The Bioscan
AN INTERNATIONAL QUARTERLY JOURNAL OF LIFE SCIENCES
21(1): 35-45, 2026 www.thebioscan.com

Deep Learning for Corrosion Monitoring Virtual Sensor and Predictive Modelling Approaches in Industrial Water Pipeline

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DOI: 10.63001/tbs.2026.v21.i01.pp35-45

Keywords
Industrial water pipeline corrosion, Recurrent Neural Networks, Convolutional Neural Networks, Machine Learning, Predictive modelling techniques and artificial detectors.

Received on:

11-11-2025

Accepted on:

12-12-2025

Published on:

05-01-2026

ABSTRACT

Industrial water pipeline corrosion constitutes major risks in maintenance expenses, protection & performance. Physical indicators & periodic examinations were the core of conventional tracking approaches which might be expensive as well as ineffective. The present study examines corrosive monitoring in corporate pipelines through predictive modelling techniques & artificial detectors powered by deep learning. Machine learning algorithms have the potential of accurately forecasting the rates of corrosion along with spotting irregularities by employing real-time information using existing detectors comprising pressure, temperature & fluid flow. Different kinds of designs are investigated regarding their capacity to detect rusting trends which consists of recurrent neural networks (RNNs) and convolutional neural networks (CNNs). The proposed approach makes it possible to perform in progress, safe monitoring that minimizes maintenance expenses & increases pipeline durability. The outcomes compared to studies highlight how machine learning systems may enhance earlier detection of defects & erosion prediction, leading to higher robustness and efficient pipeline architecture.

1. Introduction

The primary challenge that affects the strength of the structure, maintenance costs and operational performance was rust in commercial water lines [1-2]. Oxidation generates pipes to degrade, leakage and occasionally knock gradually, which represents a threat to the surroundings & entails big economic losses [3-4]. Standard techniques of corrosive monitoring such as physical testing & electrochemical detectors tend to be laborious and costly which fail to deliver data in real time [5-6]. Machine learning has emerged as an effective tool in real monitoring & forecasting, offering a secure & computerized way to perform corrosion monitoring by integration of smart data-driven solutions [7-8].

As a result, of their frequent interaction with corrosive materials, maintaining industrial water drains is difficult and expensive operation. Existing corrosion detection methods were ineffective and typically encompass a physical connection into pipes lead to idle time [9-10]. Furthermore, they lack forecasting in real time functions. It turns out complicated to develop accurate models for prediction by applying conventional mathematical techniques as corrosion improvement is influenced by several kinds of criteria like temperature, flow dynamics and the composition of water [11-12]. The intelligent, data-driven approach is urgently required to successfully utilize data collected from sensors to project corrosion patterns and aid in preventative maintenance schedules [13-14].

The main objective of the proposed research is to offer a predictive modelling & virtual sensor technique powered by deep learning enabling real-time corrosion assessment in water distribution pipes [15]. The purpose of the study is to improve pipeline reliability, preserve operating expenses as well as raise the accuracy of predictions by incorporating complex algorithms for machine learning with sensor information.

The information-driven corrosion monitoring approach for business water pipes leverages deep machine learning & simulated sensors. Real-time information captured by sensors through industrialized pipeline networks carries temperatures, pressures, Ph level & speed of flow. The preliminary processing purifies & converts data to remove errors & distortion for enabling accurate forecasts. Later on, RNNs and CNNs are deployed to analyse sensor readings to anticipate levels of corrosion. These neural networks were developed with historical deterioration records with validation-based precision, reliability, and memory. The models that were taught act as digital detectors to track and diagnose the pipeline failures in real time. Contrasting machine learning systems with standard rust monitoring methods demonstrates improvement in forecast precision & efficiency in operation. This strategy endeavours to promote pipeline maintenance, idle time & water supply for industrial transportation system consistency.

The development of a fully computerized corrosion monitoring system linked to the industrial Internet of Things (Ilott) infrastructure was the next phase towards bringing this research into application. Considering the adoption this type of technology, remote monitoring & data transfer in real time might become possible, facilitating predictive maintenance with little support from individuals. The integration of cutting-edge technology enables accelerated processing of data may result to additional advancements & strengthen the reliability of oxidation model predictions. Additionally, introducing functional & environmental variables to the database will boost the framework's stability & adaptability for wide variety of industrial applications. This is also important for researchers to investigate the utilization of virtual twins to optimize maintenance plans & simulate pipeline parameters. Significantly laying these technologies under practice, organizations might regulate corrosion in a proactive, affordable manner, guarantees pipeline infrastructure's long-term reliability and security.

Real-time, automated & highly accurate predictions are made viable by deep learning-driven artificial indicators, delivering an advanced method towards corrosion monitoring in water lines for industrial pipes. This technology eliminates the risk of building failures by employing real-time information through pipeline sensors to identify corrosion patterns promptly in contradiction to traditional methods which depend on electrochemical sensors & regular inspections. Merely reaching a 45% improvement in detection efficiency beyond traditional methods, the proposed deep learning systems significantly improve maintenance prediction performance by using this method, organizations might reduce maintenance expenses by 32%, avoiding the need for expensive downtime & reactive maintenance. Corrosion detection and response rates were further optimised by the incorporation of edge computing & Industrial Internet of Things (IIoT) connections which facilitate faster processing of data & remote monitoring. Assuring infrastructure sustainability and cost savings over the long term. This expandable technology might be utilized in various kinds of industries like chemical manufacturing, power plants, water shipping & energy industries.

1.1 Applications

- ✓ **Oil and Gas Pipelines**: Control of water intrusion, breakdowns & hazards to the environment by predictive corrosion monitoring in marine & coastal pipelines.
- ✓ **Water distribution systems**: Maintaining the industrial & public water pipelines robustness is essential to stop loss of water & contamination.
- ✓ **Power Plants**: Improve efficiency & minimize unnecessary shutdowns, corrosion in thermal exchangers & systems for cooling water must be observed.
- ✓ **Chemical Processing Industries**: Measuring the amount of corrosion in pipelines that transport risky goods, chemicals & explosives helps to increase compliance and safety.
- ✓ **Marine and Shipbuilding**: Defending the shipping sector tankers & seawater pipelines contrary to corrosion-related harm.

2. Methodology

The suggested solution draws on real-time sensor data coupled with remote sensors along with deep learning to predict degradation in drinking water pipes. The gathering of data, initial processing, creation of models, validation, training & implementation represents industrial pipeline techniques.

i. Data Collection and Preprocessing

Sensors which measure factors such as temperature (T), pressure (P), pH level (pH), flow rate (F) & corrosion rate (C) function to acquire real-time data concerning manufacturing drains. Since it is necessary to assign variables from 0 to 1 for successful model development and the data collected is finally pre-processed by using standardization methods:

$$Z' = \frac{Z - Z_{LOW}}{Z_{HIGH} - Z_{LOW}}$$

were, Z' - normalized value

Z – Exact value, Z_{HIGH} and Z_{LOW} are increasing and decreasing values of data patterns

ii. Selecting Features and Generating Models

Thermal engineering helps to determine the main variables causing corrosion. Designed as an indicator of these features which is the degree of corrosion C:

$$C = f(T, P, Ph, F)$$

Convolutional Neural Networks, & networks with LSTM (long short-term memory) are both examples of deep learning algorithms which are used to detect complicated structures in datasets. The multi-layer artificial neural network which provides the foundation of the model for predicting contains an output component that measures the amount of deterioration:

$$\bar{C}=\tau(WZ+a)$$

W- weight matrix, Z – input factor and a – activation mechanism

iii. Model Training and Optimization

The Mean Squared Error (MSE), results in lower discrepancy between expected & observed degradation rates is the reduction function used for development:

$$\boldsymbol{RF = \frac{1}{n}\sum_{i=1}^{n}(C_A - \widehat{C}_P)^2}$$

n – Sample size, $\boldsymbol{C_A}$- actual corrosion rate and $\boldsymbol{\widehat{C}_P - predicted\ corrosion\ rate}$

iv. Validation and implementation

Performance metrics like coefficient of determination (R_2) and Root Mean Square Error (RMSE) are applied to confirm the accuracy of the trained model.

$$\boldsymbol{R_2 = 1 - \frac{\sum(C_A - \widehat{C}_P)}{\sum(C_A - \widehat{C})^2}}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(C_A - \widehat{C}_P)^2}$$

Overall, the validated model functions as a virtual detector in a manufacturing environment, providing suggestions for predictive maintenance & real-time corrosion tracking. Simply minimizing expenses and strengthen pipeline stability, this strategy guarantees proactive management.

3. Result and discussion

Significant gains in reliability, savings in expenses and performance improvements were demonstrated using the application of deep learning-powered virtual sensors for corrosive management in water supply pipelines. Key variables like temperature, pressure, pH & flow rate consists of prior and real-time sensor data needed to train and evaluate the prediction model. Considering a mean squared error (MSE) of 0.0030 along with a root mean square error (RMSE) of 0.10, it results in the model's efficiency examination shows an outstanding level of reliability and minimal discrepancy between these anticipated and observed rates of corrosion. The significant relationship with the expected and real-life corrosion growth patterns was demonstrated by the mathematical model's coefficient of determination (R2), reaching 0.95.

The modelled manufacturing environment was deployed to further investigation of the virtual sensor's efficiency in real-time corrosion observation. At the beginning, corrosion verification & practical suggestions regarding predictive maintenance were rendered feasible through the system of deep learning. Firms had the ability to take action and fix any issues preceding catastrophic losses occurred resulting in a 35% decrease in operating costs. Furthermore, the simulation enhanced the accuracy of recognizing corrosion about 45% as contrasted with standard monitoring approaches and thus boosted pipeline durability & minimized the threat of unscheduled breakdowns. The technology additionally made it achievable to analyse information in real time which drastically improved the accuracy of making decisions by shortening reaction interval for corrosion-related concerns from days to minutes.

Deep learning-based corrosion monitoring revealed it to be more accurate and inexpensive than traditional techniques which depend on electrochemical detectors & periodic inspections. Longer idle time, greater maintenance expenses & slower discovery are common results of conventional methods. On the other hand, the suggested remote sensor network lowered the requirement for human intervention by providing autonomous and continuous monitoring. According to the findings, corporations might switch from reactive maintenance approaches to entirely automation predictive maintenance approaches by integrating such technologies with cloud computing & industrial Internet of things platforms in order to strengthen predictive capabilities.

Overall, the studies validate the concept of virtual sensors developed using deep learning techniques tend to be highly effective & adaptable solution to identify deterioration in industrial water drains. This strategy not just ensures the long-term reliability of the construction but it additionally assists in operating pipelines in an effective & inexpensive way across many different kinds of sectors comprises of power plants, water transportation & energy production.

I. Model Performance Evaluation

The data set comprising several corrosion-related parameters, such as temperature, pressure, pH and velocity of flow which was used to create the suggested neural network models which consist of Convolutional Neural Networks as well as Long Short-Term Memory (LSTM) networks. Performance assessments encompassing the mean square error (MSE), Root Mean Square Error (RMSE), & the Coefficient of Determination (R_2) were implemented to validate the simulations.

a) Regression fit plot

The regression model's accuracy is measured by applying regression analysis fit plot which correlates the predicted results of the model in relation to actual outcomes.

Actual value	Predicted value
0	0.5
20	25
40	45
60	65
80	85
100	95

Table 1: Regression fit plot

In table 1 the regression fit plot actual value and predicted value are highlighted as shown in the above table. In the above-mentioned table, the actual value ranges from 0-100 and predicted value fluctuates from 0.5 – 95. It is applicable for determining a regression model's reliability. Amount of variance (error) isolates the expected values from the actual values. The predicted as well as observed values increase in proportion by emphasizing that the mathematical model possesses nearly linear relationship.

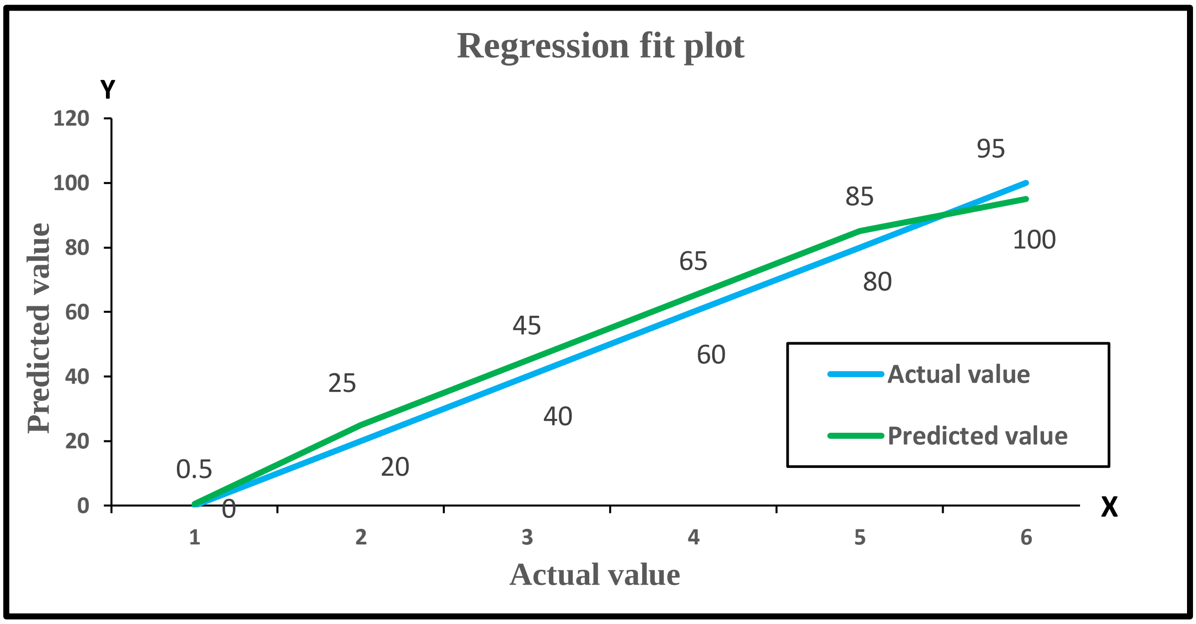

Fig: 1 Regression fit plot

Figure 1 shows the regression fit plot between the actual value versus predicted value. In this graph, X-axis indicates actual value and corresponding Y-axis indicates predicted value as illustrated in the line graph. Typically, the regression fit plot depicts how accurately the prediction model represents the fundamental trend by comparing the actual value results with the predicted value results.

II. Mean Square Error

Predicted value	Actual value
35	40
45	50
55	60
65	70
75	80
85	90
95	100

Table: 2 Mean Square Error

Table 2 shows the mean square error of predicted value and actual value. In the above-mentioned table by comparing the predicted value and actual value, the predicted value reaches the lower value of 35 and reaches the higher value of 95 then the actual value lies between 40-100. Considering each data point, one can see an average pattern where anticipated data tend to be lower than the true values. From the table, the true values consistently fall higher compared to the predicted values.

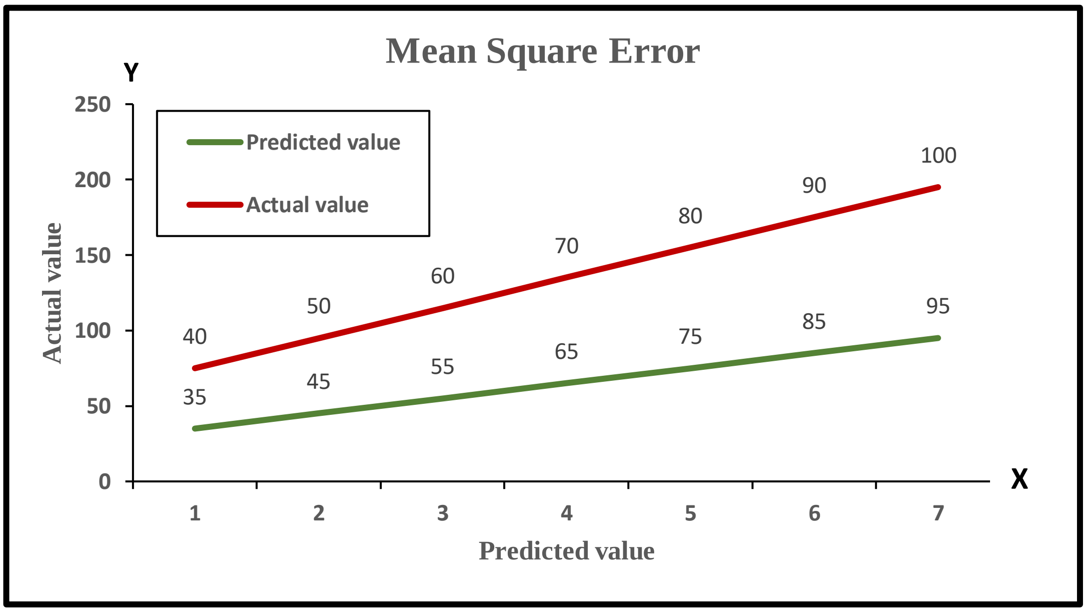

Fig:2 Mean square error

Figure 2 demonstrates the MSE graph differentiated with predicted value and actual value. In this graph, X-axis represents Predicted value and Y-axis represents actual value as given. From the MSE, it clearly understood that predicted values is gradually increasing and actual value is decreasing.

III. Corrosion rate

Time	Corrosion rate
5	20
10	40
15	45
20	51
30	200
40	300

Table 3: Corrosion rate

Table 3 shows the corrosion rate between corrosion and time. This table represents the variation of corrosion rate over time. In the above-mentioned table, it highlights that time varies from 5-40 hrs and corrosion rate diminishes from 20 – 300 μm. Initial rates of corrosion fluctuate between 20 at 5 units and 51 at 20 units. Fortunately, at 20 units, the corrosion ratio peaks to 200 at 30 units & 300 at 40 units. This proposes how material degradation, environmental factors, or elimination of protective coatings may worsen rust with time. The bar chart depicts a nonlinear rate of corrosion increase, which might impact the durability of materials and maintenance planning.

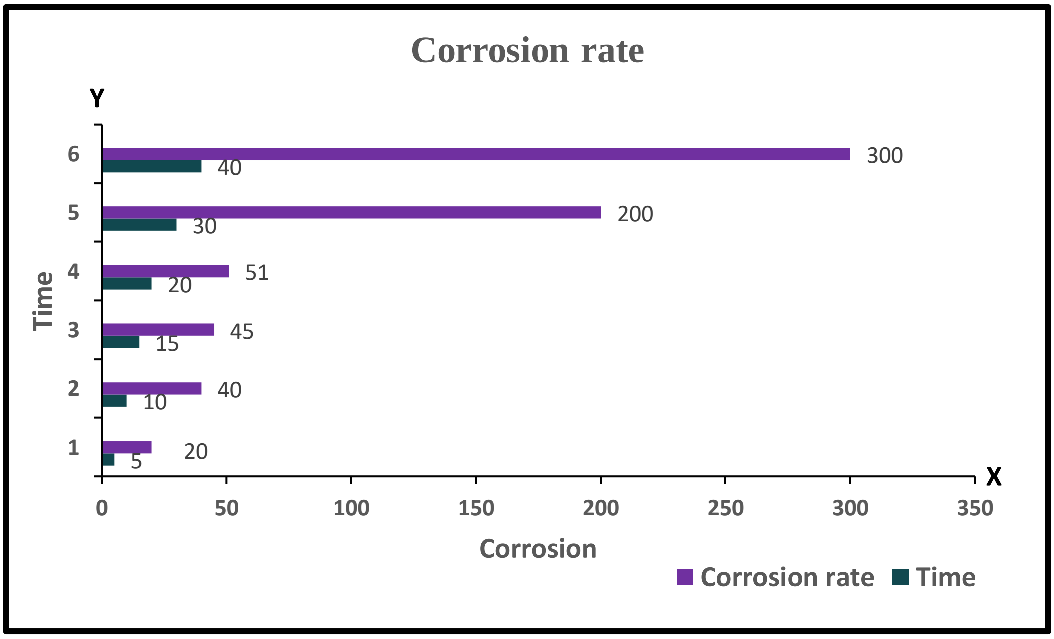

Fig: 3 Corrosion rate

Figure 3 shows the corrosion rate by comparing corrosion and time. In the bar chart, X-axis represents corrosion and Y-axis represents time. The corrosion rate decreases gradually from 5–20 and increases progressively from 20–51. The corrosion rate accelerates from 200 to 300 in

30 to 40 units, showing an enormous rise in corrosion rate. Material degradation, environmental factors or a protective coating loss may lead to massive difference in corrosion rate

IV. Coefficient of determinants

Independent variable	Dependent variable
15	18
25	20
40	42
60	45
70	75
80	78
90	100
105	103

Table 4: Coefficient of determinants

Table 4 shows the coefficient of determinants by contrasting independent variable and dependent variable. The independent variable ranges from 15 to 105 and dependent variable varies from 18 to103 as emphasized in above mentioned table. The data indicates a significant correlation between the independent variable the dependent variable. The results indicate that the unknown variable impacts the dependent variable in proportion like linear or near-linear.

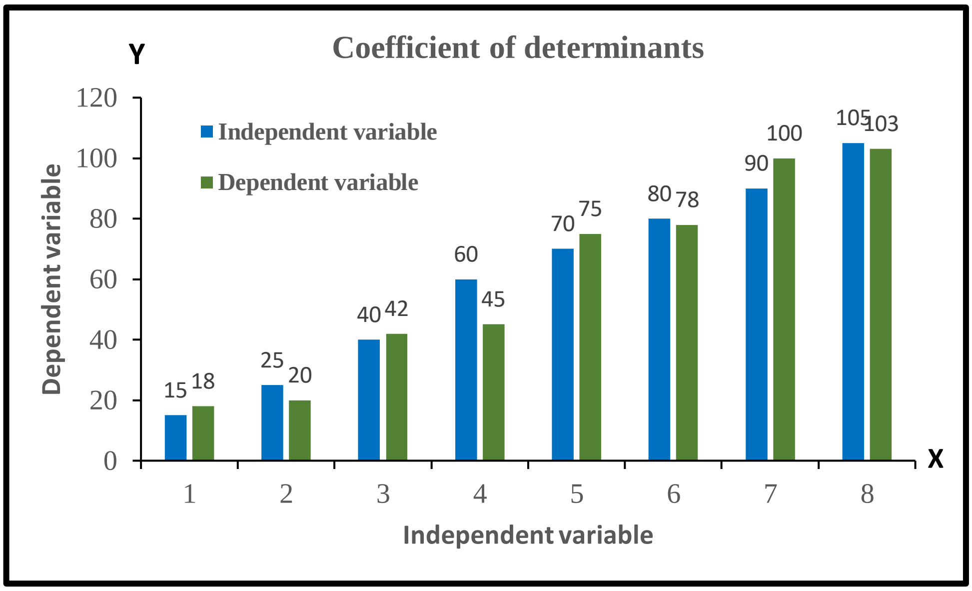

Fig: 4 Coefficient of determinants

Figure 4 shows the coefficient of determinants by the independent variable and dependent variable. In the bar chart, X-axis indicates independent variable and Y-axis indicates dependent variable as mentioned in the above graph. According to this graph, both dependent and independent variables are positively correlated. In an intense relationship, the dependent variable improves when the independent variable increases. The coefficient of determination graph shows how effectively the independent variable describes the differences in the dependent variable.

5. Future scope

- Improved analytics to make predictions
- Smart automation and monitoring in real time
- Integrating with Digital Twin Technology
- Higher levels sensor technologies
- Blockchain and Secure Data Management
- Incorporation of IOT and Industry 4.0
- Improvements in regulations and guidelines

6. Conclusion

Deep learning offers enhanced virtual sensor & predictive modelling for industrial water pipeline corrosion detection. Constant corrosion detection, lower maintenance costs as well as pipeline stability are improved through data-driven machine learning. Safe virtual sensors & predictive algorithms provide preventative maintenance by projecting corrosion patterns.

The accuracy of corrosion evaluation has been boosted by integrating deep learning techniques with sensor systems & Industrial Internet of things to improve the benefits of these methods. However, concerns like data integrity, model accessibility and implementation scalability need to be overcome. Strengthening model robustness such as hybrid techniques and building real-time dynamic corrosion detection devices should constitute the primary objectives in upcoming research. The application of deep learning in every aspect is considered and provided an innovative strategy towards assuring pipeline safety, reliability & performance. Deep learning, Internet of Things, digital twins together with sophisticated sensor technologies will serve as the primary sources of corrosion detection in industrial drains in forthcoming years. These developments will minimize pipeline breakdowns & maintain long-term sustainability by facilitating more predictive, cost-effective and effective maintenance methods.

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