What This Algorithm Does:

Step	Logic
Smooths the data	Removes sensor noise to detect true trend
Detects a stable window	Finds a low-slope, low-noise period — treats it as "normal" behavior
Compares slope	Measures how fast values are rising now, compared to baseline
Self-learns thresholds	No hardcoded values; learns from past system behavior
Classifies state	Normal, Warning, or Critical based on trend steepnes

STEP-BY-STEP EXPLANATION

Step 1: Generate or Input the Sensor Data

python
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```
sensor_data = [...100 readings...]
```

You can use real sensor readings, or generate synthetic ones like in this code:

- First 70 readings → **flat/stable**
- Last 30 readings → **slowly rising**

📦 This simulates a real-world case where your system heats up or degrades over time.

Step 2: Smooth the Sensor Data

python
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```
smoothed = savgol_filter(sensor_data, window_length=11, polyorder=2)
```

Real sensors are noisy, so we **smooth the curve** to focus on the **actual trend**, not random jumps.

🎯 Smoothing makes slope detection more accurate.

Step 3: Detect a Stable "Baseline" Window Automatically

python
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```python
baseline_start, baseline_end = find_stable_baseline(smoothed)
```

Here, the algorithm **scans the smoothed data** to find a window that is:

- Flat (slope ≈ 0)
- Low in noise (low variance)

This window is assumed to be when the system was **behaving normally**.

💡 This is your **reference point** for comparison.

Step 4: Define the Current Window (Recent Data)

python
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```python
current_window = smoothed[-24:]  # last 2 hours if 5 min interval
```

We look at the last 24 readings (2 hours) to see **what's happening now**.

Step 5: Calculate Slope for Both Windows

python
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```python
baseline_slope = (baseline_window[-1] - baseline_window[0]) /
window_size
current_slope = (current_window[-1] - current_window[0]) / window_size
```

- The **baseline slope** shows how fast the system was changing when it was healthy.
- The **current slope** shows how fast it's changing now.

📈 This tells us how much the system behavior has shifted.

Step 6: Define Dynamic Thresholds

python
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```
warning_threshold = 1.5 × baseline_slope
critical_threshold = 2.5 × baseline_slope
```

The algorithm **learns** what's “too fast” by multiplying the baseline slope.

✅ No hardcoded values — this adapts to each system's own behavior.

Step 7: Compare and Classify the System

python
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```
if current_slope > critical_threshold:
    final_state = "Critical"
elif current_slope > warning_threshold:
    final_state = "Warning"
else:
    final_state = "Normal"
```

- If the system is heating up **a lot faster** than it used to → 🔥 Critical
- If it's warming **a bit faster** than before → ⚠️ Warning
- If it's behaving similarly → ✅ Normal

Imagine this:

You're observing a **machine's temperature sensor**.

You're not just asking:

> ❌ "Is the temperature high?"

You're asking:

> ✅ "Is the machine heating up **faster** than it usually does when it's okay?"

That's the **core intuition**

> **You're comparing how fast values are changing now to how fast they used to change when things were normal.**

It's like:

- **You know how calmly your system normally behaves (baseline slope).**
- **You notice that it's now speeding up (current slope).**
- **If the current behavior is too different — you raise an alert.**

💬 Summary: What Your Algorithm Is Thinking

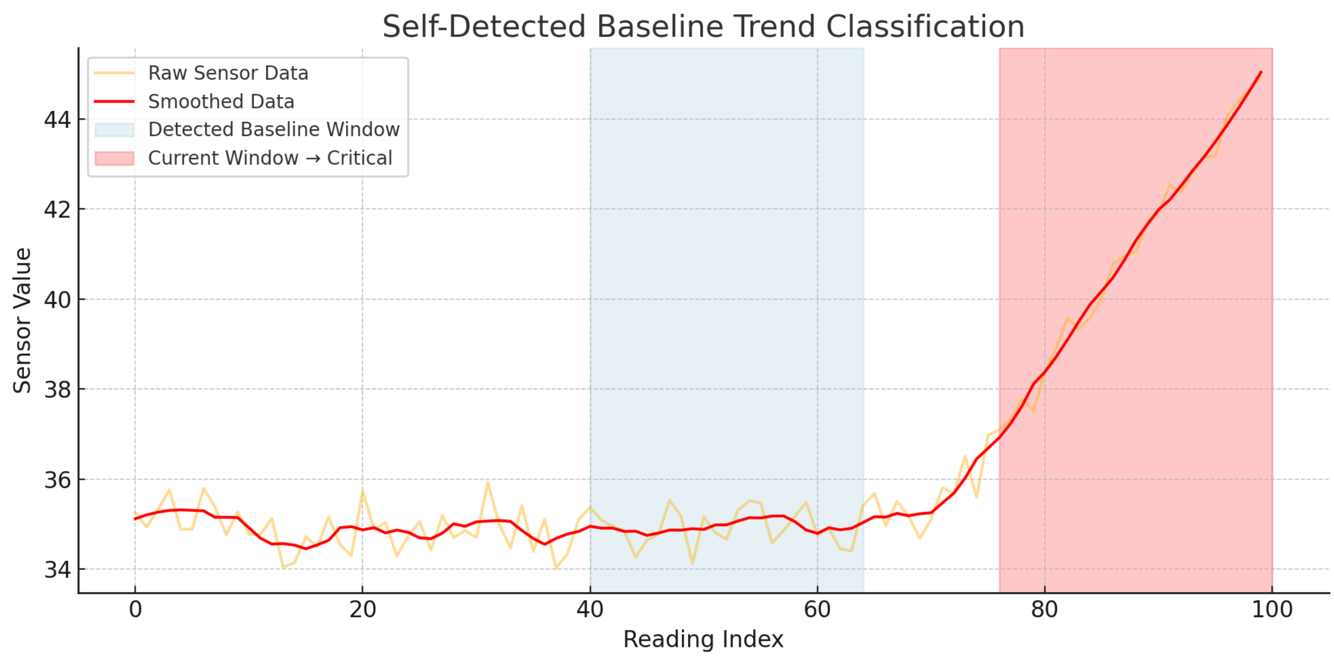
> **"I remember how the system behaves when it's calm.**
> **Now I see it's speeding up more than usual.**
> **This could be trouble — better raise a warning or alert!"**

That's intelligent behavior — not just reacting to fixed values.

logic

```
START
  |
  v
[1] Get sensor data (e.g., 100 readings)
  |
  v
[2] Smooth the data using Savitzky-Golay filter
    - Removes noise
```

```
    - Reveals the true trend
  |
  v
[3] Find a stable "baseline window"
    - Slide a fixed-size window over data
    - In each window:
        • Calculate slope = (last - first) / window_size
        • Calculate variance of the values
    - Select window with:
        • Slope ≈ 0 (almost flat)
        • Lowest variance (least noisy)
  |
  v
[4] Extract the "current window" (latest N readings)
    - This is what we want to classify
  |
  v
[5] Compute slope in both windows:
    - Baseline Slope = (last - first) / size
    - Current Slope = (last - first) / size
  |
  v
[6] Compute thresholds from baseline:
    - Warning Threshold  = 1.5 × baseline_slope
    - Critical Threshold = 2.5 × baseline_slope
  |
  v
[7] Compare current slope:
    IF current_slope > critical_threshold:
        → System State = "Critical"
    ELSE IF current_slope > warning_threshold:
        → System State = "Warning"
    ELSE:
        → System State = "Normal"
  |
  v
[8] Output:
    - Print/return system state
    - Optional: Plot smoothed curve
      with baseline and current window highlights
  |
  v
END
```



FMEA

ID	Failure Mode	Possible Cause	Effect	Severity	Detection	Mitigation
F1	No stable baseline found	All data is noisy, rising, or fluctuating	No valid reference for comparison → misclassification	High	Detected by absence of valid window	Fallback to fixed early window or use median slope
F2	Baseline slope too close to zero	Perfectly flat baseline → thresholds collapse	Even slight rise appears Critical	Medium	Check for too-small baseline slope	Add `min_slope = 0.01` threshold floor
F3	Over-adapting to rising data	Algorithm adapts to slow rising baseline → no alert triggered	Missed early warnings	High	Happens gradually	Add memory: baseline must be pre-current

F4	False Critical during short spike	Current window has a sudden short spike	Unnecessary alert	Medium	High slope with no persistence	Use multi-reading average slope or "3 consecutive alerts" rule
F5	Wrong smoothing settings	Window too wide or narrow → trend is distorted	Slope is inaccurate	Medium	Slopes behave erratically	Tune smoothing: window ≈ 10–25% of total
F6	Real change masked by noise	Slope change is hidden inside jitter	Missed warning or critical	Medium	Slope close to noise-level	Use 2nd derivative or EWMA to detect rising pattern
F7	Thresholds don’t generalize	1.5x/2.5x doesn’t work for all systems	Over- or under-sensitive alarms	Medium	Requires manual tuning	Switch to percentile-based thresholds (e.g., 85%, 95%)
F8	Rolling baseline too old or too recent	Baseline window includes rising or decaying periods	Biased slope learning → wrong threshold	Medium	Compare against annotated system states	Use a fixed-length pre-event zone or stable detection logic
F9	Time resolution mismatch	Δt is wrong (e.g., data is not 5-min intervals)	Slope becomes meaningless	High	Unexpectedly high slope	Require timestamp or resample data
F10	Data gaps or NaNs	Missing or zeroed sensor values	Slope becomes distorted	Medium	Detected by NaN check	Interpolate missing values or discard bad segments

F11	Flat system by nature	Some sensors (e.g., voltage) have near-zero slope always	Slope threshold is always breached	Medium	High alert frequency	Use absolute change + persistence logic
F12	Long system drift	System degrades slowly over days → baseline is no longer valid	Delayed alert or none at all	High	Slope keeps rising but thresholds adapt	Periodically reset or refresh baseline window

High-Risk Items

Risk ID	Why it's critical	How to handle it
F1	Without a stable baseline, system loses reference	Use fixed fallback or robust detection logic
F3	Rising baseline hides abnormal trends	Ensure baseline is *before* current window and limited in slope
F12	Long-term drift causes silent failure	Refresh baseline weekly or based on anomaly count