0.21
Lymphography	0.6	0.461538	0.4444	0.315789	0.4286	**0.6316**	0.3000	0.6	0.26
magic.gamma	0.3114	0.389067	**0.683536**	0.656263		0.3599	0.4456	0.33	0.56
mammography	**0.2872**	0.283698	0.249643	0.214502	0.6	0.2194	0.1895	0	0.13
mnist	0.1882	0.296766	0.6	**0.577472**	0.555	0.3981	0.2915	0.02	0.28
musk	0.3793	0.336842	0.281977	0.250323	0.1809	**0.472**	0.3796	0.35	0.53
optdigits	0.0347	0.042735	0.404313	0.412655	0.0522	0.0029	0.0060	**0.47**	0.03
PageBlocks	0.4463	0.402337	0.273256	0.464016	0.4286	**0.4905**	0.3954	0.11	0.19
pendigits	0.2424	0.208431	0.344751	**0.360277**	0.2644	0.2418	0.1240	0	0.08
Pima	0.2704	0.375	0.419437	**0.781609**	0.267	0.7181	0.1777	0.09	0.43
satellite	0.3867	0.491871	**0.746069**	0.703325	0.7047	0.4591	0.6244	0.46	0.57
satimage-2	0.1957	0.236364	0.209749	0.221529	0.1907	0.2	0.1627	**0.25**	0.07
shuttle	**0.8169**	0.789012	0.652542	0.561087	0.6046	0.7968	0.5767	0.01	0.59
skin	0.0469	0.029934	**0.840339**	0.81917		0.0002	0.2909	0.24	0.24
smtp	0.0044	0.004404	0.005002	0.00315		0.0046	**0.0058**	0.004	0.002
SpamBase	0.2183	0.379457	0.521976	**0.542986**	0.1943	0.1418	0.5012	0.29	0.37
speech	0.0316	0.031128	0.036145	**0.059259**	0.048	0.0326	0.0562	0.03	0.03
Stamps	0.3077	**0.675**	0.644444	0.581395	0.5909	0.2941	0.3366	0.09	0.24
thyroid	**0.3771**	0.315789	0.330097	0.333973	0.2702	0.3182	0.2584	0.17	0.14
vertebral	**0.1333**	0	0.036364	0.037037	0.0714	0	0.0385	0	0.07
vowels	0.1244	0.050251	0.181481	0.169779	0.1696	0.0741	0.1180	**0.26**	0.14
Waveform	0.0574	0.066116	**0.222222**	0.181467	0.0917	0.0642	0.1339	0	0.09
WBC	0.5556	0.540541	0.512821	0.47619	0.4878	0.5405	0.4545	**0.57**	0.31
WDBC	0.3922	0.37037	0.357143	0.3125	0.3571	**0.4082**	0.2597	0.34	0.32
Wilt	0.0401	0.013245	**0.223699**	0.017789	0.0888	0.0106	0.0232	0	0.07
wine	0.2308	0.5	0.666667	0.580645	**0.7407**	0.1905	0.4167	0.69	0.42
WPBC	0.0857	0.121212	0.151515	0.0625	0.0923	0.1127	**0.3614**	0.06	0.31
yeast	0.1618	0.14871	0.147105	0.085443	**0.299**	0.1572	0.1240	0.01	0.28
CIFAR10	0.1798	0.175743	0.221942	0.180892	**0.268**	0.198	0.1430	0.05	0.14
FashionMNIST	0.2521	0.237903	**0.465628**	0.434389	0.2865	0.3051	0.2646	0.08	0.18
MNIST-C	0.1056	0.103879	**0.432845**	0.419588	0.1287	0.1337	0.1812	0.07	0.28
MVTec-AD	0.6316	0.862069	0.848921	0.811189	0.7891	0.5682	0.7436	0.36	**0.89**
SVHN	0.0762	0.073698	0.1738	0.107527	0.0967	0.1092	0.1169	0.06	**0.18**
Agnews	0.064	0.071809	**0.131455**	0.102027	0.0623	0.0671	0.0676	0.03	0.11

Amazon	0.0665	0.084433	0.082116	**0.14746**	0.0879	0.0785	0.0484	0.07	0.1
Imdb	0.0373	0.045063	0.036543	0.170682	0.0491	0.0398	0.0442	0.02	**0.5**
Yelp	0.0968	0.118421	0.128492	0.098291	0.1148	0.1134	0.0636	0.04	**0.56**
20newsgroups	0.0959	0.085837	0.196581	0.152125	0.0987	0.0976	0.0846	0	**0.47**
BATADAL 04	0.2835	0.2767	0.359788	0.3159	0.2483	**0.3776**	0.2137	0.1	0.17
SWaT 1	0.3549	0.2825	**0.440134**	0.369		0.013	0.3183	0.24	0.31
SWaT 2	0.1216	0.106876	**0.251408**	0.2287		0.0094	0.2314	0.15	0.14
SWaT 3	**0.2594**	0.1542	0.1933	0.1732		0.1802	0.2542	0.02	0.13
SWaT 4	0.0709	0.899075	**0.972653**	0.939		0.0961	0.8813	0.18	0.16
SWaT 5	0.0195	0.030115	0.136568	0.1253		0.0059	0.0461	**0.22**	0.12
SWaT 6	0.2624	0.279098	0.301847	0.2728		0.3181	0.2925	**0.57**	0.22
ecoli	0.1778	0.185185	0	0	0.1687	**0.359**	0.2258	0.23	0.1
cmc	0.0123	0.011834	0.164948	**0.197531**	0.0349	0	0.0122	0	0.03
lympho h	**0.5455**	0.413793	0.444444	0.363636	0.3846	0.5217	0.2703	0	0.2
wbc h	0.4746	0.478873	0.444444	0.403846	0.425	0.5172	0.3516	**0.56**	0.29

Table 5.25: F1 Score values of the 9 algorithms on the 67 univariate datasets. The highest value(s) is marked in bold. The empty spaces denote that the algorithm exceeded a runtime of three hours without successfully generating results.

Dataset	ECOD	COPOD	KNN	LUNAR	GOAD	PCA	DSVDD	MGBTAI	d-BTAI
yahoo1	0.0276	0.022989	0.021277	0.014925	0.0197	0.0281	0.0235	**1**	**1**
yahoo2	0.1039	0.108108	0.216216	0.085106	0.1013	0.039	0.0889	0.4	**0.94**
yahoo3	0.1039	0.111111	0.311111	0.056911	0.0547	0.0864	0.1207	0.64	**0.88**
yahoo5	0.0779	0.042553	0.086331	0.034483	0.0385	0	0.0403	**0.5**	**0.5**
yahoo6	0.0541	0.033613	0.019656	0.016632	0.0394	0.0151	0.0377	**1**	**1**
yahoo7	0.0543	0.047619	0.037152	0.036364	0.0885	0.0324	0.0381	0.42	**0.44**
yahoo8	0.011	0.021053	0.018797	0.026273	0.0147	0	0.0112	0.01	**0.18**
yahoo9	0.0904	0.088889	0.134454	0.065844	0.086	0.0757	0.0842	0.77	**1**
Speed 6005	0.0083	0.00813	0.05	0.055556	0.007	0.01	0.0075	0.33	**0.67**
Speed 7578	0.0708	0.063492	0.097561	0.115942	0.0428	0.0769	0.2051	0.16	**0.33**
Speed t4013	0.0161	0.016461	0.066667	0.076923	0.0176	0.0267	0.0800	0.44	**0.8**
TravelTime 387	0.0158	0.017316	0.022989	0.017021	0.0054	0.0168	0.0101	0.09	**0.33**
TravelTime 451	0.0093	0.010309	0.013423	0.008929	0.0114	0.0093	0.0000	0.08	**0.17**
Occupancy 6005	0.0078	0.009009	0.011299	0.013514	0.006	0.0091	0.0102	0.12	**1**
Occupancy t4013	0.0156	0.015209	0.022727	0.012903	0.0144	0.0155	0.0148	0.5	**1**
yahoo$_{s}yn1$	0.1509	0.129032	0.118812	0.08	0.1081	0.6486	0.1304	0.29	**1**
yahoo$_{s}yn2$	0.2156	0.226415	0.382979	0.17734	0.2034	0.1302	0.1809	0.43	**0.94**
yahoo$_{s}yn3$	0.2036	0.235294	0.523077	0.133858	0.1221	0.1916	0.2429	0.76	**0.92**
yahoo$_{s}yn5$	0.1963	0.144737	0.198758	0.07024	0.1149	0	0.1212	**0.59**	0.5
yahoo$_{s}yn6$	0.0519	0.032129	0.046036	0.041408	0.0357	0	0.0235	**0.44**	0.27
yahoo$_{s}yn7$	0.1458	0.113636	0.092219	0.07619	0.0892	0.1183	0.0957	**0.33**	0.24
yahoo$_{s}yn8$	0.0314	0.047138	0.048417	0.062112	0.0274	0	0.0272	**0.1**	**0.1**
yahoo$_{s}yn9$	0.1837	0.185567	0.26087	0.128571	0.1722	0.1354	0.1706	0.11	**1**
aws1	0.0189	0.019417	0.029412	0.013889	0.0175	0.0192	0.0192	**1**	0.18
aws2	0.0196	0.006061	0.166667	0.166667	0.2222	0.3077	0.1333	**0.67**	0.31
aws3	0.0128	0.013333	0.021053	0.004988	0.0135	0.0123	0.0143	**0.67**	0.13
aws syn1	0.1695	0.17094	0.229885	0.066225	0.1538	0.1552	0.0758	0.9	**0.95**
aws syn2	0.1688	0.049566	0.645161	0.645161	0.7143	0.7843	0.0245	**0.8**	0.54
aws syn3	0.1258	0.125	0.176991	0.048662	0.1183	0.1125	0.0514	**0.9**	**0.9**
Industrial 1	0.0256	0.055	0.0741	0.0741	0.0674	0.0176	0.026	**1**	0.375
Industrial 2	0.2739	0.2963	0.5333	0.6134	0.2623	0.2623	0.2286	**1**	0.94

Table 5.26: F1 Score values of the 9 algorithms on the 31 univariate datasets. The highest value(s) is marked in bold.

Dataset	ECOD	COPOD	KNN	LUNAR	GOAD	PCA	DSVDD	MGBTAI	d-BTAI
ALOI	0.5006	0.500049	**0.586931**	0.57297	0.5199	0.5162	0.5079	0.52	0.53
annthyroid	0.6362	0.617689	0.65297	**0.880726**	0.5351	0.5939	0.5417	0.5	0.6
backdoor	0.6364	0.667839	**0.9096**	0.880904		0.8788	0.8921	0.49	0.76
breastw	0.6506	**0.976672**	0.953829	0.947232	0.943	0.6987	0.9212	0.65	0.91
campaign	0.6524	0.675778	0.628369	**0.704723**	0.6355	0.6245	0.5723	0.53	0.61
cardio	0.7509	0.806044	0.863355	**0.898903**	0.5433	0.8018	0.6400	0.64	0.72
Cardiotocography	0.5997	0.613481	**0.716825**	0.704852	0.701	0.5939	0.5537	0.59	0.61
celeba	0.6705	0.67125	0.5512	0.553441		0.7015	0.4683	**0.75**	0.55
cover	0.794	0.728794	0.6227	**0.842**		0.8361	0.4696	0.5	0.68
donors	0.7067	**0.711624**				0.5811	0.6765	0.5	0.63
fault	0.4981	0.485851	0.6742	**0.716637**		0.5431	0.5331	0.51	0.63
fraud	0.8938	0.889838	0.9015	0.8793		**0.9281**	0.7794	0.75	0.78
glass	0.5623	0.617886	0.6228	0.615447	0.613	0.5623	0.7724	0.53	**0.89**
Hepatitis	0.5321	0.685993	0.508611	0.524684	0.4862	0.5706	**0.8731**	0.44	0.48
http	**0.9517**	0.949204	0.948803			0.9516	0.4587	0.95	0.94
InternetAds	0.6608	0.68062	0.760608	0.783551	0.5326	0.6007	**0.8081**	0.62	0.63
Ionosphere	0.6181	0.551587	0.912381	0.893333	0.7663	0.641	**0.9211**	0.5	0.87
landsat	0.4862	0.499032	**0.698389**	0.643571	0.5031	0.4679	0.6252	0.44	0.56
letter	0.511	0.4847	**0.7617**	0.74	0.51	0.5137	0.6387	0.54	0.72
Lymphography	0.9718	0.950704	0.9472	0.908451	0.9437	**0.9754**	0.9014	0.97	0.88
magic.gamma	0.577	0.607467	**0.757772**	0.739217		0.6017	0.6197	0.59	0.65
mammography	0.8337	0.842778	0.792274	0.730872	**0.9718**	0.7508	0.7244	0.5	0.8
mnist	0.553	0.620569	**0.851696**	0.843281	0.8293	0.6733	0.6211	0.46	0.71
musk	0.8578	0.862118	0.916695	0.902024	0.6339	**0.9634**	0.9465	0.85	0.82
optdigits	0.4878	0.497	0.956376	**0.957856**	0.5085	0.4508	0.4555	0.88	0.42
PageBlocks	0.6989	0.690503	0.614889	**0.847926**	0.7301	0.7239	0.7189	0.53	0.55
pendigits	0.7861	0.739903	0.955839	**0.958743**	0.8539	0.786	0.6280	0.41	0.67
Pima	0.5506	0.597731	0.611985	0.830597	0.5414	**0.8503**	0.5078	0.49	0.57
satellite	0.6134	0.65824	**0.810343**	0.779802	0.7808	0.6892	0.7260	0.65	0.68
satimage-2	0.9054	0.921633	0.953332	**0.956472**	0.9412	0.9192	0.9181	0.92	0.83
shuttle	**0.9741**	0.973126	0.95899	0.939751	0.9489	0.9646	0.9141	0.5	0.9
skin	0.4587	0.459993	**0.950242**	0.942188		0.4373	0.5679	0.56	0.53
smtp	0.7997	0.80014	0.820707	**0.900206**		0.8164	0.8867	0.64	0.81
SpamBase	0.5306	0.587624	0.656111	**0.664374**	0.5039	0.4981	0.6423	0.57	0.58
speech	0.5057	0.504194	0.516843	0.567285	0.555	0.5074	**0.5838**	0.49	0.48
Stamps	0.6225	0.899885	**0.919198**	0.854682	0.8692	0.6176	0.6884	0.51	0.63
thyroid	**0.9391**	0.903366	0.911189	0.921398	0.8371	0.8713	0.8382	0.6	0.84
vertebral	**0.5048**	0.435714	0.459524	0.461905	0.4762	0.4405	0.4667	0.49	0.39
vowels	0.5734	0.498791	**0.833172**	0.826102	0.8197	0.515	0.6086	0.58	0.79
Waveform	0.5141	0.522459	**0.69372**	0.679511	0.5546	0.5224	0.6141	0.5	0.64
WBC	0.9624	0.960094	0.955399	0.948357	0.9507	0.9601	0.9437	**0.97**	0.9
WDBC	0.9566	0.952381	0.94958	0.938375	0.9496	**0.9594**	0.9202	0.95	0.94
Wilt	0.477	0.455694	**0.636765**	0.456297	0.5113	0.454	0.4541	0.48	0.48
wine	0.5954	0.841176	0.957983	0.89958	**0.9706**	0.5622	0.8824	0.96	0.88
WPBC	0.4657	0.492884	0.506834	0.471608	0.4822	0.4763	**0.5900**	0.47	0.51
yeast	0.5037	0.495611	0.502851	0.476474	**0.5554**	0.5341	0.4893	0.49	0.47
CIFAR10	0.5903	0.587581	0.6231	0.589881	**0.6731**	0.6046	0.5631	0.49	0.64
FashionMNIST	0.6474	0.640718	**0.859675**	0.835119	0.6907	0.6904	0.6844	0.51	0.76
MNIST-C	0.5308	0.529421	0.825	**0.828579**	0.55	0.5531	0.5971	0.5	0.71
MVTec-AD	0.7337	0.890275	**0.931136**	0.912283	0.9035	0.6984	0.8839	0.61	0.92

SVHN	0.5075	0.505446	0.58398	0.532056	0.5238	0.5339	0.5408	0.51	**0.73**
Agnews	0.4979	0.504	**0.551**	0.527842	0.4964	0.4999	0.5006	0.5	0.55
Amazon	0.4998	0.513895	0.512789	**0.572053**	0.5166	0.5093	0.4859	0.5	0.5
Imdb	0.4767	0.482684	0.478789	**0.617421**	0.4859	0.4785	0.4825	0.48	0.5
Yelp	0.5238	0.541053	0.547789	0.525053	0.5381	0.5367	0.4980	0.5	**0.56**
20newsgroups	0.5232	0.515208	**0.60371**	0.566282	0.5255	0.5246	0.5128	0.5	0.47
BATADAL 04	0.6658	0.6713	**0.759845**	0.7031	0.6529	0.7337	0.6234	0.52	0.68
SWaT 1	0.6528	0.6178	**0.871628**	0.818		0.0035	0.6322	0.57	0.74
SWaT 2	0.5448	0.533317	**0.838936**	0.8203		0.1082	0.6826	0.54	0.61
SWaT 3	0.7069	0.6021	**0.8477**	0.8252		nan	0.6960	0.48	0.68
SWaT 4	0.4496	0.909027	**0.978343**	0.95		0.1688	0.8950	0.47	0.31
SWaT 5	0.4736	0.491437	**0.81968**	0.816		0.1077	0.5077	0.6	0.75
SWaT 6	0.6367	0.643886	**0.8573**	0.8355		0.6664	0.6704	0.7	0.74
ecoli	0.6733	0.716616	0.465659	0.454327	0.7864	**0.8537**	0.8186	0.82	0.71
cmc	0.4796	0.477557	0.82212	**0.846585**	0.536	0.4516	0.4793	0.46	0.57
lympho h	**0.9648**	0.940141	0.947183	0.79108	0.8638	0.9613	0.8251	0.44	0.83
wbc h	0.7997	0.858543	0.869748	**0.913165**	0.8459	0.8263	0.8053	0.75	0.86

Table 5.27: AUC-ROC values of the 9 algorithms on the 67 multivariate datasets. The highest value(s) is marked in bold. The empty spaces denote that the algorithm exceeded a runtime of three hours without successfully generating results.

Dataset	ECOD	COPOD	KNN	LUNAR	GOAD	PCA	DSVDD	MGBTAI	d-BTAI
yahoo1	0.9503	0.940056	0.93512	0.906911	0.9298	0.9403	0.9415	**1**	**1**
yahoo2	0.9525	0.954577	0.980041	0.940812	0.9511	0.6383	0.9436	0.62	**1**
yahoo3	0.9518	**0.955276**	0.927018	0.856787	0.8533	0.8861	0.9022	0.94	0.94
yahoo5	0.7841	0.620987	0.789424	**0.82153**	0.6157	0.4508	0.6182	0.67	0.67
yahoo6	0.9506	0.918843	0.85921	0.833098	0.9312	0.8155	0.9280	**1**	**1**
yahoo7	0.6769	0.702326	0.681056	**0.708236**	0.6982	0.5851	0.6234	0.68	0.68
yahoo8	0.4991	0.568563	0.59521	**0.723054**	0.5126	0.4512	0.4967	0.5	0.55
yahoo9	0.9519	0.950957	0.969199	0.932117	0.9492	0.8867	0.9480	0.81	**1**
Speed 6005	0.9522	0.95118	0.992397	0.993197	0.9432	0.9604	0.9470	**1**	**1**
Speed 7578	0.9533	0.947462	0.967053	0.972841	0.9203	0.9573	**0.9862**	0.86	0.75
Speed t4013	0.9511	0.952066	0.988769	0.990373	0.9553	0.9797	0.9908	**1**	**1**
TravelTime 387	0.7837	0.788079	0.799493	0.787278	0.594	0.7867	0.6278	**0.83**	0.67
TravelTime 451	0.9509	0.955576	0.965988	0.948635	0.96	0.9509	0.4537	0.99	**1**
Occupancy 6005	0.9468	0.953762	0.96322	0.969315	0.9309	0.9544	0.9592	**1**	**1**
Occupancy t4013	0.9496	0.948159	0.965572	0.938751	0.9452	0.9492	0.9468	**1**	**1**
yahoo syn1	0.9521	0.942472	0.93679	0.901989	0.9297	0.9954	0.9432	0.58	**1**
yahoo syn2	0.9546	0.95738	**0.979903**	0.942134	0.9511	0.757	0.9435	0.64	0.97
yahoo syn3	0.9261	0.959119	0.96174	0.895702	0.8648	0.898	0.9355	0.86	**0.97**
yahoo syn5	0.8757	0.746273	**0.876435**	0.821884	0.7118	0.4518	0.7150	0.71	0.76
yahoo syn6	0.5949	0.561347	0.691577	**0.695181**	0.5702	0.4531	0.5289	0.64	0.64
yahoo syn7	0.7863	**0.788838**	0.788082	0.766213	0.628	0.7158	0.6848	0.62	0.61
yahoo syn8	0.5247	0.594162	0.674102	**0.819162**	0.5129	0.4518	0.5226	0.53	0.54
yahoo syn9	0.9522	0.952751	0.969498	0.927033	0.9483	0.813	0.9477	0.53	**1**
aws1	0.9504	0.951813	0.968511	0.932252	0.9466	0.9513	0.9513	**1**	**1**
aws2	0.9597	0.867955	0.995974	0.995974	0.9972	0.9982	0.7476	0.75	**1**
aws3	0.9486	0.950601	0.968959	0.866822	0.9513	0.9463	0.9539	**1**	**1**
aws syn1	0.9528	0.953321	0.967757	0.864293	0.9471	0.9033	0.8826	0.95	**1**
aws syn2	0.9601	0.844485	0.995539	0.995539	0.9968	0.9978	0.5647	**1**	0.77
aws syn3	0.9533	0.952989	**0.968771**	0.868704	0.95	0.9027	0.8761	0.95	0.95
Industrial 1	0.929	0.9679	0.9767	0.9767	0.9742	0.8957	0.93	**1**	0.975
Industrial 2	0.9608	0.9646	0.9869	0.9907	0.958	0.958	0.9496	**1**	0.9998

Table 3: AUC-ROC values of the 9 algorithms on the 31 univariate datasets. The highest value(s) is marked in bold.

5.3 OVERVIEW OF TECHNOLOGIES USED

Python

Python is a versatile, high-level programming language renowned for its simplicity and readability. Its extensive standard library and rich ecosystem of third-party packages make it ideal for various applications, including web development, data analysis, scientific computing, and artificial intelligence. Python's clean syntax and dynamic typing promote rapid development and easy maintenance, fostering a vibrant community of developers and researchers.

Flask

Flask is a lightweight and flexible web application framework written in Python. It provides the essentials for building web applications without imposing rigid patterns or dependencies. Flask follows the WSGI (Web Server Gateway Interface) specification and offers features like routing, templating, and session management.

TensorFlow

TensorFlow is an open-source machine learning framework developed by Google Brain. It facilitates the creation and deployment of deep learning models across a range of platforms, from CPUs to GPUs and TPUs. TensorFlow's flexible architecture allows users to define computational graphs and execute them efficiently, making it suitable for tasks like neural networks, natural language processing, and image recognition.

Keras

Keras is a high-level neural networks API written in Python, designed for ease of use and modularity. It provides a simple interface for building and training neural networks, abstracting away complexities while offering flexibility and extensibility. Keras seamlessly integrates with TensorFlow, allowing users to leverage TensorFlow's computational backend while benefiting from Keras's intuitive API for rapid prototyping and experimentation.

NumPy

NumPy is a fundamental package for numerical computing in Python. It provides powerful data structures for representing arrays and matrices, along with a collection of mathematical functions for efficient computation. NumPy's array-oriented programming paradigm enables vectorized operations, improving performance and readability.

Pandas

Pandas is a Python library for data manipulation and analysis, built on top of NumPy. It introduces DataFrame and Series data structures, which offer intuitive ways to work with structured data. Pandas simplifies tasks like data cleaning, transformation, and aggregation, enabling users to perform complex data operations with ease.

Matplotlib

Matplotlib is a comprehensive plotting library for Python, offering a wide range of static, interactive, and animated visualizations. It provides a MATLAB-like interface for creating plots and charts, with extensive customization options. Matplotlib's versatility makes it suitable for various applications, from exploratory data analysis to publication-quality figures.

Scikit-learn

Scikit-learn is a machine learning library for Python, providing simple and efficient tools for data mining and analysis. It offers a consistent API for various machine learning algorithms, including classification, regression, clustering, and dimensionality reduction. Scikit-learn emphasizes ease of use, performance, and scalability, making it accessible to both beginners and experts.

HTML & CSS

HTML (Hypertext Markup Language) is the standard markup language for creating web pages, defining the structure and content of a webpage. CSS (Cascading Style Sheets) is used to style the layout and appearance of HTML elements, enhancing the visual presentation of web pages.

Together, HTML and CSS form the foundation of web development, enabling developers to create responsive, visually appealing, and interactive user interfaces for web applications.

5.4 GRAPHICAL USER INTERFACE (GUI)

Figure 4.2 Home Page

The homepage prominently displays a brief description of anomaly detection and its significance in various industries, such as cybersecurity, finance, and healthcare. Positioned prominently on the homepage, the Data Characterization tab offers a comprehensive overview of essential dataset metrics. Users can access information such as Dataset Name, Size, Dimensions, and Anomalies, complete with percentages. The Learn More section acts as a gateway to further knowledge. Here, users can explore detailed information on Machine Learning Models.

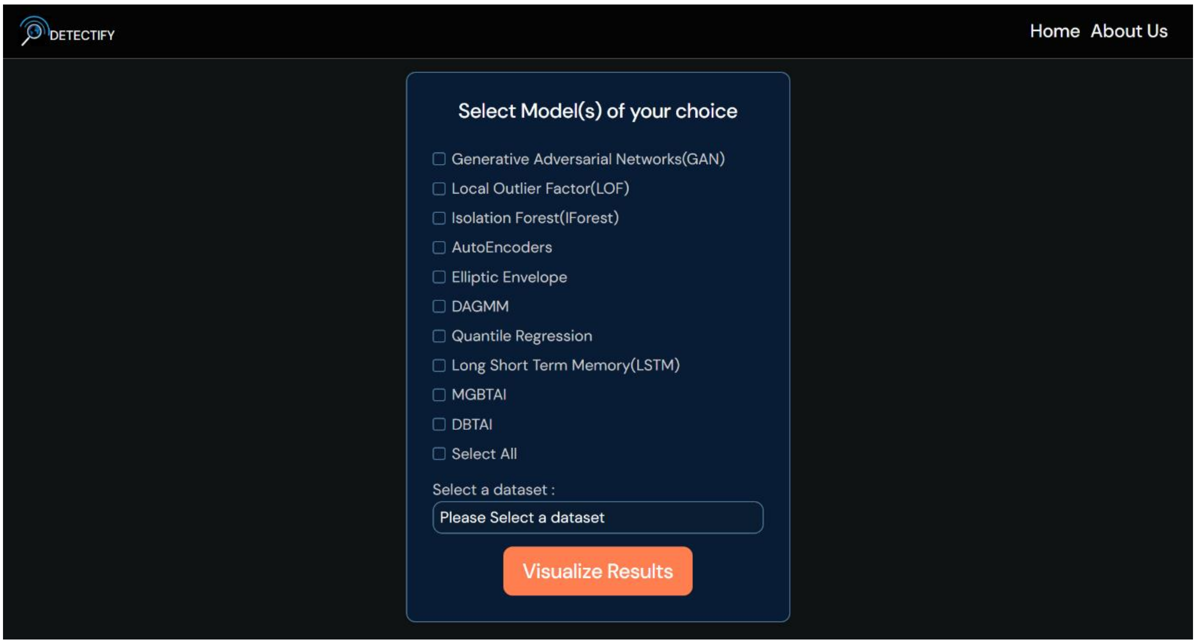


Figure 5.3 Model Selection

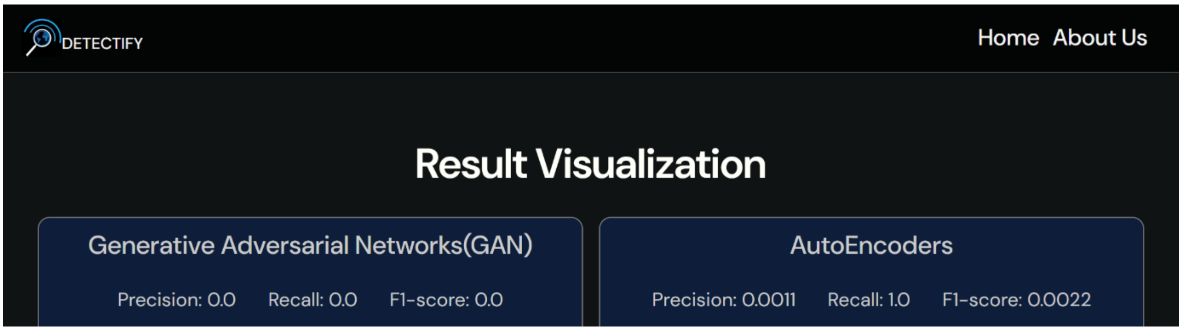
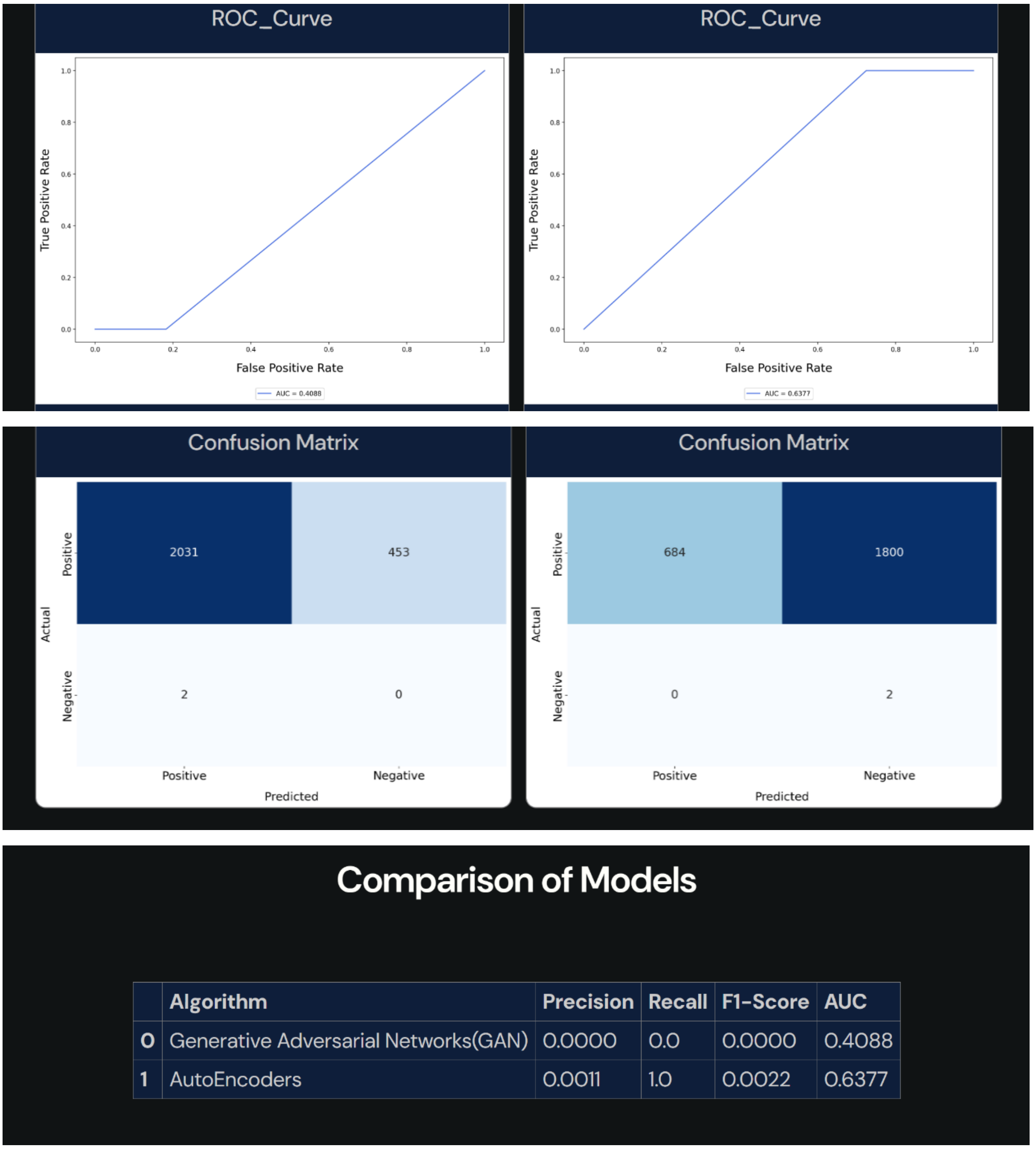


Figure 5.4 Result Visualisation

This dynamic page empowers users with the flexibility to select from a range of cutting-edge anomaly detection models, including GAN, LOF, and DAGMM. Users can also choose datasets of their preference, enabling them to tailor the analysis to their specific needs. Through intuitive visualization tools, users can explore and interpret the results effectively, gaining valuable insights into anomaly detection patterns and trends.

It presents visualizations of key performance metrics such as precision, accuracy, and F1 score, providing users with actionable insights into the effectiveness of different models for anomaly detection tasks.



	Algorithm	Precision	Recall	F1-Score	AUC
0	Generative Adversarial Networks(GAN)	0.0000	0.0	0.0000	0.4088
1	AutoEncoders	0.0011	1.0	0.0022	0.6377

Figure 5.5 Comparison of Models

Through the user-friendly interface, users gain access to dynamic visualizations of crucial performance metrics such as precision, accuracy, and F1 score. Additionally, users can delve deeper into model comparison by examining ROC curves and confusion matrices side by side.

This comprehensive analysis equips users with the insights needed to make informed decisions, ensuring the selection of the most effective anomaly detection model for their tasks.

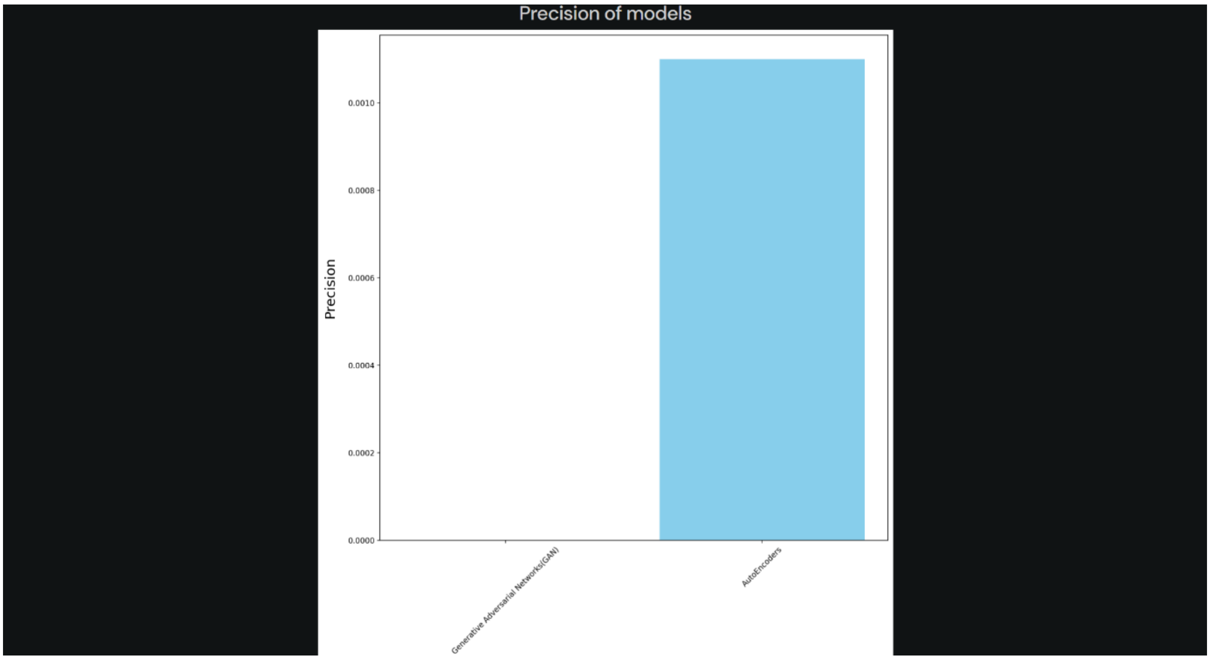


Figure 5.6 Precision Graph Comparison

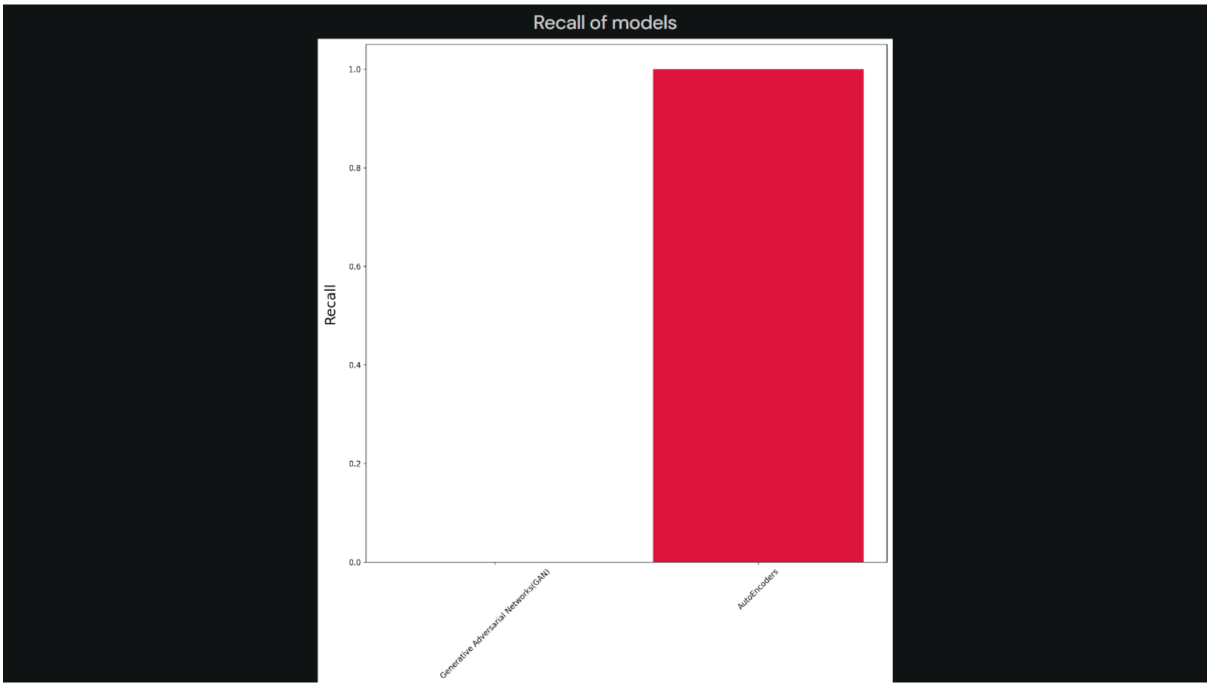


Figure 5.7 Recall Graph Comparison

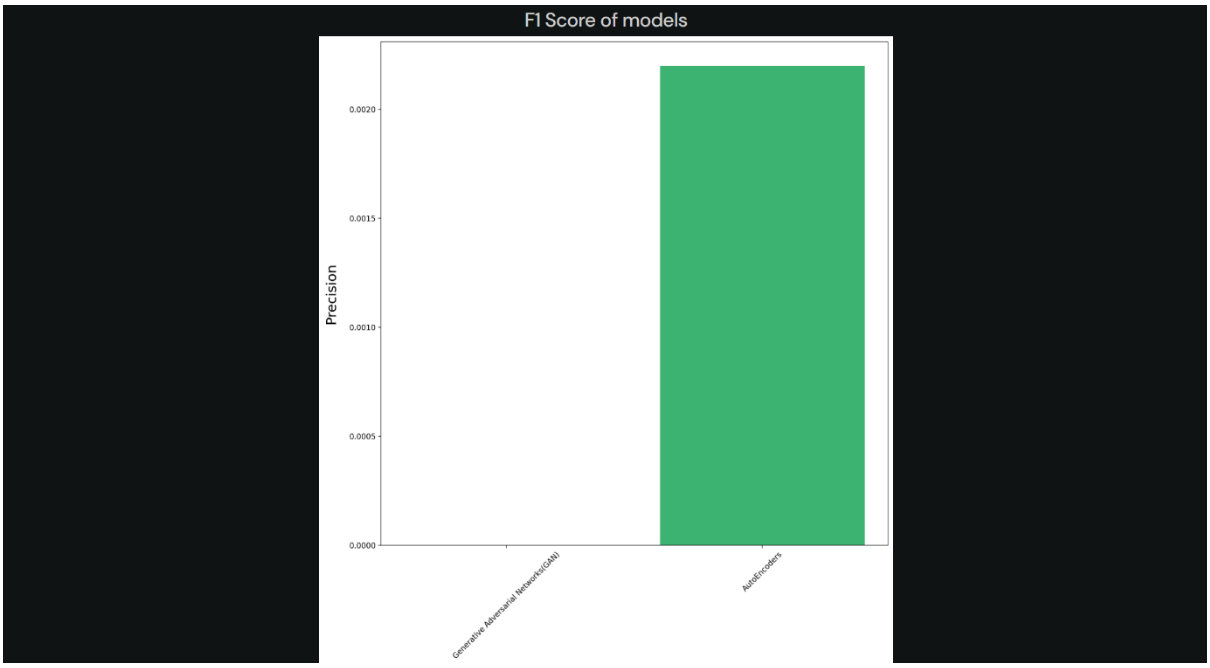


Figure 5.8 F1 Score Graph Comparison

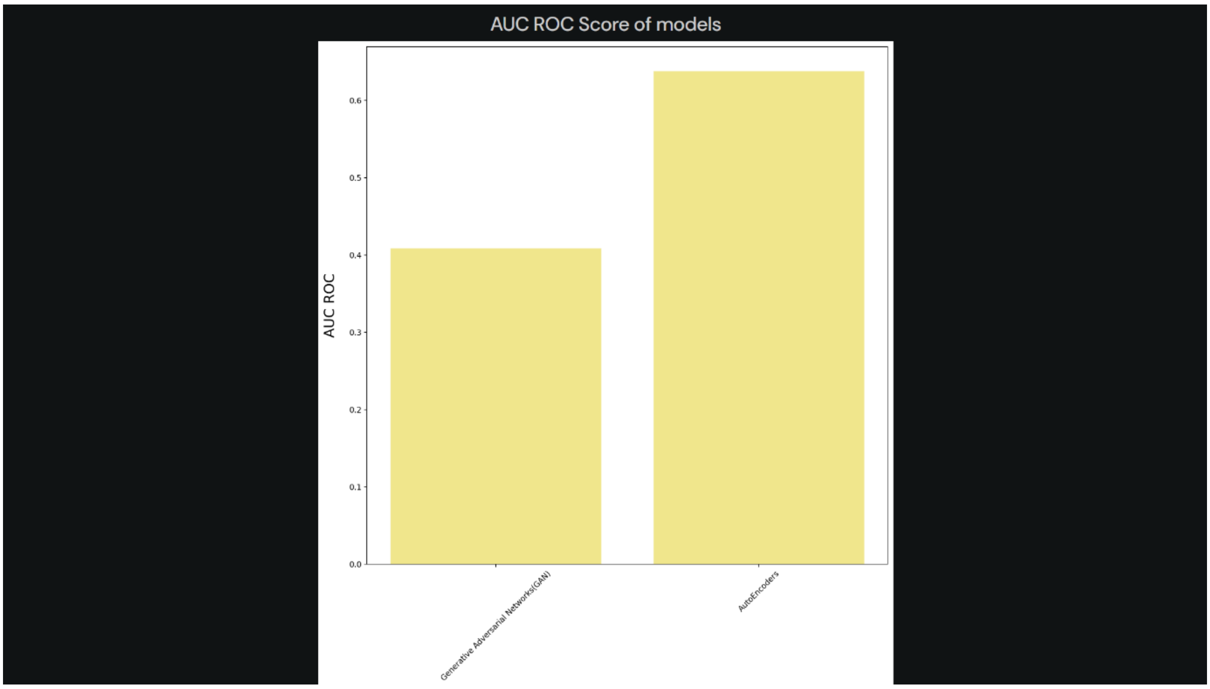


Figure 5.9 AUC ROC Graph Comparison

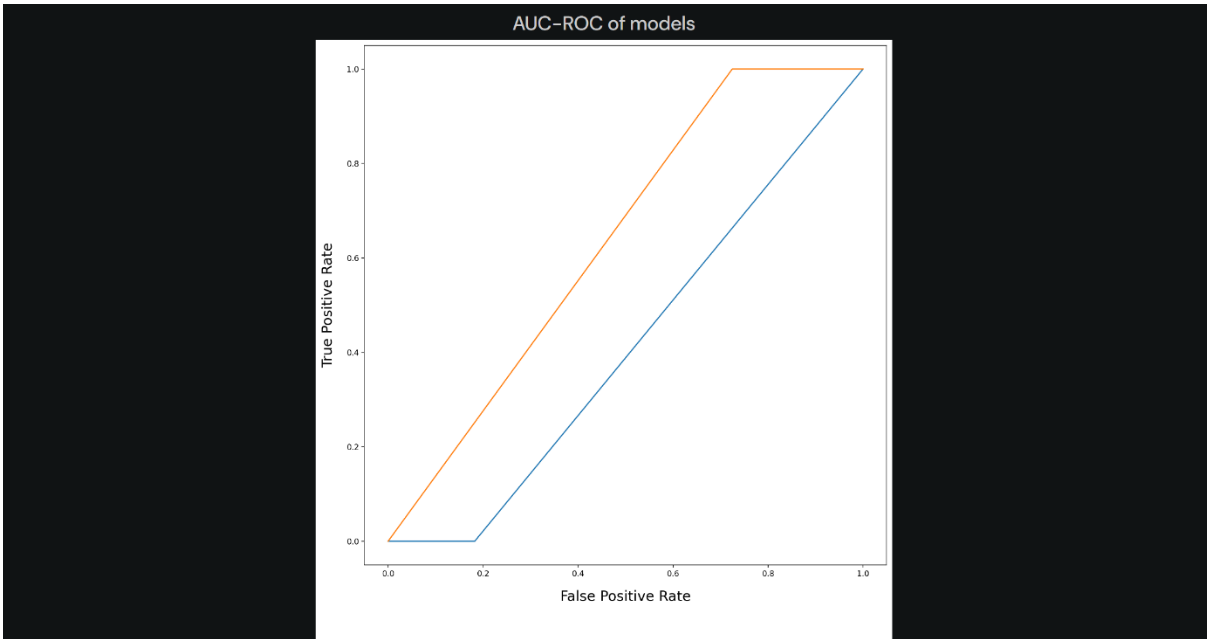


Figure 5.10 AUC ROC of Models

The Data Visualization Page offers users a versatile platform to interactively explore their datasets. Users have the autonomy to select their dataset of interest, empowering them to tailor the analysis to their specific needs. Once a dataset is chosen, users are presented with a variety of visualization options, including interactive scatter plots, informative box plots, and insightful histograms. These visualization tools provide users with a comprehensive understanding of their data, allowing them to uncover patterns, relationships, and distributions with ease. By facilitating dynamic and interactive visualizations, the platform enables users to derive actionable insights and make informed decisions based on the data exploration.

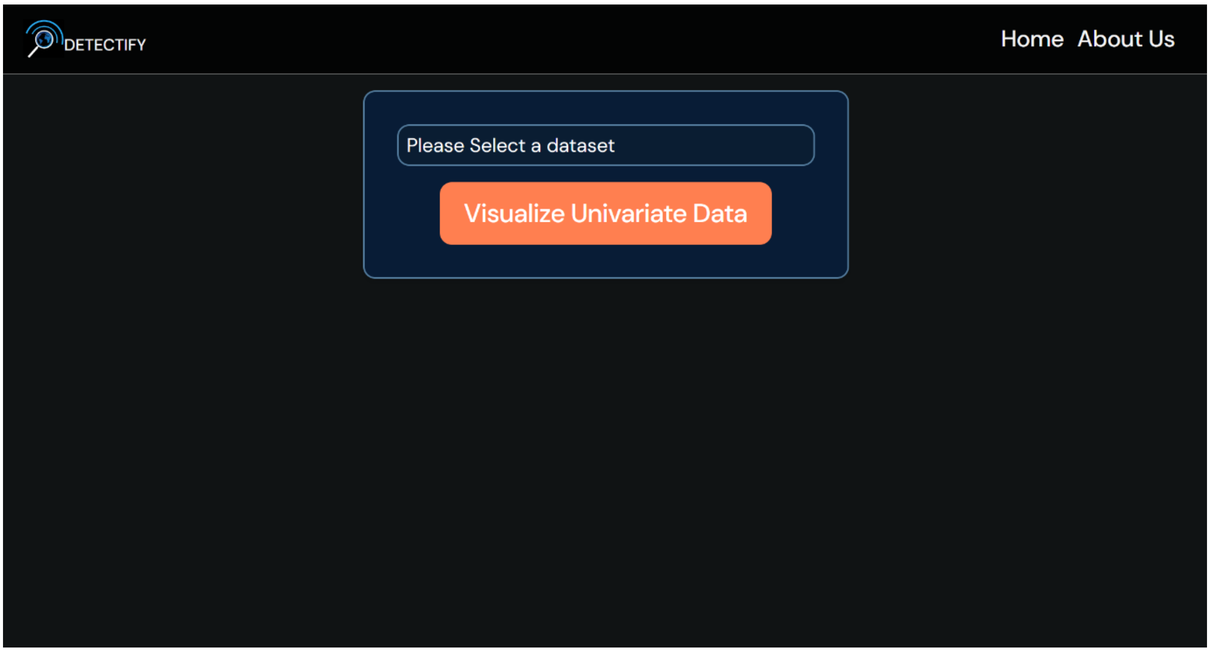


Figure 5.11 Dataset selection for visualisation

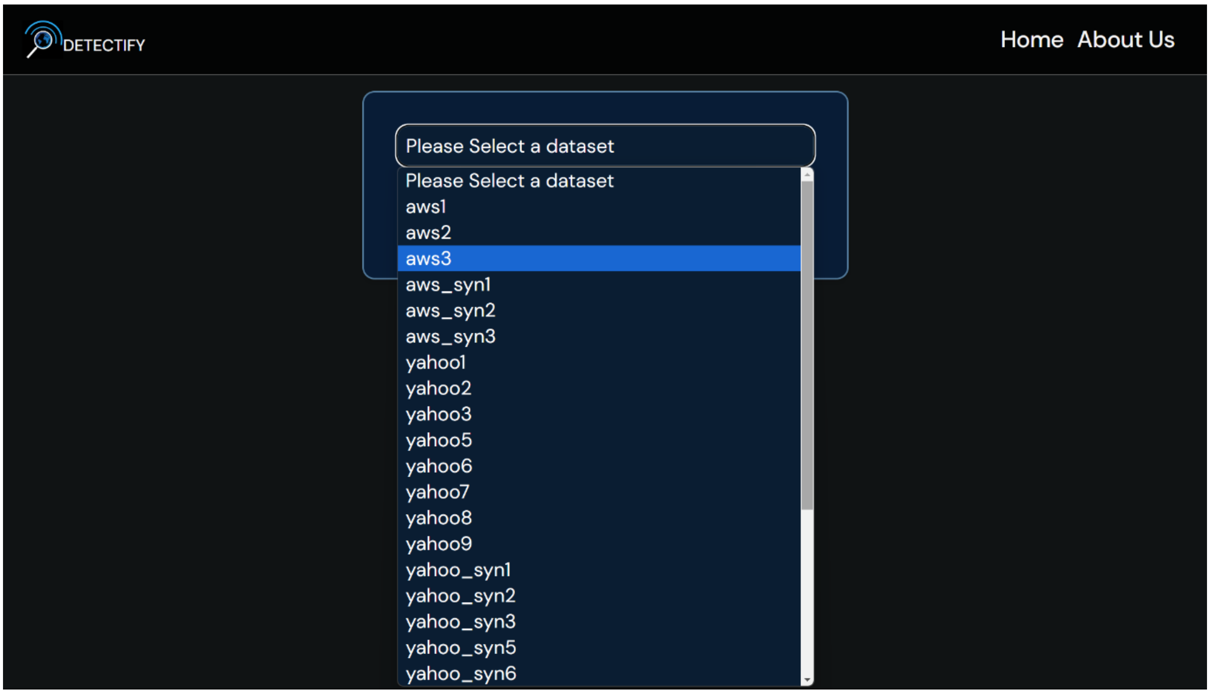


Figure 5.12 Dataset Selection.

Figure 5.13 Data Visualisation.

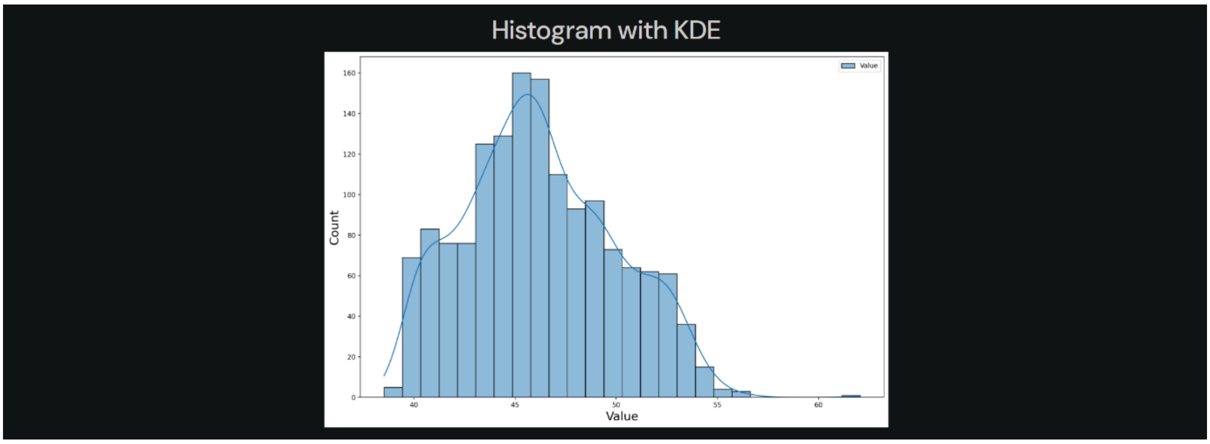


Figure 5.14 Histogram with KDE.

CHAPTER 7:

CONCLUSION AND FUTURE SCOPE

In this research paper, we embarked on a critical endeavor of benchmarking anomaly detection algorithms, addressing the imperative need for robust anomaly detection in intricate mission-critical systems. Our primary contribution is a comprehensive benchmark study evaluating a diverse array of anomaly detection algorithms across 98 datasets from public and proprietary industrial systems. Contrary to the prevailing notion, our findings highlight the superiority of tree-based algorithms, particularly MGBTAI and d-BTAI, over classical machine learning, deep learning, and outlier detection methods. These algorithms demonstrated adeptness in identifying anomalies, even in instances where anomalies occurred rarely.

Tree-based methods exhibited competitive recall values for both univariate and multivariate datasets, outperforming other algorithms in terms of precision, implying fewer false positives while maintaining competitive recall rates. This observation is particularly significant considering precision as a measure of quality, especially in operational fault detection scenarios where false positives are a concern.

Moving forward, our study lays a robust foundation for future advancements in anomaly detection, especially in complex mission-critical systems. Future research could explore hybrid models and investigate the generalization capabilities of algorithms in dynamic environments. Our graphical user interface (GUI) represents a pivotal advancement, facilitating intuitive understanding, insightful analysis, interactive exploration, and decision support for end-users in mission-critical systems. Augmenting the GUI with additional features could further enhance its utility, empowering users to address evolving challenges in anomaly detection effectively.

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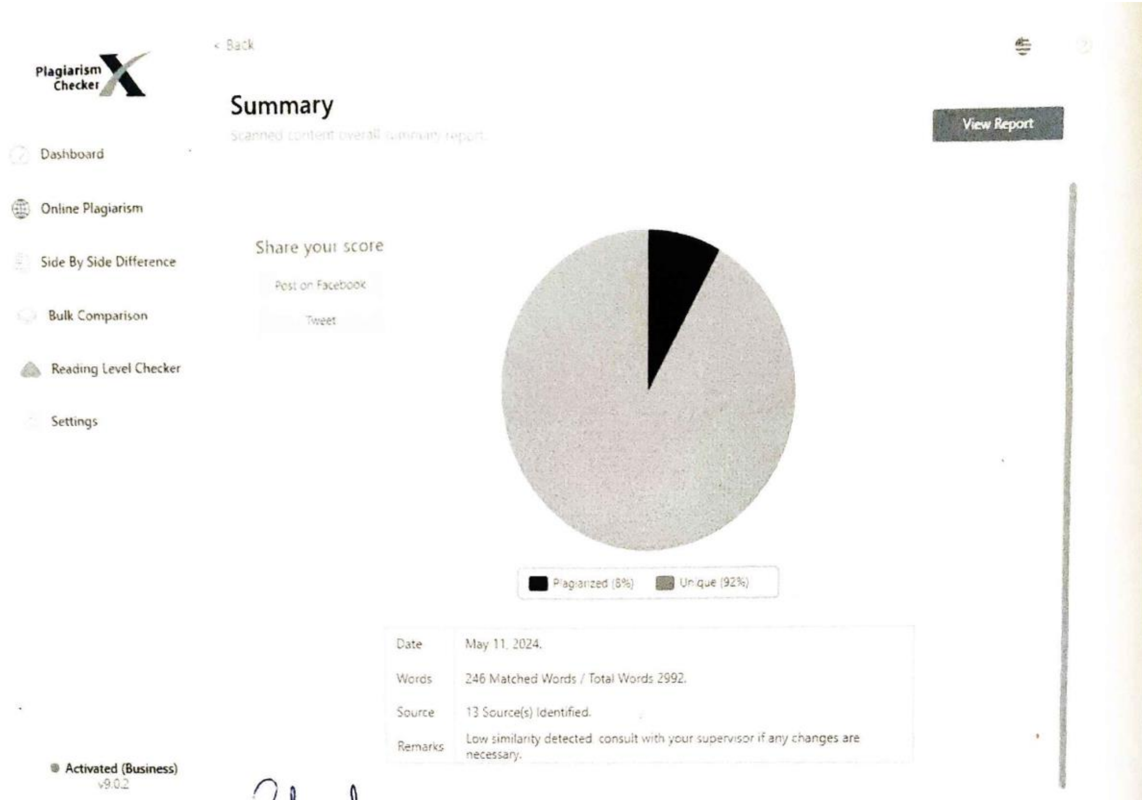

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