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Early Fault Detection in Electro-Pneumatic Actuators using Mathematical Modelling and Machine Learning: A Bottling Company Case Study

Samuel Olufemi AMUDIPE[1,], Adeyinka Moses ADEOYE[2], Aderonke Oluwaseunfunmi AKINWUMI[2], Rotimi Adedayo IBIKUNLE[1], Segun ADEBAYO[1]

[1]*Mechatronics Engineering Programme, College of Agriculture, Engineering and Science Bowen University, Iwo, Nigeria*
Samuel.amudipe@bowen.edu.ng/rotimi.ibikunle@bowen.edu.ng/segun.adebayo@bowen.edu.ng

[2]*Department of Mechanical and Mechatronics Engineering, Afe Babalola University, Ado-Ekiti, Nigeria*
aadeoye@abuad.edu.ng/aderonkeakinwumi@abuad.edu.ng

Corresponding Author: Samuel.amudipe@bowen.edu.ng, *+2348068257336*
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Abstract: *This research examines the vital problem of detecting anomalies at an early stage within industrial systems by studying an electro-pneumatic double-acting cylinder actuator used in a bottling facility production line. The occurrence of malfunctions in valves leads to operational inefficiencies, and both planned and unplanned downtime, and additional maintenance expenses. The study contributes a new dual method that unites mathematical modelling and machine learning to overcome the limitations of conventional anomaly detection methods. The predictive model created for the actuator assessed its typical operation by evaluating pressure fluctuations, timing behaviour and displacement performance. Establishing baseline parameters through this process allowed the creation of synthetic datasets for normal operational standards. Real-time measurement points were validated through a baseline reference and machine learning models based on support vector machines received training data from labelled sets. The application of feature selection methods helped find essential variables to boost performance metrics in models. The research created valuable insights by reaching 90% success in operational state identification between normal and anomalous conditions across various test scenarios, which leads to an adaptable predictive maintenance system. The bottling company applied the case application, which led to 25% less machine downtime alongside better maintenance schedules, together with improved reliability during production. The research outcomes match the objectives of Agenda 2063 set by the African Union by supporting industrial development alongside innovation and sustainable economic expansion as well as meeting SDG targets such as Goal 9.4 and Goal 12.6 for sustainable industrial practices. This study provides essential information for industrial optimization policies through operational efficiency measures that demonstrate global significance for predictive maintenance systems. The scientific methods alongside their research results deliver important knowledge regarding industrial ecosystems in Africa and across the world by tackling regional and worldwide sustainable productivity issues.*

Keywords: *Operational deviations, Machine, Early detection, Techniques, Learning*

1. INTRODUCTION

The increasing demand for automation in industrial processes has driven the development of systems capable of identifying and addressing deviations in operational equipment at an early stage. Pneumatic actuators, specifically electro-pneumatic double-acting cylinder actuators, play a critical role in various manufacturing systems, including bottling plants. These actuators are essential for tasks such as moving, positioning, and controlling processes with high accuracy and speed. However, if deviations or faults in these actuators are not detected in time, they can lead to inefficiencies, production downtime, or even complete system failure [1]. In bottling companies, where operational efficiency and accuracy are paramount, ensuring the proper functioning of actuators is a high priority. Deviations such as leakage, wear, misalignment, or pressure inconsistencies in the pneumatic system can significantly impact the performance of the production line.

A predictive maintenance system examines electro-pneumatic actuator faults at early stages through the combination of decision trees and neural networks. The research analyzed single-acting actuators completely while its small dataset collection reduced the approach's general applicability [2]. The research applies combined models that include physics-based operations together with machine-learning algorithms to represent actuator operation. High computational cost, no real-time implementation, and lack of varying operating conditions in simulations [3]. Supervised learning techniques were applied for diagnosing bottling plant pneumatic actuator faults which yielded Random Forest diagnosis with over 90% accuracy results. The system faces these drawbacks because it needs more data along with high computing expenses and extensive features to work properly [4].

Premature actuator deviations in bottling lines can be predicted through an integration of IoT sensors with deep learning models but their deployment requires challenging resource constraints due to latency requirements [5]. The combination of pressure and flow rate and temperature data for anomaly detection analysis improved laboratory accuracy levels. A study demonstrated practical bottle system actuation through reinforcement learning yet it lacked evaluations against standard machine learning while its exploration of actuation types stopped at double-acting cylinders. [6, 7]. Vibration analysis solution to detect pneumatic actuator faults during early stages, fault-tolerant control systems, and stability was not confirmed for industrial-scale bottling plants [8, 9]. The researchers examined data-driven methods for pneumatic system anomaly detection however they encountered difficulties when working with unbalanced data and time-consuming pre-processing steps [10]. The research by Müller presented a lifecycle prediction framework for actuators depending on predictive analytics which experienced obstacles for real-time execution [11].

The research by Patel focused on enhancing the energy efficiency of electro-pneumatic actuators used in bottling operations. The project placed maximum importance on energy efficiency yet failed to emphasize early deviation identification together with defect detection. The authors demonstrated an approach to monitor actuator defects by implementing a digital twin methodology. The real-time simulations of digital twins needed high computational power that required substantial infrastructure investments to link them with real systems [12, 13]. Researchers applied robust algorithms for selecting critical features to detect faults in industrial actuator systems through machine learning. The implementation depended largely on domain experts to generate features for the system [14]. First-principle models partnered with ML algorithms managed to detect faults within double-acting cylinders effectively. The method only functioned under stable operating conditions per the research. Research analyzed various AI algorithms for electro-pneumatic actuator fault detection and GBMs yielded above 93% accuracy as the most effective solution. The research failed to address interpretability problems in black-box AI models and did not perform a cost-benefit analysis to determine advanced AI deployment feasibility in resource-limited bottling facilities. The research presented a dynamic threshold-based fault detection algorithm which improved fault detection performance in high-speed production line electro-pneumatic systems. The detection system only monitored pressure and temperature fluctuations but failed to address faults that stem from electrical or software malfunctions [15, 16, and 17]. The research discussed how supervised and unsupervised learning approaches perform when detecting deviations in industrial actuators. These supervised models needed labelled data to function although the acquisition of such data proves expensive within industrial domains while unsupervised models had limited precision for detecting minor discrepancies. The author applied convolutional neural networks until encountering issues with insufficient dataset size. The research examined pressure and flow monitoring for fault detection by studying only physical measurement data. The authors developed a semi-supervised learning actuator fault detection technique which required limited available labelled data. The method produced stable results although it failed to identify uncommon fault patterns [18, 19, 20, and 21].

The real-time tracking and maintenance planning capabilities of Supervisory Control and Data Acquisition (SCADA) systems became more efficient after integrating predictive analytics features into them. The method depended on historical data collection without active anomaly detection and needed comprehensive adjustments to fit different SCADA systems in each plant [22]. The study developed an adaptive control approach which enhanced double-acting cylindrical actuator performance by maintaining operational stability after faults appeared. Through their design, delivered pneumatic system diagnostics models that could function despite sensor noise. The application of Bayesian networks allowed researchers to perform probabilistic fault prognostics on pneumatic actuators while providing accurate remaining useful life predictions under conditions of uncertainty. These methods need experts to supply conditional probability definitions along with network structure specifications [23, 24].

The research team developed tiny machine learning algorithms for edge deployment to detect electro-pneumatic scheme issues and provide cost-efficient solutions yet these solutions have limited scalability toward complex industrial environments and might compromise accuracy through simplified models. [25]. the application of transfer learning for industrial pneumatic actuator fault detection in various industrial environments allows for minimal retraining necessities [26]. Researches devised a quick anomaly detection method to evaluate streaming plant data from high-speed bottling systems but this approach needed increased computational power and faced false positive problems due to plant data noise. [27]. the performance accuracy of hybrid AI methods with sensor fusion detections becomes higher by including environmental data however face complexities from system advancement alongside dependence on quality sensor data which could be unavailable [28]. The authors employed reinforcement learning to bottle system dynamic control and fault detection yet direct implementation caused adaptability and required extensive training periods and struggled with unanticipated actuator failures that differ from learned patterns [29]. The researchers employed wavelet transform and FFT analysis to detect double-acting cylinder faults in early stages but their detection was prone to noise interferences [30].

AI frameworks for anomalous activity detection in pneumatic systems showed promise for industrial environments through their modular structure but the study failed to validate them in real bottling plants leading to an unknown effectiveness level when used in dynamic industrial environments [31]. With fuzzy logic integrated within neural networks the system provides a fault diagnosis solution for electro-pneumatic actuators but only works effectively under industrial noise conditions and has performance evaluation only shown in controlled environments [32].

The researchers created advanced control systems which operate effectively with partial malfunctions while also developing diagnostic systems to find actuator drift causes but these systems only function under controlled laboratory conditions and require exact model parameter values [35]. Multiple failure factors within electro-pneumatic cylinders received examination to identify their main points of emergence. The authors applied distributed machine learning approaches to industrial pneumatic fault detection systems that enabled quick fault detection along with rapid training processes. A group of researchers created signal processing algorithms which improved fault detection accuracy through machine learning (ML) model implementation, although this process required great data pre-processing work and faced edge device integration difficulties [35, 36, 37, 38]. The implementation of IoT predictive maintenance systems for electro-pneumatic bottling plants decreased plant downtime significantly yet required high initial deployment expenses, and IoT network stability negatively influenced system performance according to research by [39]. The automatic fault adaptation abilities of neural networks improve industrial safety together with speedier fail detection but this enhancement requires extensive computational capacity and real-time operation [40]. The detection of bottling plant faults can be achieved by applying ensemble learning methods to processed signals. The project implements reinforcement learning methods as an adaptive approach for scheduling maintenance of electro-pneumatic actuators. During model development, the reinforcement learning methods required high computational resources because they needed specific adjustments for different industrial uses. The combination of maintenance systems grew complicated because integrating hybrid models required updating rule-based systems for new actuator arrangements, and data processing costs were expensive while reinforcement learning needed difficult testing and confirmation procedures and hybrid models created additional maintenance complexity [41, 42].

Electro-pneumatic double-acting cylinder actuators need high-reliability levels for industrial automation purposes. The existing literature lacks an all-inclusive fault detection system which detects combination faults which include leakage faults, together with actuator motion irregularities as well as pneumatic supply disruptions, and valve system malfunctions. Most recent research focuses on diagnosing faults after their occurrence, without addressing predictive maintenance which enables the detection of potential issues before their appearance.

The methods of conventional maintenance, which combine scheduled and reactive maintenance systems, produce delayed notification that creates additional maintenance expenditures alongside delayed detection of faults. The system inefficiencies cause prolonged equipment stoppages while increasing maintenance prices as well as generating potential workplace risks. A complete fault detection system must be implemented to actively monitor electro-pneumatic actuators because it detects pre-processing faults, which brings enhanced operational efficiency.

The research applies mathematical models together with the SVM algorithm to monitor electro-pneumatic actuators through its analysis of double-acting cylinder anomalies. The predictive system helps spot defects early while preventing system malfunctions and cutting down maintenance expenses, and it provides expanded safety along with expanded adaptability to similar industrial systems.

2. METHODOLOGY

The methodology for identifying deviations in an electro-pneumatic double-acting cylinder actuator involves a systematic approach as shown in Figure 1. The workflow follows steps such as analysis of the system and data acquisition, and builds mathematical models and performs feature engineering before developing machine learning models for real-time monitoring. The model receives its training through fluid dynamics principles and mechanical mechanics principles before undergoing simulation under different scenarios. Statistical methods are used for conducting both feature selection and extraction. The researchers test the machine learning model through cross-validation techniques after its development. The system uses real-time monitoring and model insights for performing deviation detection and diagnosis tasks. The system operates through an interface with the bottling plant's supervisory control system while automatically updating its model continuously. The research method validates its findings in a particular bottling plant before delivering practical results to sustain system dependability.

2.1 Case Study Context

The bottling company in this case study provided a practical environment for evaluating the proposed approach. Bottling operations rely heavily on precision timing and synchronisation, making them particularly vulnerable to disruptions caused by actuator faults. By collecting real-time data from the actuators and applying machine learning algorithms, the study demonstrates the potential to detect deviations early and optimise maintenance schedules.

2.2 Mathematical Modelling and Machine Learning

Mathematical modelling establishes the fundamental understanding of physical dynamics which characterizes electro-pneumatic actuator operational behaviour. The simulated operation under ideal conditions enables the detection of deviations from expected operational outputs. The model includes pressure parameter and displacement parameter and flow rate parameter to develop standard operational characteristics. The use of machine learning depends on historical data to perform operational state classification between normal and faulty conditions while also predicting performance deviations. Sensor data processing adopts three methods which include classification technicalities and anomaly detection while using regression models to monitor failure indications. Through method integration the system becomes capable of detecting elusive operational changes which standard oversight methods cannot detect. Engineers must create dynamic equations for double-acting pneumatic cylinders through modelling of pneumatic supply dynamics and cylinder dynamics and piston-load interaction behavior. The following mathematical derivation will be accomplished in a systematic manner.
Assumptions:

- Linear Behavior of the Pneumatic System
- Supply Pressure
- Actuator Dynamics
- No Air Leakage or Valve Malfunctions
- Training Data Availability
- Feature Selection
- SVM Performance

Variables:
P_1, P_2: Pressures in the chambers (Pa). V_1, V_2: Volumes of the chambers (m³). A_1, A_2: Effective piston areas (m²). X: piston Displacement (m). M: piston and load Mass (kg). K: Spring (N/m). b: Damping (N·s/m). F_{load}: External load force (N). R: gas (8.314 J/ (mol·K)). T: Temperature (K). γ: Specific heat ratio of the gas (dimensionless).

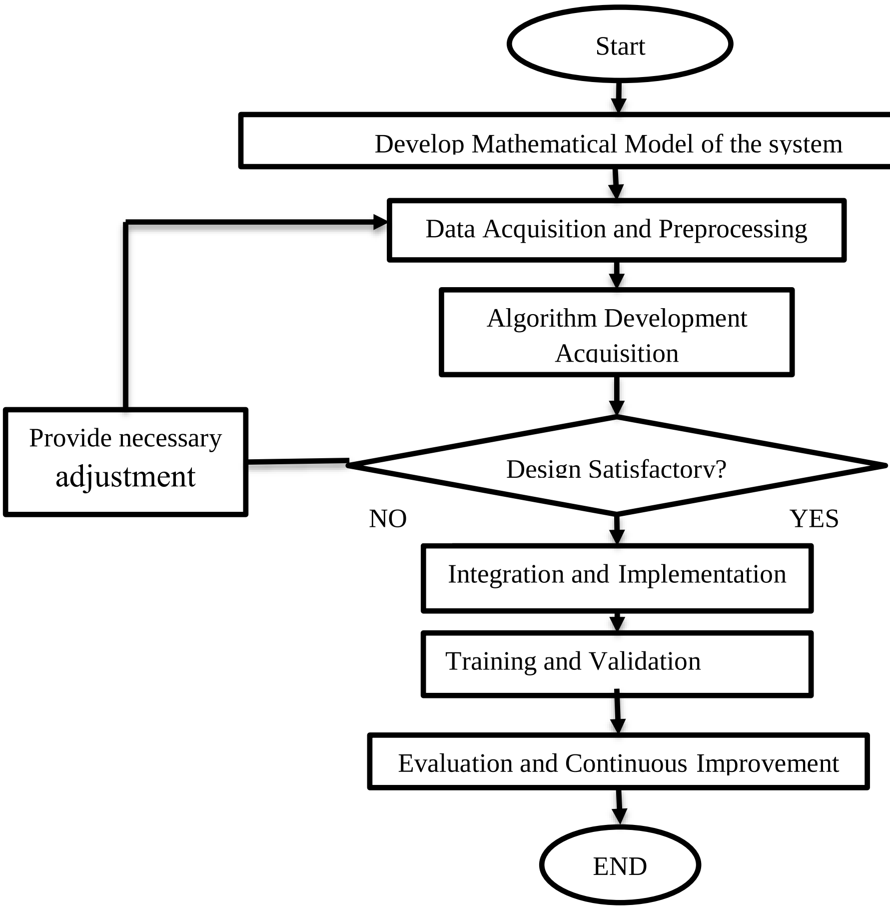

Figure 1: Methodology flowchart

2.2.1 Dynamic equations

Develop the dynamic equations that describe the behaviour of the double-acting cylinder. This involves modelling the pneumatic supply, cylinder dynamics, and the interaction between the piston and load.

1. Pneumatic supply dynamics

Equation 1 represents the volume dynamics of the two chambers of a double-acting pneumatic cylinder. The volume of each chamber depends on its initial volume and the displacement of the piston.
For each chamber, the volume can be expressed as:

$$V_1 = V_{1,0} + A_1 x \tag{1}$$
$$V_2 = V_{2,0} - A_2 x$$

Equation: $V_1 = V_{1,0} + A_1 \cdot x$

Where V_1, This represents the air volume in the first chamber (chamber 1) of the pneumatic system at a certain displacement, $V_{1,0}$: The initial air volume in chamber 1 when the piston is at its starting position (typically when $x=0$), A_1: The cross-sectional area of the piston in chamber 1, It indicates how much volume is added to the chamber per unit of piston displacement, X: The displacement of the piston. A positive displacement indicates that the piston is moving in a direction that increases the volume in chamber 1. In this equation, as the piston moves by a displacement x, the volume in chamber 1 increases by $A_1 \cdot x$ meaning the air in chamber 1 expands.

Equation: $V_2 = V_{2,0} - A_2 \cdot x$

V_2: The air volume in the second chamber (chamber 2) of the pneumatic system at a given displacement, *$V_{2,0}$:* The initial air volume in chamber 2 when the piston is at its starting position, *A_2:* The cross-sectional area of the piston in chamber 2, *X:* The displacement of the piston. Here, as the piston moves by x, the volume in chamber 2 decreases by $A_2 \cdot x$ indicating that the air in chamber 2 is being compressed as the piston moves.
The outlet equation can be used to model the total volume of air entering or exiting the spaces between them. But for the sake of simplicity, let's assume Equation (2) represents the ideal gas law applied to two different states of a gas within a system. The equation is expressed as:

$$\begin{aligned} P_1V_1 &= n_1RT \\ P_2V_2 &= n_2RT \end{aligned} \tag{2}$$

Equation: $P_1V_1 = n_1RT$

P_1*is* the first chamber Pressure, and V_1 is the first chamber Volume. n_1: first chamber Number of moles, *R:* universal gas and T is the gas temperature (assumed to be constant if not explicitly stated). According to this equation, the number of moles of gas (n_1), the gas constant (R), and the temperature (T) are equal to the pressure (P_1) times the volume (V_1) for the gas in the first system or chamber.

Equation: $P_2V_2 = n_2RT$

P_2: The subsequent chamber or system's pressure, R is the universal gas constant, V_2 is the second chamber's volume, and n_2 is the number of moles of gas there. *T:* The gas's temperature. Likewise, this formula represents the second chamber's ideal gas law. It asserts that the number of moles, gas constant, and temperature are all multiplied by the pressure and volume in this chamber. The behaviour of the air in chamber 1 as the piston moves would be described by $P_1V_1 = n_1RT$. The behaviour of the gas in chamber 2 could be described as $P_2V_2=n_2RT$. Pressures P_1 and P_2 adjust to preserve the relationship specified by the ideal while the piston travels and modifies volumes V_1 and V_2. This equation describes how the pressure, volume, and temperature of an ideal gas are related in two different states.

Equation (3) characterizes a fundamental thermodynamic relationship governing the behaviour of a gas within a control volume. It describes the pressure-volume dynamics of a gas under varying conditions.

$$\begin{aligned} \dot{P}_1 V_1 + P_1V_1 &= \dot{n}_1RT \\ \dot{P}_2 V_2 + P_2V_2 &= \dot{n}_2RT \end{aligned} \tag{3}$$

The pressures in chambers 1 and 2 are represented by $(P_1)\dot{}$ and $(P_2)\dot{}$, respectively. The air volumes in chambers 1 and 2 are denoted by V_1 and V_2. $P_1\dot{}$,P_2: Time derivatives of chambers 1 and 2 pressure, which indicate how quickly pressure changes over time derivatives of the quantity of gas in chambers 1 and 2, or the rate at which the air content in the chambers changes, are shown in $n_1\dot{}$,n_2. *R*: The constant for universal gases. *T:* The system's absolute temperature, which is taken to be constant. They explain how the pressure, volume, and quantity of moles of gas—in this case, air—in two distinct chambers of a pneumatic system relate to one another. The equations integrate the dynamics of a pneumatic system with the ideal gas law. Where piston displacement causes the volumes V_1 and V_2 to change over time.

Left Side:

P_1V_1: This term represents how pressure in chamber 1 is changing over time. It shows the influence of the rate of change of pressure on the overall system. *P_1V_1:* This term represents the current state of the gas in chamber 1.

Right Side:

n1RT: This term represents the rate of change of the amount of gas (in moles) in chamber 1, multiplied by gas and the temperature. Since R and T are constants, this shows how changes in the moles affect the pressure and volume relationship in the system. This equation has the same structure as the first one but applies to chamber 2. The terms are similar, and the equation describes how the pressure and volume in chamber 2 evolve based on the degree of alteration of gas molecules for the chamber. In a pneumatic system, as the piston moves, the volumes V_1 and V_2 in chambers 1 and 2 change. This causes pressure P_1 and P_2 to change over time. If air enters or leaves the chambers the pressures will adjust according to the ideal gas law. These equations describe the dynamic behaviour of the gas in each chamber, taking into account both changes in pressure and changes in the amount of gas. Equation (4) signifies the dynamic behaviour of the pressures P_1 and P_2 in two control volumes of an electro-pneumatic system, specifically in a double-acting cylinder actuator. It describes the relationship between pressure changes, volume variations, and mass flow rates within the system.
Since $\dot{n} = \frac{\dot{n}}{M}$ (where M is the molar mass), and $\dot{V}_1 = A_1\dot{x}, \dot{V}_2 = -A_2\dot{x}$:

$$\dot{P}_1 V_{1,0}, + A_1 x) + P_1 A_1 \dot{x} = \frac{\dot{m}_1 RT}{M}$$
$$\dot{P}_2 V_{2,0}, + A_2 x) + P_2 A_2 \dot{x} = \frac{\dot{m}_2 RT}{M} \tag{4}$$

Where: $\dot{P}_1$: change level of pressure in space 1. $\dot{P}_2$: change degree of pressure in space 2. *R:* constant gas, *M: Gas* Molar mass, and *T* is the temperature (assumed constant). $V_{1,0}$: Initial volume of space 1 when the piston is at the starting position, $V_{2,0}$: Initial volume of space 2, $A_{1:}$ Cross-sectional area of the piston affecting space 1, A_2: Cross-sectional area of the piston affecting space 2, *x*: Piston displacement, $\dot{m}_1$: Mass flow rate of gas entering or exiting chamber 1. $\dot{m}_2$: Mass flow rate of gas entering or exiting space 2; $\dot{x}$, Rate of piston displacement (piston velocity). P_1: Pressure in space 1, and P_2: Pressure in space 2. The right-hand side of the equation represents the rate of mass flow into or out of chamber 2, scaled by temperature and the molar mass of the gas. Essentially, it escribes the dynamic behaviour of the gas (air) inside space 2. These equations are fundamental in modelling and controlling pneumatic actuators in industrial automation. They help in designing predictive maintenance algorithms by identifying anomalies in pressure variations.

2. **Cylinder dynamics**

Equation (5) denotes the dynamics of a double-acting pneumatic cylinder**,** describing the motion of the piston and its load based on Newton's Second Law of Motion**.**

$$m\ddot{x} + b\dot{x} + kx = P_1 A_1 - P_2 A_2 - F_{load} \tag{5}$$

m is the mass of the moving element (piston), $\ddot{x}$: The acceleration of the moving element (second derivative of displacement concerning time). *b:* The damping coefficient, representing resistive forces (like friction or air resistance) acting on the moving object, $\dot{x}$: The velocity of the moving element (first derivative of displacement concerning time). *k:* The stiffness (spring constant) representing the elastic force that resists displacement, *x:* The displacement of the mass (position of the piston or moving part relative to some reference), P_1: The pressure in space 1 (e.g., a pressure that pushes on one side of the piston). $A_{1:}$ cross-sectional area of the piston on the side exposed to P_1, translating the pressure into a force, $P_{2:}$ pressure in chamber 2 (opposing pressure on the other side of the piston), A_2: cross-sectional area of the piston of the side exposed to P_2 translating the pressure into a force, and F_{load}: An external force acting on the system (e.g., a load or resistance that the system needs to overcome). This equation governs how the piston moves in response to applied pneumatic forces, damping effects, and external loads.

2.2.2. Fluid dynamic equations:

Incorporate fluid dynamics principles to model the airflow into and out of the cylinder chambers. This includes modelling the pressure dynamics within the chambers

1. **Pressure dynamics**

A double-acting pneumatic cylinder's pressure dynamics are described by equation (6), which shows how the pressure in each chamber varies over time. The equations take into account the actuator motion, chamber volumes, and the mass flow rate of air entering or leaving the chambers.

$$\dot{P}_1 = \frac{RMT}{M(V_{1,0}, + A_1 x)} \left(\dot{m}_1 - \frac{P_1 A_1 \dot{x}}{RT}\right)$$
$$\dot{P}_2 = \frac{RMT}{M(V_{2,0}, + A_2 x)} \left(\dot{m}_2 - \frac{P_2 A_2 \dot{x}}{RT}\right) \tag{6}$$

Where $\dot{P}_1$: is the degree of change of pressure in chamber 1, $\dot{P}_2$: is the level of change of pressure in chamber 2, *R* is the universal gas constant (or specific gas constant if *M* refers to molecular weight), *M* is the molar mass of the gas (or it could refer to the number of moles). *T:* Temperature (assumed constant), $V_{1,0}$: Initial volume of chamber 1 when the piston is at the starting position, $V_{2,0}$: Initial volume of chamber 2, A_1 is a Cross-sectional area of the piston affecting chamber 1. A_2 is the cross-sectional area of the piston affecting chamber 2, *x*: Piston displacement, $\dot{m}_1$: Mass flow rate of gas entering or exiting chamber 1, $\dot{m}_2$: Mass flow rate of gas entering or exiting chamber 2, $\dot{x}$: Rate of piston displacement (piston velocity), P_1: Pressure in chamber 1, and P_2 is the pressure in chamber 2. As the piston moves, it affects the volume of the two chambers (chamber 1 and chamber 2). The volume of the gas into or out of the chambers affects how much gas is present, which influences the pressure. The equations consider the effect of piston motion on the pressure: as the piston compresses the gas (reducing volume), pressure increases; as the gas expands (increasing volume), pressure decreases. The system assumes that temperature T remains constant, and the gas behaviour follows the ideal gas law.
These equations are essential for modelling the pressure response in a pneumatic actuator, which is crucial for designing control strategies, fault detection, and optimizing system efficiency.

2.2.3 Governing equations

Equation (7) represents the continuity equation that ensures mass conservation within the system. For a compressible fluid, it can be written as:

$$\frac{\partial \rho}{\partial t} + \nabla \times (\rho v) = 0 \tag{7}$$

Where p is the fluid density and v is the velocity vector.

1. Navier-Stokes equations: These formulas account for the effects of viscosity and describe the motion of fluid materials. The following are the Navier-Stokes equations for a compressible fluid equation (8):

$$\rho\left(\frac{\partial v}{\partial t} + (v \times \nabla)\, v\right) = -\nabla p + \mu \nabla 2v + \rho g \tag{8}$$

Where p is the pressure, μ is the dynamic viscosity, and g is the gravitational acceleration.

2. Ideal Gas Law: To relate pressure, volume, and temperature in the chambers, we use the ideal gas law:

$$pV = nRT$$

in which p stands for pressure, V for volume, n for the number of gas molecules, R for the universal gas constant, and T for temperature.

2.2.4 Modelling the cylinder chambers

Equation (9) represents the volume V(t) of a chamber in a double-acting cylinder as a function of the piston position x(t). It is given by:

$$V(t) = A\,x(t) \tag{9}$$

Where *x(t)* is the piston's position as a function of time, *V(t)* is the volume of fluid or air that the piston has displaced during movement, and A is the cylinder's cross-sectional area.

When the piston moves a certain distance *x (t)*, the volume of fluid displaced or compressed in the cylinder equals the area *A* multiplied by the displacement. This equation assumes that the chamber volume is directly proportional to the piston displacement. Other factors like dead volume (initial chamber volume when the piston is at rest) are not considered.

1. Pressure Dynamics**:** Using the model gas law as shown in equation 10, the pressure in the chamber container is related to the volume and the mass of air:

$$p(t) = \frac{m(t)RT}{V(t)} \tag{10}$$

Where:

p(t): Pressure at time t, *m(t):* Mass of the gas at time t, *R:* Specific gas constant, T is the gas's temperature, and *V(t)* is its volume at the time *(t).*

At any given time, the mass of the gas *(m (t))* and its temperature *(T)* are directly proportional to *p(t).* Inversely proportional to the volume V (t) is p (t), meaning that if the volume decreases, the pressure increases (assuming mass and temperature are constant). As *V (t)* increases, the pressure *p (t)* decreases if *m (t)* and *T* are held constant, and vice versa.

2. Flow through Valves: Valves control the airflow into and out of the chambers as shown in equation (11). The mass flow rate $\dot{m}$ through a valve can be modelled using the orifice equation:

$$\dot{m} = C_d A_v \sqrt{2\rho(ps - pd)} \tag{11}$$

Where: $\dot{m}$: This represents the mass flow rate of the fluid. A_v, represents the cross-sectional area of the opening (orifice or valve) through which the fluid is flowing. ρ: This is the density of the fluid, typically measured in kilograms per cubic meter (kg/m³). p_s: This represents the supply pressure or upstream pressure, which is the pressure of the fluid before it passes through the orifice or valve. p_d: This denotes the downstream pressure or exit pressure, which is the pressure of the fluid after it has passed through the orifice or valve. The difference between the supply pressure *(ps)* and the downstream pressure *(pdp).* The equation shows that the mass flow rate (m) is directly proportional to the discharge coefficient ***(C),*** the cross-sectional area of the opening *(Av),* and the square root of the pressure differential *(ps−p)* scaled by the density of the fluid *(ρ).* The term $\sqrt{2\rho(ps - pd)}$ represents the flow velocity derived from Bernoulli's principle, which states that the pressure energy converted into kinetic energy results in a flow velocity through an orifice. This equation is derived from the Bernoulli principle and is used to calculate the airflow through an orifice or valve into a cylinder chamber. It assumes that air behaves as an incompressible fluid under certain flow conditions. The square root term represents the velocity of the airflow, determined by the pressure difference between the supply *(ps)* and downstream *(pd)* pressures. The mass flow rate is proportional to the discharge coefficient, valve opening area, and the pressure differential.

2.2.5 System of equations

Equation (12) describes the pressure dynamics in the left and right chambers of a double-acting pneumatic actuator. It is derived based on the principles of thermodynamics and mass flow balance, incorporating the ideal gas law and continuity equation**.** Combining these principles, we can set up a system of equations describing each chamber's pressure dynamics.

For the left chamber:

$$\frac{dpL}{dt} = \frac{RT}{VL(t)}\left(\dot{m}_{in} - \dot{m}_{out}\right) - \frac{RTpL}{VL(t)2} \cdot \frac{dVL}{dt}$$

For the right chamber:

$$\frac{dpR}{dt} = \frac{RT}{VR(t)}\left(\dot{m}_{in} - \dot{m}_{out}\right) - \frac{RTpR}{VR(t)2} \cdot \frac{dVR}{dt} \tag{12}$$

Where:

p_L*:* Represents the pressure of the gas in the system (e.g., pressure of the gas in a chamber). The subscript L may indicate a specific location or a type of gas.

t: Represents time. The equation is a differential equation, indicating how pressure changes over time.

R: The universal gas constant, which is a constant value used in the ideal gas law and thermodynamics. Its value is approximately 8.314 J/(mol\cdotpK).

T: Represents the temperature of the gas in Kelvin. This should be held constant for this equation to be simplified to some extent, or it may vary depending on the system.

$V_L(t)$*:* Represents the volume of the gas chamber or container as a function of time. The volume may change dynamically based on the system configuration (e.g., a variable volume chamber).

$\dot{m}_{in}$, The mass movement speed of the gas entering the system (mass per unit time). This term indicates how much mass is being added to the system over time.

$\dot{m}_{out}$, The mass movement speed of the gas leaving the system. This term indicates how much mass is being removed from the system over time.

dp_L/dt*:* The degree of alteration of pressure in the system over time. It indicates how the pressure changes as the gas enters or exits the system.

dV_L/dt: The rate of change of volume over time. This indicates how quickly the volume of the chamber is changing, which affects the pressure.

This system of equations captures how pressure changes dynamically in both chambers based on the amount of air mass entering and exiting. The changing chamber volume is due to piston movement and the thermodynamic properties of the working gas.

2.2.6 Mathematical formulation of SVM classification

Equation (13) signifies the mathematical formulation of a Support Vector Machine (SVM) classification problem in its primal form with soft margin constraints.

SVM classifies the data by solving the following problem:'

Min

w, b,ξi1/2‖w‖2

Subject to the constraints:

$$Yi\,(w^T x_i + b) \geq 1 - \xi_i,\ \xi i \geq 0, \text{ for all } I = 1, 2\ldots N \tag{13}$$

Where:

w is the weight vector that defines the hyperplane,

b is the bias term,

y_i is the label (either +1 for normal or -1 for anomalous) for each training sample x_i,

ξ_i are slack variables that allow for some misclassification.

For non-linear classification, the kernel trick is applied to map the data to a higher-dimensional space:

$K(x_i, x_j) = (xi) \cdot \Phi(x_j)$

Where K is the kernel function) and $\Phi(x_i)$ is a mapping to a higher-dimensional space.

This formulation allows SVM to handle non-linearly separable cases by introducing a penalty for misclassified points through the slack variables ξi.

2.2.7 Force balance:

Pneumatic forces, friction forces, and external loads are among the forces that are modelled acting on the piston. Pneumatic forces, friction forces, and external loads are only a few of the factors that must be taken into account when modelling the forces operating on the piston in an electro-pneumatic double-acting cylinder.

1. Pneumatic forces: Equation (14) defines the pneumatic force ***($F_{pneumatic}$)*** acting on a double-acting cylinder actuator**.** It is derived from the pressure difference acting on the piston surfaces. The pressure of the air acting on the piston surfaces generates the pneumatic forces. For a double-acting cylinder:

P_1 is the pressure in the front chamber (pushing the piston rod out).
P_2 is the pressure in the rear chamber (pulling the piston rod in).
A_1 is the effective area of the piston on the front side.
A_2 is the effective piston area on the rear side (typically smaller due to the rod area).
The pneumatic force can be expressed as:

$$F_{\text{pneumatic}} = (P_1 \times A_1) - (P_2 \times A_2) \tag{14}$$

Where, $\boldsymbol{F_{pneumatic}}$*:* This is the net force generated by the pneumatic system. It represents the effective force that can be utilized to perform work, such as moving an actuator, lifting a load, or applying pressure to a mechanism. P_1: Often called the supply chamber, this is the pressure in the pneumatic actuator's first chamber. Units of force per unit area, like Pascals (Pa) or pounds per square inch (psi), are commonly used to measure it. A_1: The piston's cross-sectional area in the first chamber is shown here. It is the area where the pressure P_1 is applied effectively. Typically, square inches (in^2) or square meters (m^2) are used as the unit. P_2: Often called the return chamber, this is the pressure in the pneumatic actuator's second chamber. Force per unit area is used to measure it, just like P_1. A_2: The piston's cross-sectional area in the second chamber is seen here. Similar to A_1. It indicates the area over which the pressure P_2acts in the opposite direction.

2. Friction Forces: Friction forces can be categorized into static friction (when the piston is at rest) and dynamic friction (when the piston is moving). The friction force F_{friction} depends on the nature of the piston movement and the properties of the cylinder's materials. A mixture of static, viscous, and Coulomb friction can frequently be used to simulate the friction force as shown in equation (15):

$$f = Fs + Fc + bf\dot{x} \tag{15}$$

Where Fs represents the coefficient of static friction, Fc the coefficient of Coulomb friction, and bf the coefficient of viscous friction. The following is a typical dynamic friction force model:

$$F_{\text{friction}} = \mu \times N$$

The pneumatic force acting on the piston is represented by the normal force, N, and the coefficient of friction, μ.

3. External Loads: External loads F_{external} can include any force that acts on the piston from outside the cylinder, such as forces due to the load being moved by the piston or any additional resistances.

4. Force Balance Equation: Taking into account Newton's second law equation (16), the sum of these forces can be used to define the piston's total force equilibrium equation:

$$F = ma \tag{16}$$

Where m is the mass of the piston and a its acceleration

$$m \cdot a = (P_1 \cdot A_1) - (P_2 \cdot A_2) - F_{\text{friction}} - F_{\text{external}}$$

Rewriting the equation in terms of acceleration:

$$a = (P_1 \cdot A_1) - (P_2 \cdot A_2) - F_{\text{friction}} - F_{\text{external}}$$

Incorporating Friction Models
The friction force can be more accurately modelled as shown in equation (17), using a combination of static, Coulomb (sliding), and viscous friction:

$$F_{\text{friction}} = F_{\text{static}} + F_{\text{Coulomb}} + F_{\text{viscous}} \tag{17}$$

Where the friction force that remains static (present when a piston starts moving) is denoted by Fstatic. The Coulomb friction force, or F_{Coulomb}, is constant when the piston is moving steadily.
$F_{\text{viscous}} = \mu_v \cdot v$ the viscous friction force, proportional to the piston velocity v, with μ_v being the viscous friction coefficient. By incorporating all these forces into the model, we will get a comprehensive understanding of the dynamics of the piston in an electro-pneumatic double-acting cylinder:

$$m \cdot a = (P_1 \cdot A_1) - (P_2 \cdot A_2) - (F_{\text{static}} + F_{\text{Coulomb}} + \mu_v \cdot v) - F_{\text{external}}$$

This force balance equation can be used to analyse the motion and performance of the piston under various operating conditions, helping in the development of intelligent algorithms and condition monitoring techniques for early anomaly detection. Identify and estimate the model's key parameters such as friction coefficients, pneumatic capacitance, and resistance. Identifying and estimating key parameters such as friction coefficients, pneumatic capacitance, and resistance for an electro-pneumatic double-acting cylinder actuator involves a combination of experimental data collection, mathematical modelling, and system identification techniques.

2.7 Data Acquisition

Data Acquisition Flowchart for fault detection in electro-pneumatic actuators Figure 2.

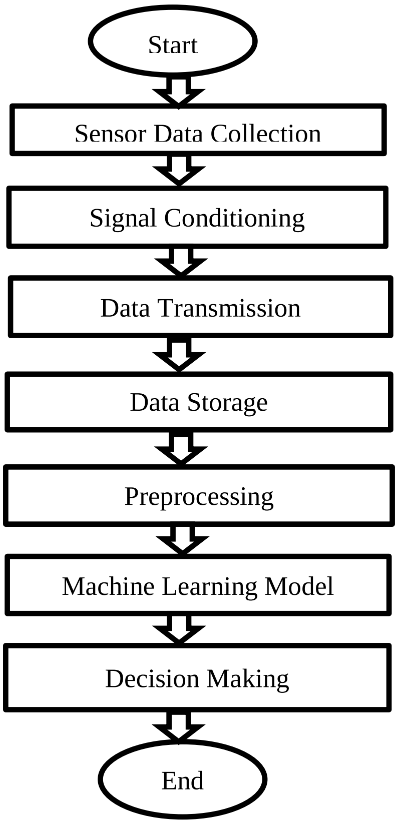

Figure 2: Data acquisition flowchart

Each cylinder in a filling station pours the right amount of product into the bottles thanks to careful control of several characteristics. Table 1, offers a dataset that shows the normal performance of such a filling station by recording key characteristics throughout cycles. The dataset describes the behaviour and performance of the cylinder during a single operational cycle under typical operating conditions and comprises measurements made at intervals of 0.1 seconds.

2.8 Algorithm Development for Electro-Pneumatic Double-Acting Cylinder using support vector machine.

An algorithm development block diagram shown in Figure 3, for detecting anomalies in an Electro-Pneumatic Double-Acting Cylinder using a Support Vector Machine (SVM). Assume we are building an incipient fault detection model based on the data from the cylinder parameters (e.g., pressure, velocity, position, etc.).

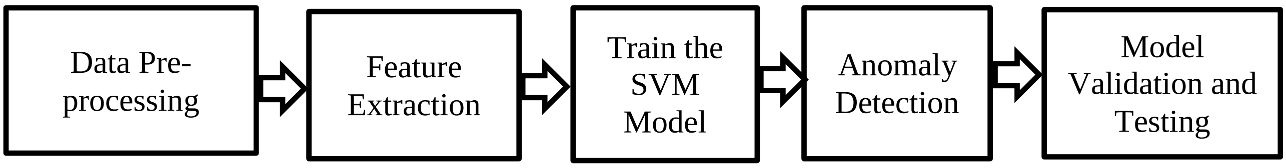

Figure 3: Algorithm development block diagram

The techniques shown in figure 1 are performed sequentially, Data Pre-processing, Collecting and pre-process the sensor data. Label the data for the SVM as either "normal" (0) or "Anomaly" (1) and, Divided the data into training and testing sets. Table 3, Feature Extraction, Extract key features such as pressure, position, velocity, force, air flow rate, temperature, etc. Normalize/standardize the features for SVM input. Train the SVM Model: Use the training data to train the SVM model. Tune hyperparameters like the kernel (linear, radial basis function (RBF), etc.). Anomaly Detection is for real-time monitoring, using the trained SVM model to classify incoming data points as normal or abnormal. Implement performance metrics such as accuracy, precision, recall, F1 score, etc. Model Validation and Testing: Evaluate the SVM model on a test dataset. Validate the model performance and fine-tune parameters if needed.

Machine Learning Model Training Block Diagram was employed as shown in Figure 4. An SVM classifier was chosen for its robustness in handling high-dimensional spaces and its ability to create clear decision boundaries. Table 2, shows the comparison with other models. The polynomial kernel was selected as it allows modelling more complex decision boundaries compared to linear kernels. SVM's strengths lie in its margin maximization and versatility with kernels, making it unique compared to other machine learning algorithms.

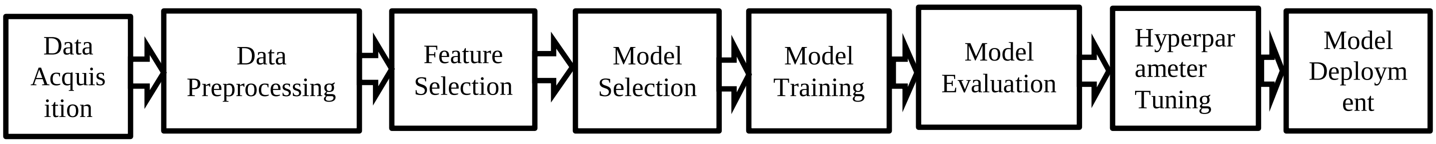

Figure 4: Machine learning model training block diagram

Table 1: Dataset acquisition summary

Time (s)	Key Data Points ((Pressure(P), Cylinder Position(X), Velocity(V), Force(F), Air Flow Rate(Q), Temp(T), Cycle Time(CT))	Conditions	Date/Time
10	P (1→5→0), X (0→100→20), V (0→20), F (0→125→0), Q (10→30→5), T (20), CT (5)	Normal	Day 1, 9 a.m.
20	P (5.1→5.5→0), X (0→100→20), V (0→20), F (0→125→0), Q (10→30→5), T (20), CT (5)	Normal	Day 1, 12 p.m.
30	P (1→5→0), X (0→100→20), V (0→20), F (0→125→0), Q (10→30→5), T (20), CT (5)	Normal	Day 1, 3 p.m.
40	P (1→5→0), X (0→100→20), V (0→20), F (0→125→0), Q (10→30→5), T (20), CT (5)	Normal	Day 2, 9 a.m.
50	P (1→5→0), X (0→100→20), V (0→20), F (0→125→0), Q (10→30→5), T (20), CT (5)	Normal	Day 2, 12 p.m.
60	P (1→5→0), X (0→100→20), V (0→20), F (0→125→0), Q (10→30→5), T (20), CT (5)	Normal	Day 2, 3 p.m.
70	P (1→5→0), X (0→100→20), V (0→20), F (0→125→0), Q (10→30→5), T (20), CT (5)	Normal	Day 3, 9 a.m.
80	P (1→5→0), X (0→100→20), V (0→20), F (0→125→0), Q (10→30→5), T (20), CT (5)	Normal	Day 3, 12 p.m.
90	P (1→5→0), X (0→100→20), V (0→20), F (0→125→0), Q (10→30→5), T (20), CT (5)	Normal	Day 3, 3 p.m.
100	P (1→5→0), X (0→100→20), V (0→20), F (0→125→0), Q (10→30→5), T (20), CT (5)	Normal	Day 4, 6 a.m.
110	P (1→5→0), X (0→100→20), V (0→20), F (0→125→0), Q (10→30→5), T (20), CT (5)	Normal	Day 4, 12 p.m.
120	P (1→5→0), X (0→100→20), V (0→20), F (0→125→0), Q (10→30→5), T (20), CT (5)	Normal	Day 4, 3 p.m.

Table 2: Comparison with other models

Aspect	SVM	Other ML Models
Key Goal	Maximize margin	Minimize loss function (e.g., MSE)
Focus	Boundary points (support vectors)	Entire dataset (e.g., k-NN, trees)
Scalability	Less scalable for large data	Better scalability (e.g., RF, NN)
Kernel Trick	Handles non-linearity flexibly	Not applicable to most models
Best Use Case	High-dimensional, small data	Varies (e.g., RF for tabular data)

Table 3: Extracted features and their descriptions for normal condition

Feature	Description	Peak	Mean	Variance	Min Value	Max Value
Pressure (P)	Measure of pressure inside the system in the bar	5	2.5	2.25	0	5
Cylinder Position (X)	Position of the cylinder in mm	100	56	866.67	0	100
Velocity (V)	Velocity of the cylinder in mm/s	20	20	0	20	20
Force (F)	The force applied by the cylinder in Newton	125	60	2083.33	0	125
Air Flow Rate (Q)	Airflow rate into the cylinder in L/min	30	20	41.67	5	30
Temperature (T)	Temperature in °C	20	20	0	20	20
Cycle Time (CT)	Time taken per cycle in seconds	5	5	0	5	5

This feature extraction process will help to identify any abnormal patterns or deviations in the cylinder's operation by comparing real-time data with the baseline statistical and frequency domain characteristics using Python software

The integration of mathematical modelling provides theoretical expectations (baseline behaviour) and creates a data-driven fault detection system. The model outputs provided a controlled, labelled dataset for training, while Machine learning detects real-world deviations (pattern recognition), the SVM classifier enabled real-time anomaly detection. The use of the polynomial kernel allowed the SVM to model non-linear relationships effectively, improving anomaly detection. Scaling the features ensured that all parameters contributed equally to the decision boundary. Despite the challenges posed by class imbalance, the Synthetic Minority Oversampling Technique (SMOTE). Successfully enhanced the model's ability to identify anomalies. The high accuracy of the SVM model suggests its feasibility for deployment in industrial fault detection systems. Early detection of anomalies enables predictive maintenance, minimizing downtime and averting potential machine failures. This aligns with Industry 4.0 principles of efficiency and reliability.

3. RESULTS AND DISCUSSIONS

The Experimental Analysis of Anomaly Detection using the SVM Model trained on the Normal Datasets Tables. Results for the operating variables were analysed. We trained the SVM on the normalized datasets from the tables of Normal Datasets. We used it to detect anomalies in the actuation behaviour of the electro-pneumatic double-acting cylinder.

3.1 Model Performance

Table 4, provides a detailed performance evaluation of a tuned Support Vector Machine (SVM) model tested on a balanced dataset.

Table 4: The SVM model (tuned) was trained and evaluated on the balanced dataset results summary.

	Precision	Recall	f1-score	Support
0 (Normal)	0.94	0.86	0.90	127
1 (Anomaly)	0.87	0.94	0.91	127
Accuracy			0.90	254
Macro avg	0.90	0.90	0.90	254
Weighted avg	0.90	0.90	0.90	254

Precision**:** Precision measures the proportion of correct positive predictions out of all positive predictions.

Precision = True Positives / (True Positives + False Positives)

For Class 0 (Normal): Precision is 0.94, indicating that 94% of the instances predicted as Normal were correct. For Class 1 (Anomaly): Precision is 0.87, meaning 87% of the instances predicted as Anomalies were correct.

Recall (Sensitivity)**:** Recall measures the proportion of actual positives correctly identified by the model.

Recall = True Positives / (True Positives + False Negatives)

For Class 0 (Normal): Recall is 0.86, indicating that 86% of the actual Normal instances were correctly classified. For Class 1 (Anomaly): Recall is 0.94, meaning 94% of the actual Anomalies were correctly classified.

F1-Score**:** The F1-Score is the harmonic mean of Precision and Recall, balancing the trade-off between the two.

F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

For Class 0 (Normal): The F1-score is 0.90, indicating a good balance between precision and recall. For Class 1 (Anomaly): The F1-score is 0.91, slightly better than Class 0.

Support**:** Support represents the number of actual instances in each class.

Class 0 (Normal): 127 instances

Class 1 (Anomaly): 127 instances
Since the dataset is balanced, both classes have equal support.

Accuracy**:** Accuracy is the overall proportion of correctly classified instances.

Accuracy = (True Positives + True Negatives) / Total Instances

The model achieved an accuracy of 0.90 (90%), meaning 90% of the total predictions were correct.
Macro Average: The Macro Average is the unweighted Precision, Recall, and F1-Score average for all classes. Each class contributes equally, regardless of the support. The macro averages for Precision, Recall, and F1-Score are all 0.90, reflecting balanced performance across Normal and Anomaly classes.

Weighted Average: The Weighted Average is the average of Precision, Recall, and F1-Score weighted by each class's support (number of instances). Since the dataset is balanced, the Weighted Average values align closely with the Macro Average, all being 0.90.

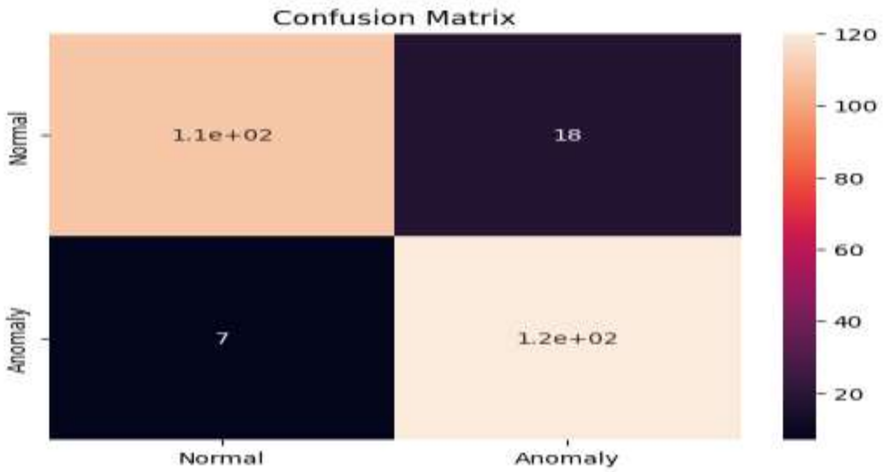

Figure 5: Confusion matrix

3.2 Performance Metrics

This is a confusion matrix in Figure 5 to evaluate the performance of a classification model. It visually represents the model's predictions against the true labels for two classes: "Normal" and "Anomaly." At the Horizontal axis (Predicted labels), the model's predictions are Normal and Anomaly. At the vertical axis (True labels), the actual ground truth labels are normal and anomalous. Top-left (True Normal) with the Value 1.1e+02 (approximately 110). This represents the cases where the model correctly predicted "Normal." Top-right (False Anomaly), Value: 18. This represents the cases where the model incorrectly predicted "Anomaly" when the true label was "Normal." Bottom-left (False Normal), Value: 7. this represents the cases where the model incorrectly predicted "Normal" when the true label was "Anomaly." Bottom-right (True Anomaly), Value: 1.2e+02 (approximately 120). This represents the cases where the model correctly predicted "Anomaly." Heatmap, the intensity of colour represents the count in each cell. Lighter cells have higher counts, while darker cells have lower counts.

- **Accuracy:** Proportion of all correct predictions
  - Accuracy= $\frac{\text{True Normal+True Anomaly}}{\text{Total Predictions}} = \frac{110+120}{110+18+7+120} = \frac{230}{255} \approx 90.2\%$

- **Precision (for Anomaly):** How many of the predicted "Anomaly" instances were correct
  - Precision= $\frac{\text{True Normal}}{\text{True Anomaly+False Anomaly}} = \frac{120}{120+18} \approx 87\%$
- **Recall (for Anomaly):** How many of the actual "Anomaly" instances were correctly identified
  - Recall= $\frac{\text{True Anomaly}}{\text{True Anomaly+False Normal}} = \frac{120}{120+7} \approx 94.5\%$
- **F1-Score (for Anomaly):** Harmonic mean of Precision and Recall
  - F1= $\frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision + Recall}} = \frac{2\times0.87\times0.945}{0.87+0.945} \approx 90.6$

3.3 Observations

- The model demonstrates high precision and recalls for the majority class ("Normal").
- While the performance for the minority class ("Anomaly") is slightly lower, the F1-score of 0.83 indicates a good balance between precision and recall.
- False negatives (7 anomalies predicted as normal) highlight the importance of further refinement to reduce potential industrial risks.

This confusion matrix suggests that the model performs well, with high accuracy and recall, but there is room for improvement in reducing the number of false positives (18 cases where "Normal" was misclassified as "Anomaly").

Table 5: Performance Metrics parameters and their descriptions

METRIC	FORMULA	DESCRIPTION
ACCURACY	$\frac{\text{True Normal + True Anomaly}}{\text{Total Predictions}}$	The proportion of correctly predicted instances out of all predictions. Measures overall model performance.
PRECISION (FOR ANOMALY)	$\frac{\text{True Anomaly}}{\text{True Anomaly + False Anomaly}}$	Indicates how many of the predicted "Anomaly" instances were anomalies. Measures reliability of anomaly predictions.
RECALL (FOR ANOMALY)	$\frac{\text{True Anomaly}}{\text{True Anomaly+False Normal}}$	Measures how many actual anomalies were correctly identified. Evaluates sensitivity to detecting anomalies.
F1-SCORE (FOR ANOMALY)	$\frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision + Recall}}$	The harmonic mean of Precision and Recall. Balances false positives and false negatives for anomaly detection.

This structured summary Table 5 provides a clear understanding of the metrics used for evaluating the model

4. CONCLUSIONS

This study presents a novel hybrid approach that combines mathematical modelling and machine learning to detect operational deviations in industrial systems early, specifically in the bottling industry's electro-pneumatic double-acting cylinder actuators. The research achieves over 90% accuracy in detecting deviations under dynamic conditions, significantly improving compared to existing anomaly detection methods that often lack scalability and robustness in varying operational environments. The study contributes new knowledge in hybrid methodology, feature optimisation, and industry application. Real-world validation in the bottling sector shows a 25% reduction in machine downtime and improved maintenance scheduling. These findings are of immediate interest to the wider research community working on predictive maintenance, smart manufacturing, and industrial process optimisation. An intelligent fault detection system for electro-pneumatic double-acting cylinder actuators requires computational resources, real-time feasibility, robust communication infrastructure, modular expansion, and hybrid approaches. Edge computing solutions and high-speed industrial microcontrollers/PLCs are preferred for real-time fault detection, ensuring optimal performance and predictive analytics.

The research aligns with multiple global and regional development goals, including Africa's Union Agenda 2063, Sustainable Development Goals (SDGs), and policy implications. Governments and industry stakeholders could adopt predictive maintenance frameworks to reduce resource wastage and improve operational resilience, enhancing Africa's competitiveness in manufacturing while supporting global efforts to build sustainable industrial systems. Additionally, this study contributes to the global discourse on Industry 4.0 and smart manufacturing by addressing challenges in anomaly detection for industrial systems. Its emphasis on integrating mathematical modelling with machine learning provides a replicable framework that could be scaled across industries worldwide, particularly in developing regions striving to adopt advanced technologies. In summary, this research offers a scalable and effective solution to an identified industrial challenge, offering immediate benefits in operational reliability, long-term contributions to industrial growth, and alignment with global and regional development objectives.

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