



## **Multivariate Anomaly Detection for IoT Medical Sensors**

**SUBMITTED BY –**

**RONIT SINGH**

**DEPLOYED PROJECT LINK:** <https://ai-anomaly-detection.streamlit.app/>

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# 1.INTRODUCTION

## 1.1 Project Overview

The primary goal of this project is to provide a robust, user-friendly platform for the real-time detection of anomalies in multivariate time series data sourced from Internet of Things (IoT) sensors within the medical field. In modern healthcare, continuous patient monitoring and medical device supervision generate vast streams of complex data. This platform addresses the critical need to automatically analyse this data to identify subtle, clinically significant deviations from normal physiological or operational baselines. The solution is an interactive web application, built with Stream-lit, that leverages powerful machine learning algorithms to uncover hidden patterns and flag potential issues. This enables a crucial shift from reactive to proactive clinical intervention and predictive equipment maintenance.

## 1.2 Key Features

- 1.2.1 Medical IoT Focus: The platform is specifically tailored for the unique challenges of medical sensor data, such as heart rate, SpO2, blood pressure, and device temperature.
- 1.2.2 Multiple ML Models: The system integrates several proven anomaly detection algorithms, including Isolation Forest, PCA-based detection, and Autoencoders, allowing users to select the most appropriate model for their specific dataset.
- 1.2.3 Intuitive Clinical UI: A clean, interactive user interface is designed for clinical researchers and biomedical engineers, enabling seamless data upload, configuration, and analysis without requiring deep programming knowledge.
- 1.2.4 Explainable AI (XAI): The platform goes beyond simple detection by providing feature attribution analysis, which pinpoints the specific sensor readings (e.g., "a sudden drop in pressure") that contributed most to a detected anomaly.
- 1.2.5 Advanced Visualizations: It features a comprehensive analytics dashboard with interactive timelines, severity distribution charts, and detailed tables to facilitate in-depth exploration of anomalous events.
- 1.2.6 Real-time Alerting: The application includes an integrated alert system capable of sending SMS notifications via Twilio when severe anomalies are detected, enabling immediate response.

## 1.3 Target Audience

This document and the accompanying platform are designed for a professional audience, including:

- 1.3.1 Biomedical Engineers: For monitoring and maintaining the performance and safety of medical devices.
- 1.3.2 Data Scientists & Clinical Researchers: For analysing patient sensor data to uncover trends and predict adverse health events.
- 1.3.3 Healthcare IT Professionals: For deploying and managing data-driven monitoring tools within a clinical environment.

## 2.SYSTEM ARCHITECTURE

### 2.1. Architectural Diagram

This is the most important part of the section. You should create a simple flowchart or block diagram that visually represents how data moves through your application and how the different Python modules interact with each other.

*Example Flow:* **User Interface (app.py)** → **Data Processing (data\_processor.py)** → **ML Model (anomaly\_models.py)** → **Feature Attribution (feature\_attribution.py)** → **Results & UI (app.py)**

**2.2. Module Descriptions** Here, you'll briefly explain the role of each Python file, giving context to the diagram above.

- 2.2.1 app.py:** This is the main entry point of the application. It handles the user interface, manages the overall workflow, and calls the other modules to perform specific tasks.
- 2.2.2 data\_processor.py:** This module is responsible for all data preparation, including loading the CSV file, cleaning the data (e.g., handling missing values), and preprocessing it for the machine learning model.
- 2.2.3 anomaly\_models.py:** This file contains the core machine learning logic. It includes the different algorithms (Isolation Forest, PCA, etc.) used to detect anomalies in the sensor data.
- 2.2.4 feature\_attribution.py:** After an anomaly is detected, this module analyses it to determine which specific sensors or features were the most significant contributors, providing explainability for the results.
- 2.2.5 utils.py:** This is a collection of helper functions used across the entire application for common tasks like formatting scores, validating data, and creating summary reports.

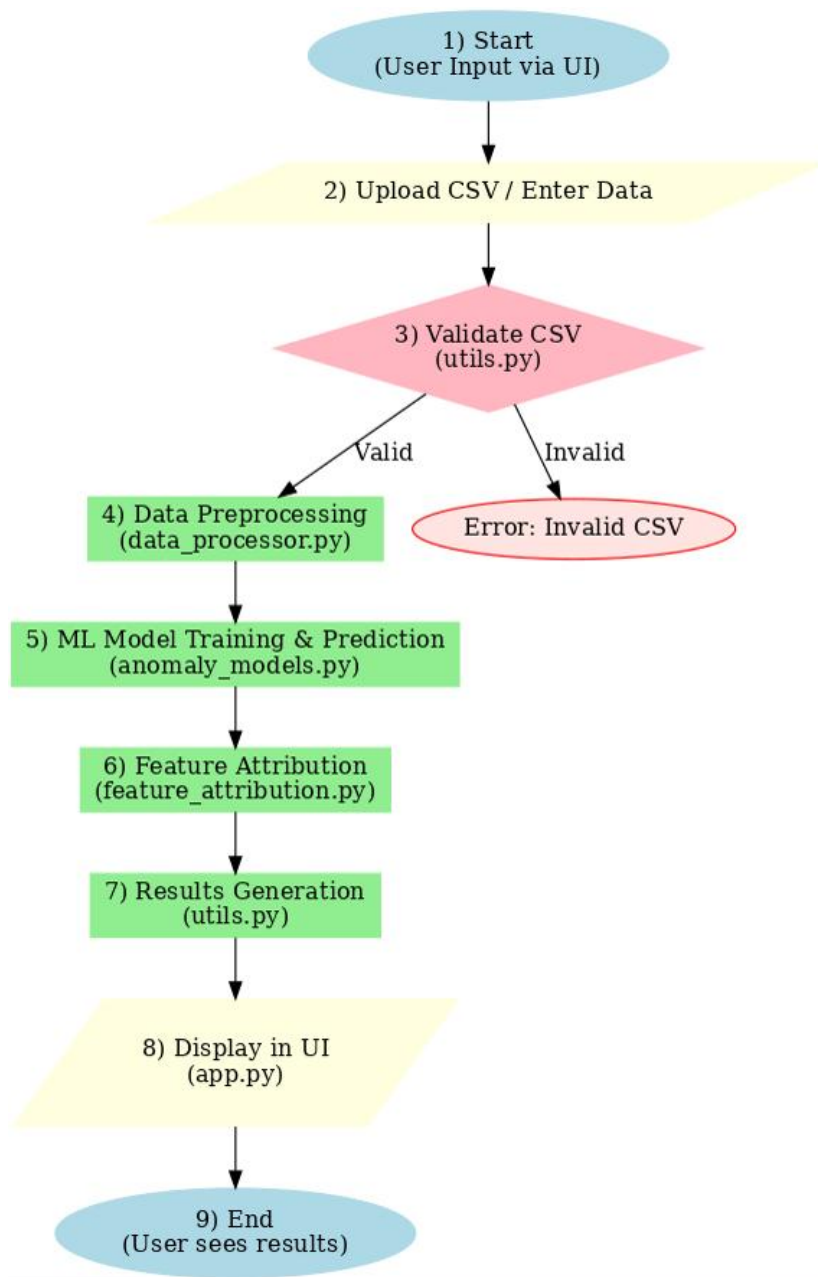


Fig: Application logic and data flow diagram

## 3.USER GUIDE

### 3.1. Prerequisites

**3.1.1 Python:** Version 3.8 or higher.

**3.1.2 pip:** The Python package installer.

### 3.2. Technical Stack & Setup

This project is built with the following technologies. All required libraries can be installed via a requirements.txt file.

#### 3.2.1 Programming Language

**Python** is the primary language used for development.

**3.2.2 Libraries & Dependencies** To install all necessary libraries, create a file named requirements.txt, paste the content below into it, and then run the command `pip install -r requirements.txt`.

- a) Numpy 1.26.4
- b) Pandas 2.2.3
- c) scikit-learn 1.5.2
- d) tensorflow 2.17.0
- e) Plotly 5.24.1
- f) Streamlit 1.38.0
- g) python-dotenv 1.0.1
- h) Twilio 9.7.1

- ☐ Numpy : Used for efficient numerical computations and array operations.
- ☐ pandas: Powers high-performance data manipulation and preprocessing.
- ☐ scikit-learn: Implements traditional ML models like Isolation Forest and PCA.
- ☐ Tensorflow: The deep learning framework used for Autoencoder and LSTM models.
- ☐ Plotly: Creates the interactive visualizations in the dashboard.
- ☐ Streamlit: Builds the frontend web application and user interface.
- ☐ twilio: Manages sending SMS alerts when critical anomalies are detected.

#### iii) Hardware Requirements

- a) The application runs on **standard computing resources** (CPU/GPU).
- b) No specialized hardware is required, but performance on large datasets will benefit from a more powerful CPU or a compatible GPU for TensorFlow models.

#### iv) SMS Notifications

- a) The platform integrates with the **Twilio API** for sending real-time SMS alerts.
- b) Alerts are automatically triggered when a calculated anomaly score exceeds a threshold of **90**.

### 3.3. Running the Application

Once the dependencies are installed, you can launch the application with the following command:

Bash

Stream-lit run app.py

### 3.4. Project Resources & Links

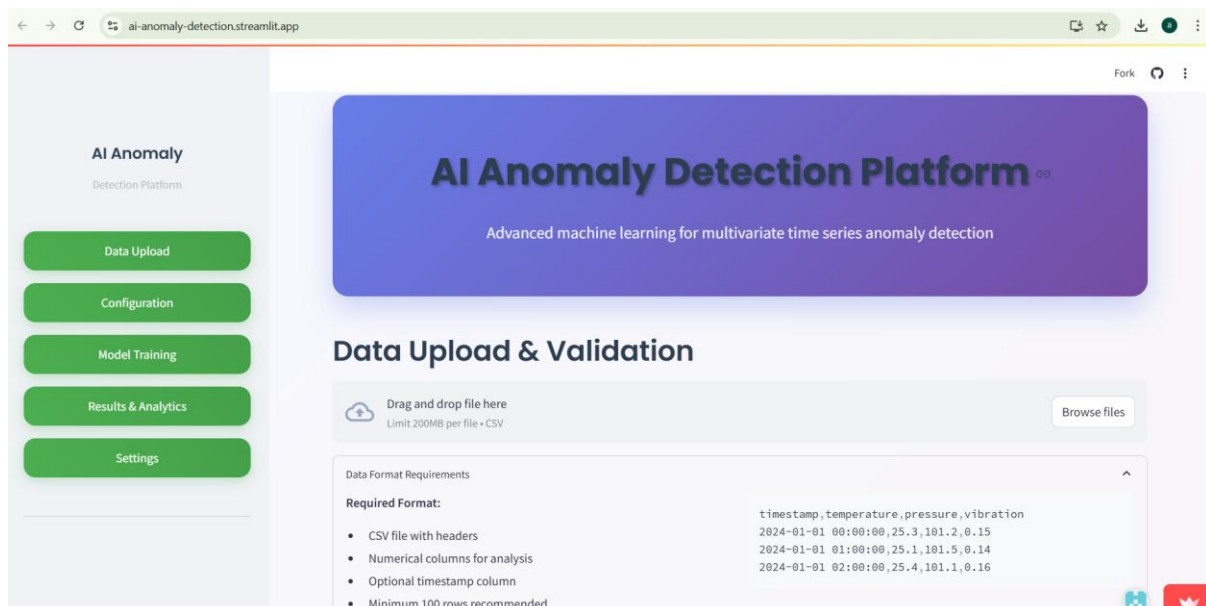
- a) **GitHub Repository:** <https://github.com/ronitsingh2704/ai-anomaly>
- b) **Deployed Application:** <https://ai-anomaly-detection.streamlit.app/>
- c) **Dataset:**  
<https://drive.google.com/file/d/1v3u5qxUR616vZjJH7gflpKyKCzzB45wc/view?usp=sharing>

### 3.5. Step-by-Step Walkthrough

1. **Data Upload:** Explain how to upload a CSV file and the required data format.
2. **Configuration:** Guide the user on selecting features, defining the training period, and choosing an algorithm.
3. **Model Training:** Describe what happens when the user clicks the "Start Training" button.
4. **Results & Analytics:** Explain how to interpret the results dashboard.

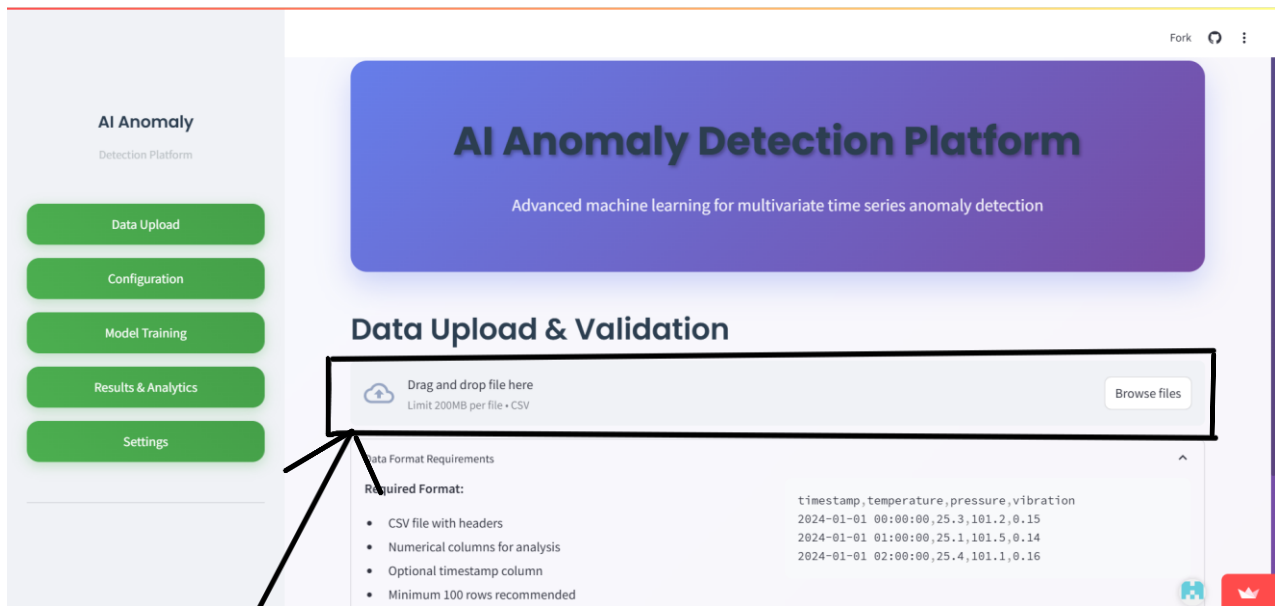
### 3.6 STEP BY STEP ANALYSIS

#### 3.6.1 The main landing page of the AI Anomaly Detection Platform.



- i) Live Link: <https://ai-anomaly-detection.streamlit.app/>

#### 3.6.2 Uploading Dataset



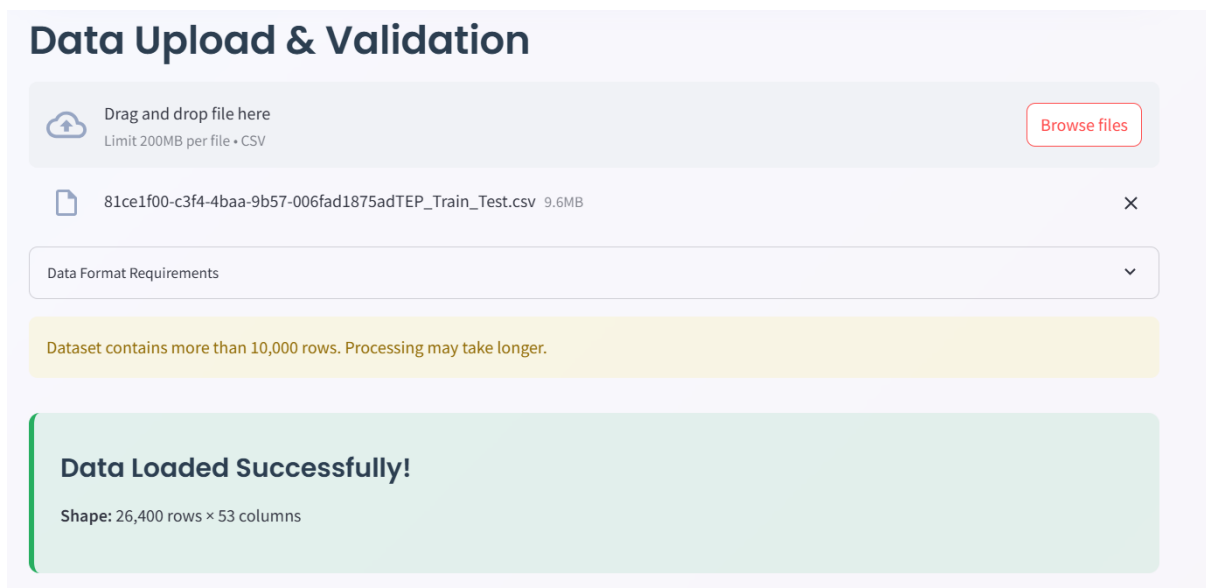
j) **DATASET:**

<https://drive.google.com/file/d/1v3u5qxUR616vZjJH7gflpKyKCzzB45wc/view?usp=sharing>

k) The dataset is a multivariate time-series CSV file containing simulated readings from medical IoT sensors, such as temperature and pressure, designed for anomaly detection.

### How to Upload

- Drag and drop your CSV dataset file directly onto the upload area.
- Alternatively, click the "Browse files" button to select the dataset from your computer.
- Once uploaded, a preview of the data will appear for validation.



### 3.6.3 Data Preview:



In this preview, you should verify the following:

- Correct Columns:** Ensure that all column headers are present and have been read correctly.
- Data Alignment:** Check that the data in the rows appears in the correct columns (e.g., numbers are under the temperature column, dates are under timestamp).
- Successful Parsing:** Confirm that the table appears as expected, which indicates a successful upload.

**AI Anomaly**  
Detection Platform

Data Upload  
Configuration  
Model Training  
Results & Analytics  
Settings

**Data Preview** Statistics Data Types

First 10 rows:

	Time	AFeedStream1	DFeedStream2	EFeedStream3	TotalFeedStream4	RecycleFlowStream8	ReactorFeedRateStream6	ReactorPressurePagauge
0	1/1/2004 0:00	0.2504	3,674	4,529	9.232	26.889	42.402	2,704.3
1	1/1/2004 0:01	0.2511	3,659.4	4,556.6	9.4264	26.721	42.576	2,705.2
2	1/1/2004 0:02	0.2504	3,660.3	4,477.8	9.4426	26.875	42.07	2,706.2
3	1/1/2004 0:03	0.2498	3,661.3	4,512.1	9.4776	26.758	42.063	2,707.2
4	1/1/2004 0:04	0.2941	3,679	4,497	9.3381	26.889	42.65	2,705.1
5	1/1/2004 0:05	0.293	3,691.7	4,502.2	9.378	27.111	41.999	2,703.6
6	1/1/2004 0:06	0.243	3,658.8	4,541.6	9.3374	26.623	42.448	2,704.5
7	1/1/2004 0:07	0.2409	3,653.3	4,500	9.3495	27.075	42.412	2,704.5
8	1/1/2004 0:08	0.2942	3,654.3	4,454.7	9.3213	27.363	42.238	2,703.2
9	1/1/2004 0:09	0.2937	3,675.9	4,487.4	9.4107	26.809	42.144	2,705.2

Last 5 rows:

	Time	AFeedStream1	DFeedStream2	EFeedStream3	TotalFeedStream4	RecycleFlowStream8	ReactorFeedRateStream6	ReactorPressurePagauge
26,395	1/19/2004 7:55	0.2739	3,638.5	4,512.7	9.348	26.764	42.231	2,711.1
26,396	1/19/2004 7:56	0.2541	3,656.7	4,490.2	9.3897	27.067	42.065	2,711.1
26,397	1/19/2004 7:57	0.2566	3,645.5	4,506.3	9.4222	26.647	42.139	2,711.1
26,398	1/19/2004 7:58	0.2199	3,686.1	4,507	9.3934	26.625	42.214	2,711.1
26,399	1/19/2004 7:59	0.2231	3,664.2	4,482.3	9.4352	27.163	42.283	2,705.2

Proceed to Configuration

- Once you have verified the data, proceed to the **Configuration** page to set up the analysis parameters.

### 3.6.4 Feature Selection and configuration

## Feature Selection & Configuration

### Timestamp Column

Select timestamp column

Time

### Feature Columns

Select features for anomaly detection

AFeedStream1 x

DFeedStream2 x

EFeedStream3 x

TotalFeedStream4 x

RecycleFlowStre... x

ReactorFeedRat... x

ReactorPressure... x

ReactorLevel x

ReactorTempera... x

PurgeRateStream9 x

- a) Feature Columns: In this multi-select box, you choose the specific numeric columns (sensor readings) that you want the model to analyse for anomalies. You can select one or multiple features.

## Feature Selection & Configuration

### Timestamp Column

Select timestamp column

Time

### Feature Columns

Select features for anomaly detection

ProductSepTempDegC

ProductSepLevel

ProdSepPressurekPagauge

ProdSepUnderflowStream10

StripperLevel

StripperPressurekPagauge

StripperUnderflowStream11

ReactorFeedRat... x

ReactorPressure... x

ReactorLevel x

ReactorTempera... x

PurgeRateStream9 x

### 3.6.5 Normal Period Definition:

- i) Specify the date range or row indices that represent a known "normal" or healthy baseline period. The machine learning model will be trained exclusively on this portion of the data.

## Normal Period Definition

### Training Period Configuration

Training start date

2004/01/01

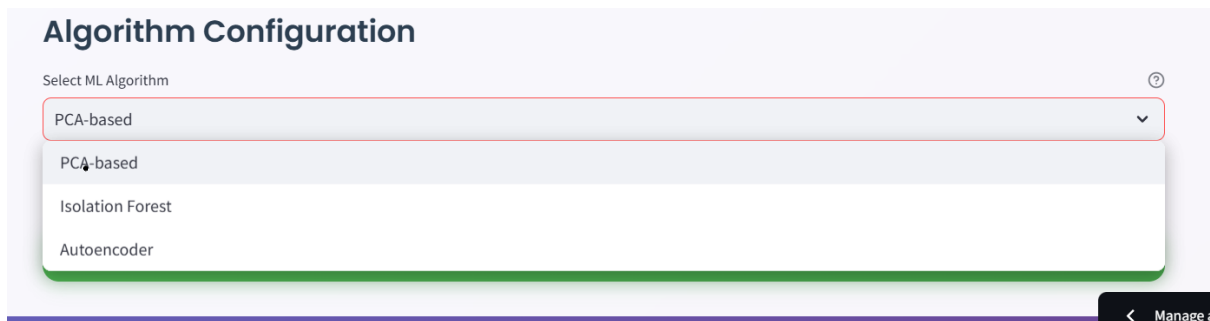
Training end date

2004/01/08

Training period: 7 days

### 3.6.6 Algorithm Selection:

i) Choose the machine learning algorithm you want to use for detection (e.g., **Isolation Forest**, **PCA**, **Autoencoder**).



i) **PCA-Principal Component Analysis (PCA)** is a dimensionality reduction technique that detects anomalies by identifying data points with a high **reconstruction error** when trying to rebuild them from the learned patterns of normal data.

ii) **Isolation Forest** - **Isolation Forest** is an algorithm that isolates data points using random trees, identifying anomalies because they are "**few and different**" and therefore require fewer splits to be separated from normal data.

iii) **Autoencoders** - An **Autoencoder** is a neural network trained to reconstruct its input, detecting anomalies as data points that it fails to rebuild accurately (resulting in a high **reconstruction error**) because they don't match the patterns of the normal data it was trained on.

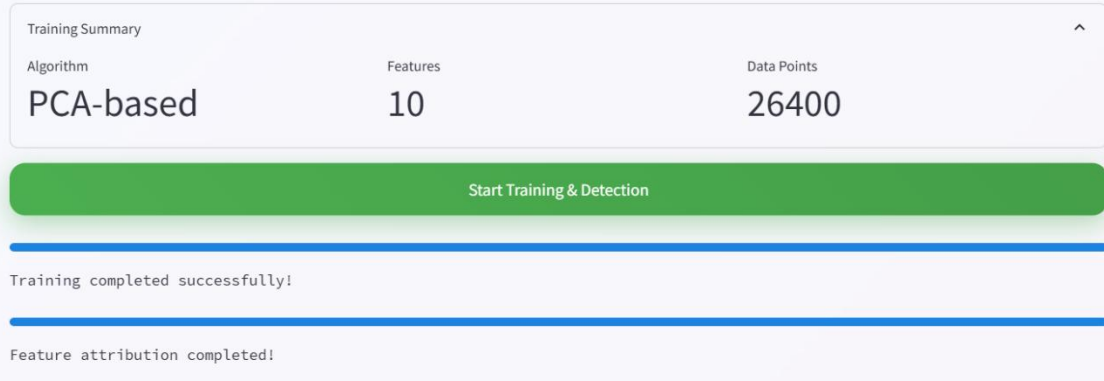
ii) **Advanced Parameters:** This section allows you to fine-tune the behavior of the selected algorithm. For example, you can adjust the "**Expected anomaly rate**" for an Isolation Forest or the "**Number of PCA Components**" for a PCA model. These settings allow you to customize the model's sensitivity and complexity.



Once you have set all the parameters, click the '**Save Configuration & Proceed**' button to begin the model training process.

### 3.6.6 Model training

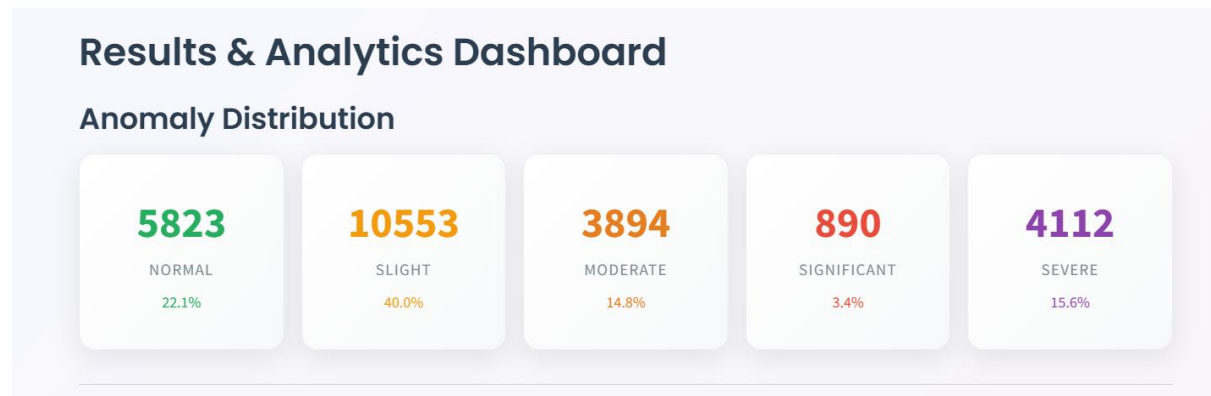
## Model Training & Anomaly Detection



### 3.6.7 Results and analytics

#### i) Anomaly Distribution Summary


At the top of the dashboard, you will find metric cards that provide a high-level summary of the results. These cards display the total count and percentage of data points categorized by their calculated severity, giving you an immediate overview of the dataset's overall health. The categories include Normal, Slight, Moderate, Significant, and Severe.



#### ii) Real-time SMS Alert System

The platform includes a real-time alert system to notify you of critical anomalies. You can enter a phone number in the input field and click the **"Send SMS Alert"** button. An alert is sent if the analysis has detected any "Severe" anomalies (score > 90), summarizing the number of critical events found.

**Important Note:** The integrated Twilio service can only send SMS messages to phone numbers that have been verified in your Twilio account. For testing and demonstration, please use a pre-verified number, such as +91 9410964040.

 **Real-time Alert System**

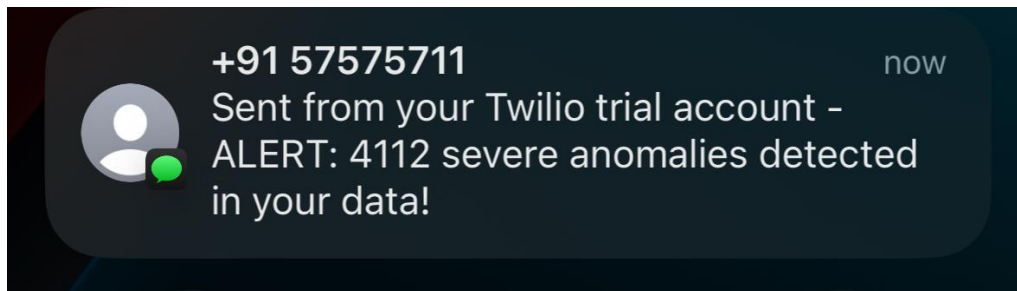
Phone Number (with country code) ?

+91 9410964040

Send SMS Alert

SMS alert sent to +91 9410964040!

### Received Message:

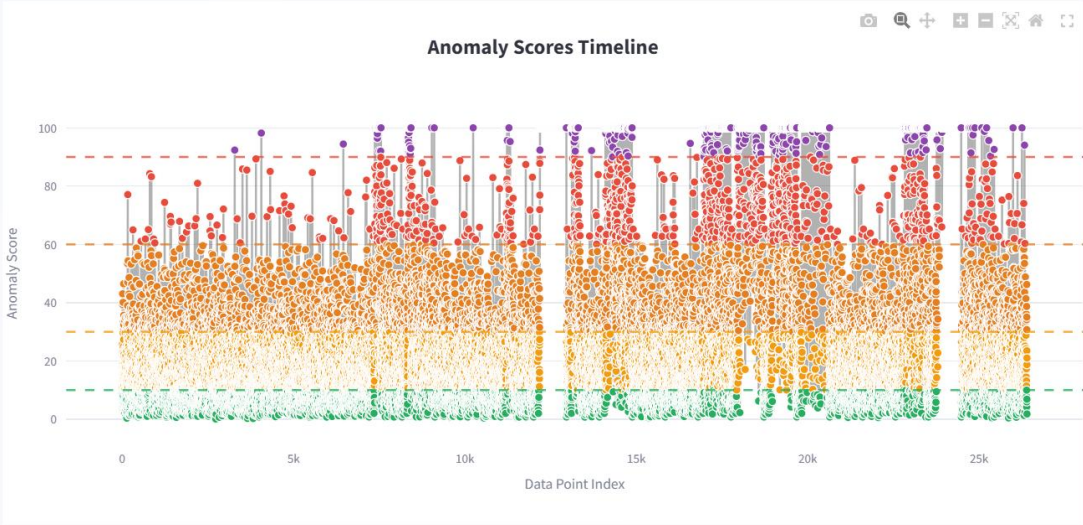


### iii)Interactive Visualizations

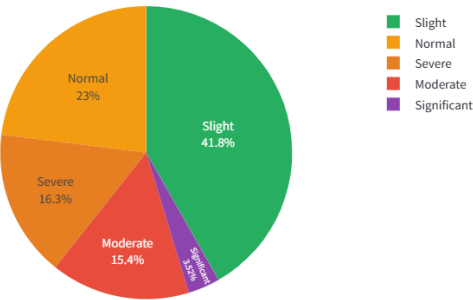
The dashboard includes several interactive graphs to help you explore the results in detail:

- Anomaly Scores Timeline:** This is the main line chart that plots the Abnormality\_score for every data point over time. It allows you to pinpoint the exact moments when anomalies occurred and observe their severity.
- Top Anomalies Bar Chart:** This horizontal bar chart displays the data points with the highest anomaly scores. It helps you quickly identify and focus on the most critical events that require immediate attention.
- Feature Contribution Analysis:** This chart shows which features (sensors) were the most frequent root causes of the detected anomalies. Use this to understand *why* an anomaly occurred, which is crucial for diagnosis.
- Severity Distribution Pie Chart:** This pie chart provides a visual breakdown of the percentage of anomalies in each severity category, offering a clear view of the overall proportion of alerts.

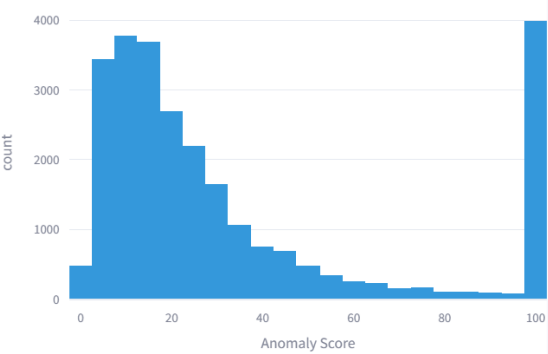
## Interactive Visualizations

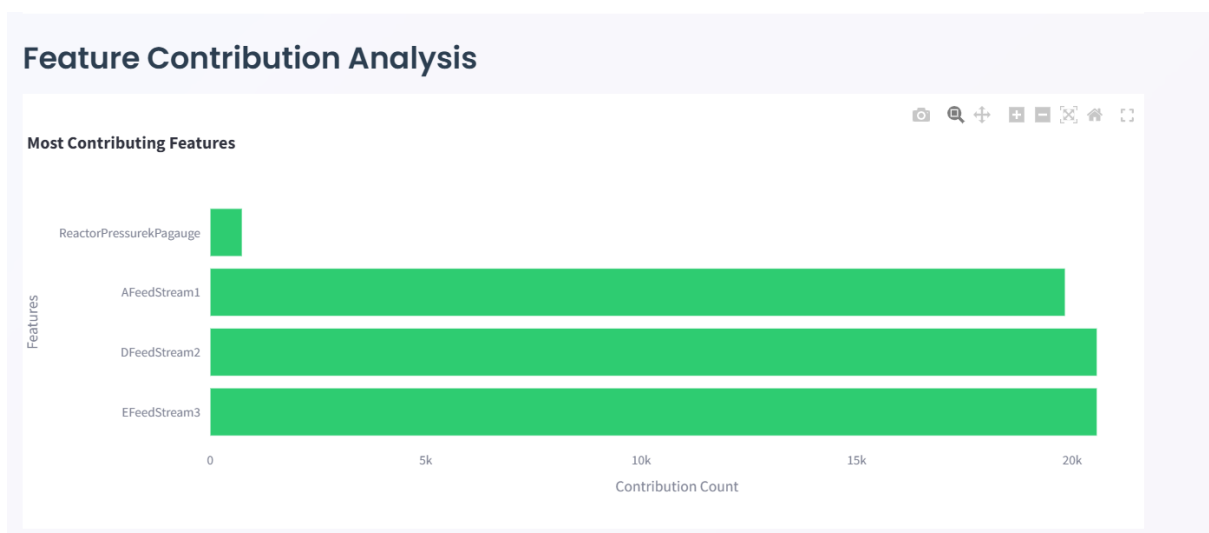
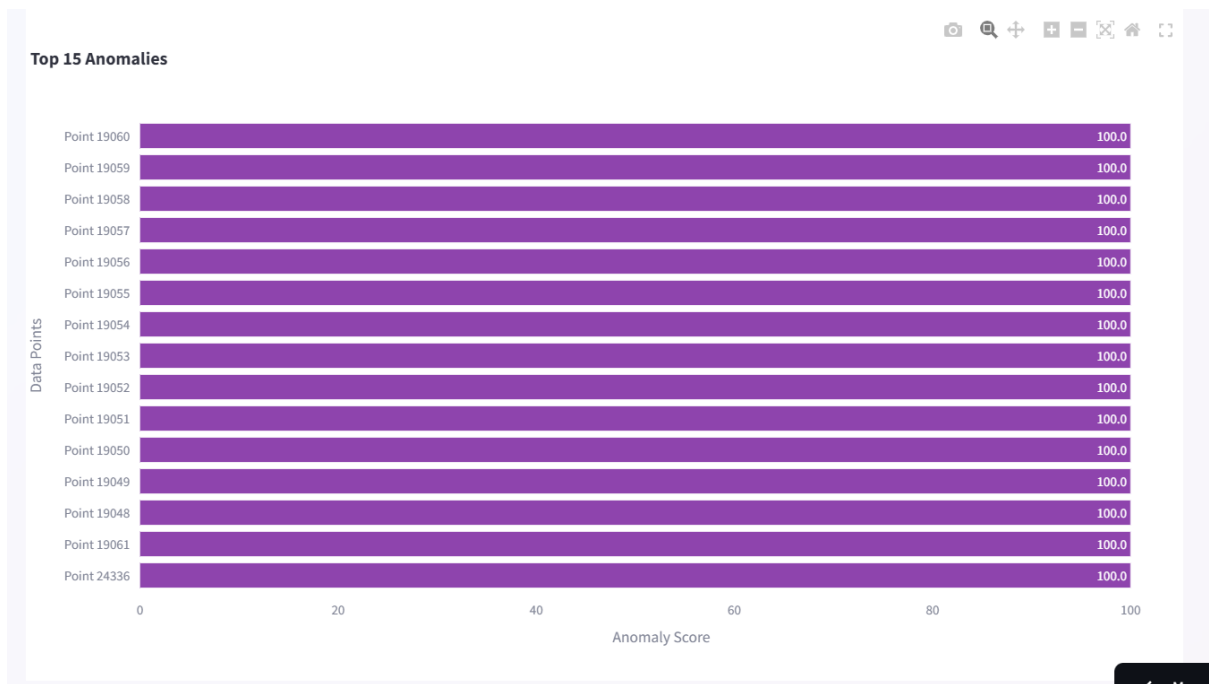


**Severity Distribution**



**Score Distribution**





#### e) Detailed Results Table

At the bottom of the dashboard is an interactive table that provides the most granular view of the results. It contains your original data enriched with the new output columns: Abnormality\_score and the top contributing features (top\_feature\_1, etc.).

Above the table, you will find several controls that allow you to customize the view:

**Adjust by Anomaly Score:** You can filter the results using the "Minimum Score" and "Maximum Score" sliders to view only the data points that fall within a specific score range.

**Adjust Rows Displayed:** You can control how many rows you need to see by selecting a value from the "Show rows" dropdown menu. This is useful for focusing on a specific number of top anomalies.

## Detailed Results Table ↗

Minimum Score

Maximum Score

Show rows

0

100

0

100

0

100

50



	Time	AFeedStream1	DFeedStream2	EFeedStream3	TotalFeedStream4	RecycleFlowStream8	ReactorFeedRateStream6	ReactorPressurekPag
17,061	1/12/2004 20:21	0.2722	3,659.1	4,588.1	9.3879	26.846	42.376	2,
17,060	1/12/2004 20:20	0.2714	3,664	4,561	9.4656	26.921	42.198	2,7,
17,057	1/12/2004 20:17	0.2918	3,677.5	4,504.9	9.267	27.044	42.365	2,7,
17,056	1/12/2004 20:16	0.2936	3,662	4,520	9.4769	26.698	42.569	2,7,
17,055	1/12/2004 20:15	0.2105	3,667.6	4,444.5	9.2889	27.026	42.411	2,7,
17,054	1/12/2004 20:14	0.212	3,668.4	4,458.3	9.2968	26.674	42.365	2,7,
17,053	1/12/2004 20:13	0.2281	3,648.2	4,513.1	9.4768	26.937	42.177	2,7,
17,048	1/12/2004 20:08	0.204	3,646.3	4,450.2	9.3063	26.663	42.581	2,
17,046	1/12/2004 20:06	0.2848	3,697	4,485.9	9.5327	26.923	42.619	2,7,
17,045	1/12/2004 20:05	0.2691	3,607.7	4,480.6	9.3674	27.342	42.581	2,7,
17,044	1/12/2004 20:04	0.2778	3,688.5	4,581.1	9.4881	26.888	42.558	2,

### f) Export Results

The platform allows you to export your analysis for offline use or reporting. You have two functions for downloading the results, available as buttons at the bottom of the page:

i) **Download Enhanced CSV:** This button exports the complete dataset as a CSV file. This file includes all of your original data columns along with the newly generated Abnormality\_score and the seven top\_feature columns, making it ideal for further analysis in other tools like Excel or Tableau.

ii) **Download Summary Report:** This button generates a human-readable text file (.txt) that summarizes the key findings of the analysis. This report includes overall statistics, the distribution of anomalies by severity, and a list of the top 10 most critical anomalies, making it perfect for quick reports and stakeholder updates.

## Export Results ↗

Download Enhanced CSV

Download Summary Report



**Downloaded Enhanced CSV FILE →**

<

## Downloaded Report Summary→

```

File Edit View H1  B I  A
|
ANOMALY DETECTION SUMMARY REPORT
Generated: 2025-08-24 16:37:52
=====

OVERVIEW:
- Total Data Points: 26,400
- Algorithm Used: PCA-based
- Features Analyzed: 10

SEVERITY BREAKDOWN:
- Normal (0-10): 5823 (22.1%)
- Slight (11-30): 10553 (40.0%)
- Moderate (31-60): 3894 (14.8%)
- Significant (61-90): 890 (3.4%)
- Severe (91-100): 4112 (15.6%)

STATISTICS:
- Mean Score: 33.89
- Median Score: 20.72
- Max Score: 100.00
- Standard Deviation: 32.19

TOP ANOMALIES:
1. Row 24336: Score 100.0
2. Row 19061: Score 100.0
3. Row 19048: Score 100.0
4. Row 19049: Score 100.0
5. Row 19050: Score 100.0
6. Row 19051: Score 100.0
7. Row 19052: Score 100.0
8. Row 19053: Score 100.0
9. Row 19054: Score 100.0
10. Row 19055: Score 100.0

=====
End of Report

```

## 4. Appendix

The appendix contains supplementary material that is important for reference but doesn't fit in the main flow of the report.

### 4.1 Full requirements.txt

For reproducibility, this file lists the exact versions of all Python libraries used in the project. This allows anyone to create an identical environment by running `pip install -r requirements.txt`

```
numpy==1.26.4
pandas==2.2.3
scikit-learn==1.5.2
tensorflow==2.17.0
plotly==5.24.1
streamlit==1.38.0
python-dotenv==1.0.1
twilio==9.7.1
```

### 4.2 Configuration Parameters

This table lists the user-configurable parameters available in the application's UI, along with their default values and a brief description.

Parameter	Default Value	Algorithm	Description
<b>Expected Anomaly Rate</b>	0.1	Isolation Forest	The estimated proportion of anomalies in the dataset.
<b>Number of Trees</b>	100	Isolation Forest	The number of random trees to build in the forest.
<b>PCA Components</b>	5	PCA-based	The number of principal components to use for the model.
<b>Encoding Dimension</b>	10	Autoencoder	The size of the compressed data representation in the neural network.
<b>Training Epochs</b>	50	Autoencoder	The number of times the neural network will be trained on the data.

**THANK YOU**