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Research Article

An ML-Enabled Framework for Resilient Data Pipelines with Intelligent Anomaly Detection and Automated Recovery Mechanisms

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Abstract

The contemporary data-intensive computing systems demand the establishment of strong data pipelines that can be utilized in order to sustain the active continuous running of the system in case of the occurrence of runtime anomalies and system errors. In this paper, introduce an ML-based framework of resilient data pipelines that combines smart anomaly detection with automated recovery controls to allow self-healing data pipeline processes. The pipeline will be run on the Google Cluster Traces dataset, which is systematically preprocessed, including data cleaning, anomaly labeling, and min-max normalization to generate high-quality inputs for training the model. The suggested model utilizes a hybrid CNN-LSTM model, where former part of workload trace patterns is extracted by the CNN, and the latter part captures the temporal relationships between successive pipeline actions by the LSTM, allowing for accurate anomaly classification. As an experimental analysis of the Google Cluster Traces dataset shows, the proposed CNN-LSTM model achieves an accuracy (acc) of 95.45% and precision (prec), recall (rec), and F1-score (F1) of 93.65%, 96.34%, and 94.51%, respectively, which is superior to all the base models addressed in this work. The framework is intended to be deployed in cloud computing systems and has been shown to apply to distributed, data-intensive systems that require high availability and consistent service reliability. It is also extended to IoT and cyber-physical systems as a direction for future work.

Keywords: *Anomaly Detection, Automated Recovery Mechanism, Google Cluster Traces Dataset, Machine Learning, CNN-LSTM, Data Pipeline.*

Introduction

Resilient data pipelines have become an important element of modern distributed computing and data-driven systems [1][2]. As organizations increasingly rely on real-time analytics and data processing on a large scale, pipeline failures have significant operational implications. Industry studies project that unexpected issues with data downtime cost businesses thousands of dollars per minute, and have downstream impacts on decision-making and service provision [3][4]. Providing pipeline continuity, reliability and data integrity has thus turned into a critical system engineering issue.

These pipelines are supposed to efficiently deal with heterogeneous data streams, variable workloads and dynamic infrastructure backgrounds with minimal downtimes and degraded performance [5]. Resilience not only imply fault tolerance and having two or more resources at the same time but also intelligent monitoring and prompt response to operations failure. Anomaly detection is valuable to encourage resilience by identifying unforeseen variations in the behavior of pipelines that may indicate failures, performance bottlenecks or data quality issues [6][7]. The time-honoured rule-based types of monitoring are inherently limited in their nature of relying on hard and fast pre-defined thresholds. They are inefficient in adapting to changing workloads distributions, cannot identify new types of anomalies not considered during the system design, and generate too many false positives in dynamic working conditions, which explains why a data-driven, machine learning-based approach to pipeline monitoring is valuable [8].

Conversely, anomaly-detection systems seek to detect anomalies in trends of metrics of data rates, latency, error rates, schema evolution and data distributions [9][10]. Appropriate and timely detection of these anomalies is essential to prevent cascading failures and ensure data system continuity. Therefore, automated recovery mechanisms are needed to execute specific recovery actions (such as restarting processes, rerouting traffic, or quarantining components) with minimal human intervention, to provide timely and cost-effective recovery.

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Predefined or dynamic recovery responses can be triggered by automated recovery modules, including the restarting of failed processes [11], the diversion of flows, the isolation of faulty components, or the initiation of data recovery processes [12][13]. These mechanisms enhance system availability and robustness by minimizing the operational overhead and response time caused by manual operations [14][15]. The combination of anomaly detection and automated recovery enables a closed-loop, self-healing environment that allows data pipelines to deliver more efficient processing with minimal downtime.

Machine learning (ML) has enabled adaptive and intelligent strategies for anomaly detection and automated recovery, allowing systems to learn historical pipeline behavior, identify latent failure signatures, and trigger context-aware remediation actions [16][17]. ML models are able to learn the historical behavior of pipelines, detect latent patterns that predict an imminent failure and suggest or initiate appropriate recovery measures [18][19]. Classification, clustering, time-series forecasting, and reinforcement learning are used to increase the accuracy of detection of anomalies and facilitate the use of context-sensitive recovery choices [20]. As a result, ML-enabled systems can be used to advance to autonomous and self-regulating data infrastructures, and they are thus a prospective solution to the next generation of resilient data pipelines [21][22].

Motivation and Contribution

Recent data-centric platforms demand high-throughput, dependable data pipelines to enable cloud services, IoT, CPS, and business analytics. Nevertheless, dynamic workloads, hardware and software malfunctions are likely to lead to the occurrence of these pipelines running anomalies and failures. The conventional approach of monitoring based on rules is not suitable for identifying complex patterns and is not autonomous (capable of responding), and available ML-based solutions lack integrated temporal-spatial awareness and automated recovery capabilities, and continue to require significant manual intervention during fault resolution. Therefore, an ML-enabled framework that unifies real-time anomaly detection with automated recovery is necessary to realize self-healing pipeline behavior, enhance operational reliability, and ensure sustained service availability in large-scale data-intensive environments. This research makes several key contributions are discussed below:
A ML-based resilient pipeline architecture. A novel end-to-end architecture with both smart anomaly detection and repair mechanisms to support self-healing data pipeline operations.

End to end preprocessing and evaluation pipeline A systematic data preprocessing workflow Cleaning Data preprocessing workflow, including labeling, normalization using real-world Google Cluster Traces, and performance assessment utilizing common metrics like F1, rec, acc, and prec.

A hybrid DL system that uses CNN as a spatial feature extractor and LSTM as a temporal dependency learner to allow efficient detection of complex runtime anomalies in scale trace data.

Automated recovery and resilience management incorporates recovery testing procedure, downtime calculation, resource optimization and MTTR calculation to allow autonomous fault resolution with minimum human intervention.

Self-healing infrastructure to increase continuity framework shows how proactive anomaly detection and recovery strategies that use intelligent recovery mechanisms can greatly increase the reliability of operations, service continuity, and business resiliency in contemporary data-oriented systems.

Justification and Novelty

This work has justified that modern digital infrastructures are becoming more reliant on resilient data pipelines that are capable of supporting continuous operations without all types of anomalies that are not predictable and system failures. Current monitoring and ML-based sources of anomaly detection are inadequate as they either are based on fixed rules, they cannot model temporal-spatial correlations within pipeline behaviour, or lack self-recovery methods, which lead to long downtime and reduced performance The novelty of this work lies in end-to-end integration of capabilities that existing solutions address in isolation: (1) a hybrid CNN-LSTM architecture that jointly models spatial workload patterns and temporal behavioral sequences for accurate anomaly classification; (2) an automated recovery module directly coupled to detection outputs, enabling immediate corrective action upon anomaly confirmation; and (3) a comprehensive resilience evaluation layer measuring recovery time, system downtime, resource utilization, and MTTR. Together, these components form a closed-loop, self-healing data pipeline architecture that operates with minimal human intervention and is validated on a real-world production cluster dataset.

Literature review

Several significant research studies on automated recovery mechanisms and anomaly detection using machine learning models have been thoroughly reviewed. Table I provides a comparison of the studies, detailing their data sets and approaches, main techniques, limitations and future research directions, to inform and guide the proposed framework.

Munir *et al*. (2019) Presented DeepAnT, a DL model using CNN predictors for unsupervised time-series anomaly detection. DeepAnT effectively identifies point and contextual anomalies across 15 real and synthetic time series, without the need for training labels. The approach uses a predictor to learn the next value of the time-series and identifies anomalies based on a learned threshold. Although DeepAnT shows promising

unsupervised detection, it lacks automated recovery mechanisms and does not assess resilience metrics, and is not suitable for end-to-end pipeline resilience management [23].

Konda (2021) developed an ML approach to self-healing microservices, combining anomaly detection, predictive analytics and reinforcement learning to automate the detection and recovery from failures. The system uses log and metric data for proactive recovery, root cause investigation, and real-time anomaly detection, employing a continuous learning loop that combines supervised and unsupervised algorithms to improve detection accuracy over time [24].

Vertuam Neto *et al*. (2021) anomaly detection in trace streams that satisfy practical needs. Auto cloud is an online clustering method that is autonomous, evolutionary, recursive, and uses minimal memory to deliver real-time insights from aberrant patterns. Additionally, this clustering approach requires prior application domain expertise or even prior training. In the trials, 630 datasets were created using 6 distinct anomalies and 6 process models, for a total of more than 1,000. The algorithm's ability to spot irregularities in these event traces made it possible to create more reliable information systems based on an automated evaluation of planned business process execution for compliance [25].

Mulongo *et al*. (2020) backup power sources, such diesel generators. SVM, KNN, LR, and classification approaches are used to understand the patterns of gasoline use to identify anomalies in the data that was captured. These methods leverage the generator's standard feature engineering, selection, and model classifiers to identify abnormalities associated with the data from Telefrag base stations about fuel usage. Lastly, a test is conducted on these classifiers' performance. Fuel theft results from base station maintenance deficiencies and mechanical fuel level gauge malfunctions, which contribute to fuel consumption of these generators. MLP achieves the K-fold cross-validation test's maximum evaluation measurement score of 96% [26].

Li *et al*. (2019) due to the dynamic complexity of these systems, threshold-based anomaly detection techniques are insufficient, and supervised machine learning approaches lack labelled information, they cannot utilize the large amounts of data. A GAN-based unsupervised multivariate anomaly detection method is used to identify abnormalities among the system's many variables (sensors and actuators). The generator and discriminator use a single anomaly score known as the DR-score, rather than handling each data stream separately, to identify anomalies by reconstructing MAD-GAN and discrimination utilizing datasets gathered from actual CPS, the Secure Water Treatment (SWaT) [27].

Wen and Keyes (2019). In DL efforts pertaining to time series AD, a transfer learning framework is utilized. Using this method, a model is pre-trained on a large-scale synthetic univariate time-series dataset, and its weights are subsequently fine-tuned on small-scale univariate or multivariate datasets that include classes of unobserved abnormalities. This approach is based on CNNs. Several synthetic and actual data sets are connected in a new network for the multivariate scenario [28].

Kim and Cho (2018) a neural network for efficiently modeling the spatial and temporal information included in traffic data, which is a one-dimensional time series signal, and a method for automatically extracting trustworthy spatial-temporal informative qualities from raw data. With an overall accuracy of 98.6% and recall of 89.7% on the test dataset, the CNN layer reduces frequency fluctuation in spatial information on Yahoo's well-known Webscope S5 dataset, while the DNN layer converts the data into machine learning approaches [29].

Table 1 Comparative analysis of recent studies on automated recovery mechanisms with anomaly detection using machine learning model

Author/Year	Dataset	Methodology	Key Technique	Challenges	Future Work
Althoey *et al.* (2022)	619 literature-based data points (FA, SF, LP, CWB → CWA)	Supervised ML modeling with training (70%) and testing (30%)	Gene Expression Programming (GEP) with multi-metric validation	Model limited to admixture-based concrete; relies on secondary (literature) data; excludes environmental factors, healing time, and real-time crack evolution	Incorporate experimental/field datasets, additional healing agents and environmental parameters; compare GEP with deep learning and hybrid AI models
Konda (2021)	Microservices logs & metrics data	Self-healing framework for failure detection and recovery based on ML	Anomaly Detection Predictive Analytics Supervised + Unsupervised ML	Dynamic failure detection- Automated root cause analysis- Adaptive recovery policies	Continuous learning loop for improved accuracy; extend RL policies for more diverse failure patterns
Vertuam Neto *et al.*, (2021)	630 datasets of event trace streams from 6 anomaly types	Recursive online clustering for anomaly detection	Autonomous clustering (no prior domain knowledge) Evolutionary & memory-efficient	Real-time anomaly detection in traces- Lack of labeled training data	Potential integration with conformance checking for robust business process monitoring

Mulongo *et al.* (2020)	Fuel consumption recordings from TeleInfra base stations	Supervised anomaly detection via feature engineering, model training	SVM- KNN- Logistic Regression- MLP (score 96%)	Fuel pilferage- Noise/perturbations in fuel gauges- Maintenance issues	Extend model deployment to real-time fraud detection and integrate sensor calibration techniques
Li *et al.* (2019)	SWaT dataset: Cyber-Physical Secure Water Treatment	Using Generative Adversarial Networks (GANs) for unsupervised multivariate anomaly detection	MAD-GAN Discrimination + Reconstruction scoring (DR-score)	Lack of labeled data- Dynamic interdependencies among multivariate signals	Improve scalability for industrial CPS and explore hybrid GAN models for better interpretability
Wen, Keyes & Analytics (2019)	Synthetic + real time-series datasets	CNN-based segmentation + transfer learning for time-series anomaly detection	Convolutional Neural Networks (CNN): Cross-domain learning transfer	Limited labeled anomaly data- Unseen anomaly classes	Expand transfer learning across heterogeneous sensors; investigate multi-task learning
Kim & Cho (2018)	Traffic time-series data (1-D) + Yahoo Webscope S5	Neural architecture combining CNN + DNN for spatial-temporal feature extraction	CNN for spatial smoothing- DNN for anomaly classification	Capturing spatial-temporal dependencies- Feature extraction from raw signals	Apply to broader IoT domains; integrate RNNs/LSTMs for improved temporal modeling

Research gap: Across the reviewed studies, a consistent pattern emerges: individual works address either anomaly detection (Li *et al.* [27], Kim and Cho [29], Wen and Keyes [28]) or recovery and self-healing mechanisms (Konda [24], Vertuam Neto *et al.* [25]) in isolation, using heterogeneous datasets and evaluation criteria that preclude direct comparison. Unsupervised approaches such as MAD-GAN partially address the labeled data challenge but lack pipeline-level orchestration and recovery integration. There is no solution that offers an integrated end-to-end architecture that links anomaly classification in real-time with automated recovery using metrics in a data pipeline. Despite the use of ML techniques such as RL, CNNs, SVM, KNN, and GANs, existing solutions remain fragmented, focusing on isolated tasks like detection or classification rather than integrated, resilient pipelines. They either depend heavily on labeled data with limited generalization or lack self-recovery capabilities, while GAN-based approaches still fail to achieve end-to-end orchestration and resilience. A unified ML-enabled framework that integrates real-time spatiotemporal anomaly detection with automated recovery orchestration — validated on production-scale pipeline data using both classification and resilience metrics remains an open research challenge. This gap motivates the end-to-end self-healing architecture proposed in this paper.

Research Methodology

The proposed ML-enabled framework for resilient data pipelines follows a systematic six-stage pipeline, as illustrated in Fig. 1: dataset acquisition, data preprocessing (cleaning, labeling, normalization), train-test splitting, CNN-LSTM model training, performance evaluation, and automated recovery execution. First, the Google cluster traces dataset is pre-processed on a large scale three important stages data cleaning to remove inconsistencies and missing values, data labeling to remove normal and anomalous patterns, and data normalization to align features within the same scale. To facilitate effective model creation and testing, from the processed data, training and testing sets are developed. The core classification model uses a hybrid CNN-LSTM architecture, where time dependencies in sequential data pipeline behaviors are captured by LSTM networks and spatial aspects of trace patterns are captured by CNNs, resulting in intelligent anomaly detection capabilities.

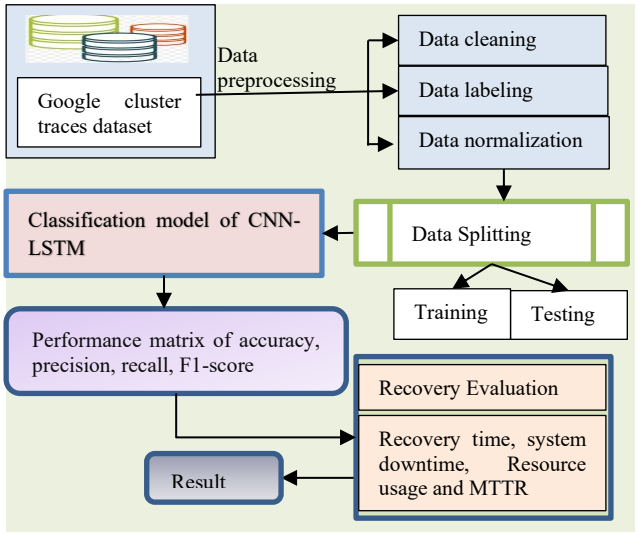

Fig. 1 Proposed Flowchart for Automated Recovery Mechanism in Anomaly Detection using Machine Learning

After the model training, the performance can be evaluated in a form of a comprehensive performance matrix that uses criteria such as F1-score, recall, accuracy, and precision to assess classification's efficacy process a successful anomaly detection is made, framework activate automated recovery processes including recovery testing protocols, recovery time and system downtime measurements, resource utilization optimization, and Mean Time to Repair (MTTR) calculation so that the service disruption is minimal. This entire workflow of aggregated outcomes the framework can ensure pipeline resiliency by using proactive anomaly

detection and intelligent recovery automation, resulting in the creation of an automatic self-healing data infrastructure that has minimal human involvement and optimal system reliability and business continuity.

Data Collection

The cluster provides resource allocation, service migration and auto-scaling to simulate faults and train automatic recovery procedures. The Google Cluster Traces dataset is a collection of resource usage data from a Google production data center from about 12,500 machines across 29 days. It includes CPU/memory requests and usage rates, task scheduling, job priorities, and failure logs, at a millisecond resolution. For this research, task duration and CPU usage were considered as main features for anomaly detection. The dataset was chosen for its large size, representativeness and the variety of fault conditions it captures, such as resource exhaustion, cascading task failures and scheduling anomalies - making it a suitable choice for training and testing a pipeline resilience model. Here are a couple of the visualizations:

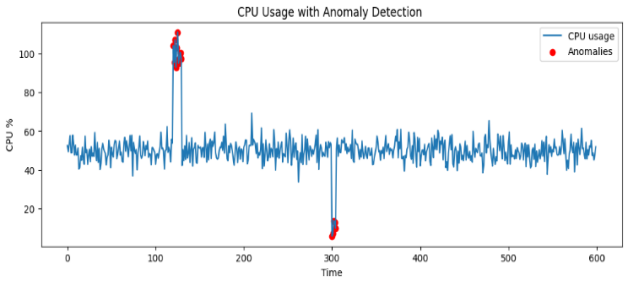

Fig.2 CPU usage with Anomaly Detection

The chart shows CPU usage over time with mostly steady values around 40–60%, interrupted by sharp spikes near 140–160 and a deep drop near 300 in Fig. 2. Red dots these anomalies. The line plot is labeled "CPU Usage with Anomaly Detection," with time on the x-axis and CPU percentage.

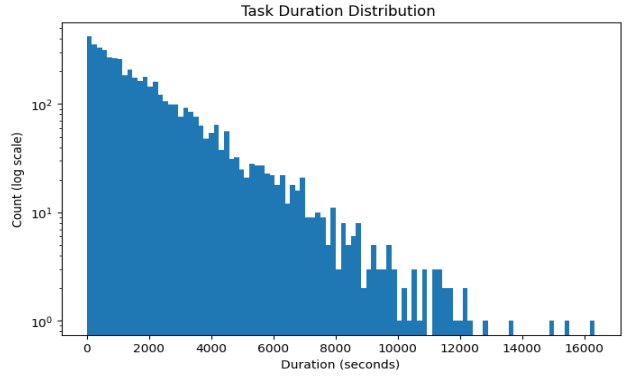

Fig.3 Histogram of Distribution in task duration

Task Duration Distribution" shows in Fig. 3 often different task durations occur, measured in seconds. The x-axis spans from 0 to around 16,000 seconds, while the y-axis features a logarithmic scale for counts. Most tasks have short durations, with counts decreasing steadily as durations increase. Beyond roughly 6,000 seconds, tasks become much rarer, and only a few extremely long tasks appear in the far right tail of the distribution.

Data Pre-Processing

Google Cluster Traces dataset was processed in order to have clean and reliable inputs to detect anomalies. Missing values, duplicates and corrupted logs were removed during data cleaning. Labeling was applied to the information to distinguish between typical and abnormal behavior. Data normalization was applied to stabilize model training. Lastly, analysis, dataset was separated into training and testing data. The following is an overview of the entire preparation workflow.

Data cleaning: The cleaning stage prepares the data by removing noise, inconsistencies, and missing information, which facilitates the study of raw data. Outliers, or anomalous system behaviour, are found and eliminated as they might skew model training and result in erroneous forecasts. Similarly, the dataset's null or non-existent values are either imputed using statistical techniques.

Data Labelling

Data labeling assigns a binary class to each record: normal (0) or anomalous (1). In this study, a record was labeled anomalous if its CPU utilization exceeded the rolling mean by more than two standard deviations within a 60-second sliding window, or if a task failure event co-occurred with memory utilization above 90% of the available capacity. All remaining records were labeled as normal. This heuristic-based labeling strategy was chosen due to absence of ground-truth fault annotations in Google Cluster Traces dataset. The resulting label distribution reflects the inherent class imbalance of real-world anomaly data, with anomalous instances comprising approximately 5–8% of total records. To mitigate the effect of class imbalance during training, class weights were applied inversely proportional to class frequency.

Data Normalization

Normalization is the numerical characteristics are rescaled to a standard range (usually 0-1 or -1 to 1) such that each variable contributes equally to the training of the model. It transforms the characteristics range (Z-score normalization, Min-Max) scaling to produce a uniform distribution. Normalization use the general Equation (1):

$$x' = \frac{(x - \min(x))}{\max(x) - \min(x)} \quad (1)$$

In this equation, x' prime is new value, the new value, x old values and min (x) and max(x), are minimum and maximum of feature.

Data Splitting

The data was split chronologically between 80% for training and 20% for testing while maintaining temporal order of events to avoid leaking future events into the training data, which is important for time-series anomaly detection. 10% of training set was reserved for validation set to track convergence and implement early stopping. Splitting by time ensures that the model has not "seen" the events on which it is evaluated, and therefore gives a more accurate picture of how it performs in the real world.

Classification equation of CNN-LSTM Model in automated recovery in anomaly detection

The unique structure of CNNs (weight sharing and local receptive fields) allows them to capture spatial features and local features from signals effectively [30]. CNN captures variation trends between neighboring time steps by performing one-dimensional convolution operations on time series built with a sliding window. Equation (2) computes the convolutional layer for an input sequence $\mathbf{X}\in\mathbb{R}T\times d$, where d is feature dimension and T is window length.

$$h_t^{(c)} = \sigma\left(\sum_{k=0}^{k-1} w_k \,.\, x_{t+k} + b\right) \quad (2)$$

Where kernel size is indicated by K, the kernel weight by Wk, the nonlinear activation function (like ReLU) by $\sigma(\cdot)$ and the bias term by b. The model can recognize short-term feature patterns, such as abrupt voltage changes and unusual temperature increases, by using convolution processes.

The gradient vanishing issue of conventional recurrent neural networks (RNNs) was successfully addressed by LSTM networks, which were composed of input, forget, and output gates. Several LSTM variations were examined, as well as the function of gating methods in reducing gradient vanishing. Equations (3) to (8) provide an LSTM cell's update Equations:

$$f_t = \sigma\left(w_f \cdot \left[h_{t-1,} x_t\right] + b_f\right) \quad (3)$$
$$i_t = \sigma\left(w_i \,.\left[h_{t-1,} x_t\right] + b_i\right) \quad (4)$$
$$\widetilde{c_t} = tanh(w_c.[h_{t-1}, x_t] + b_c) \quad (5)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \widetilde{c_t} \quad (6)$$
$$o_t = \sigma(w_o \cdot [h_{t-1}, x_t] + b_o) \quad (7)$$
$$h_t = o_t \odot \tanh(c_t) \quad (8)$$

Where ht is hidden state at time step t, æ is Hadamard product, and σ stands for sigmoid activation function. In this work, the CNN component applies one-dimensional convolutions over sliding windows of pipeline trace data to extract short-range spatial patterns, such as abrupt CPU spikes, sudden drops in task throughput, and transient memory bursts. The LSTM component then processes the resulting feature sequences to capture long-term temporal dependencies, including gradual resource exhaustion trends, recurring failure cycles across scheduling windows, and slow-evolving degradation signatures that instantaneous detection methods cannot reliably identify. The combination of both components enables the model to detect both sudden point anomalies and sustained contextual anomalies within a single unified architecture.

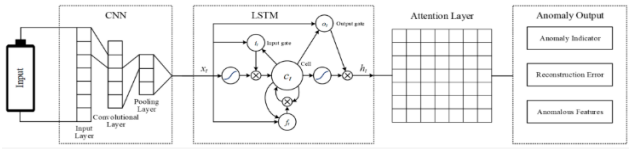

Fig.4 CNN-LSTM–Attention Model flowchart

Fig. 4 illustrates the full CNN-LSTM-Attention architecture. Following the LSTM layer, an attention mechanism assigns scalar weights to each hidden state h_t based on its relevance to the anomaly classification decision. In Equation (9), attention weight for time step t is calculated:

$$\alpha_t = \frac{\exp(w^T \tanh\,(W_a h_t + b_a))}{\sum_j \exp\,(w^T \tanh\,(W_a h_j + b_a))}, c = \sum_t \alpha_t\, h_t \quad (9)$$

The output layer receives this context vector for final categorization. The attention mechanism enables the model to focus on the input sequence segments that are most relevant to anomalies, improving precision for sparse, high-impact anomalies that may be diluted across long normal-operation windows.

The CNN layer was made up of 64 filters with a kernel size of three and ReLU activation, followed by max pooling with a pool size of two. There were 128 hidden units in the LSTM layer. To lessen overfitting, a dropout rate of 0.3 was implemented following each LSTM layer. The Adam optimizer and binary cross-entropy loss were used to construct the model. Early halting was employed and training for up to 50 epochs was conducted when validation loss did not improve for five consecutive epochs. The batch size was sixty-four. Each experiment was conducted using TensorFlow 2.x and Keras in Python 3 on a workstation with an Intel Core i7 CPU and 16 GB of RAM.

Evaluation Metrics

Classification measures and resilience measures were used to test proposed architecture. The detection performance was often assessed using rec, acc, prec, and F1, which was computed using TP, FP, TN, and FN. Furthermore, recuperation time, system downtime, resource usage, and MTTR were determined to test the capability of the framework to autonomously reinstate normal operation. These metrics give the effectiveness of anomaly detection as well as of operational self-healing.

Accuracy: It is calculated as the proportion of accurately classified records to all records, as shown in Equation (10):

$$Accuracy = \frac{\text{TP+TN}}{\text{TP+Fp+TN+FN}} \quad (10)$$

Precision: It is ratio of correctly predicted anomaly occurrences to each instance predicted as an Anomaly, as shown in Equation (11):

$$Precision = \frac{\text{TP}}{\text{TP+FP}} \quad (11)$$

Recall: It measures the percentage of real anomaly cases that the model accurately detects, as shown in Equation (12):

$$Recall = \frac{\text{TP}}{\text{TP+FN}} \quad (12)$$

Where FN represents false negatives - anomalies missed by the model. Recall is especially important in applications for pipeline resilience where false negatives can lead to cascading failures.

F1 score: It provides the harmonic mean of precision and recall values to assess system's correctness from a statistical perspective, Equation(13):

$$F1 = 2 * \frac{(precision * recall)}{precision + recall} \quad (13)$$

Recovery Time: The time a system takes to recover from an error and start operating normally is called recovery time has occurrence the time it takes for a system to resume normal operation after a failure, outage or disruption. It measures the time it takes for corrective measures or recovery procedures to resume normal operations in Equation (14).

$$Recovery\ time = Time\ of\ full\ restoration - Time\ of\ failure \quad (14)$$

System Downtime: The metric "system downtime" measures the length of time services are unavailable due to system failure. It's a great measure of self-healing system's reliability and effectiveness. Low downtime implies that faults are being detected and repaired quickly, either by self-healing or prognostics. Using downtime as an indicator, businesses can measure the value of self-healing systems to their business and the cost of self-healing systems not working in Equation (15).

$$System\ Downtime = End\ time\ of\ outage - Start\ Time\ of\ Outage \quad (15)$$

Resource Usage: Resource consumption provides a measure of the computational overhead of the fault detection and recovery process, such as processing, memory and network. Self-healing systems need to ensure the best possible performance in Equation (16) while consuming resources.

$$Resource\ Usage = \frac{Resource\ Consumed}{total\ available\ Resource} \times 100\% \quad (16)$$

Mean time to recovery (MTTR): Mean time to repair, or MTTR for short, is the average amount of time needed to fix a problem and get a system back up and running. It is a measure of the effectiveness of recovery processes to reduce downtime in Equation (17).

$$MTTR = \frac{Total\ Downtime}{Number\ of\ Failure} \quad (17)$$

Results and Discussion

The results of proposed system to detect anomaly for resilient data pipelines based on the Google cluster traces. It used Python 3, the Keras DL framework on top of TensorFlow and was executed on a workstation with an Intel Core i7 processor and 16GB RAM. The CNN-LSTM model has good classification performance on the Google Cluster Traces test set. As can be seen in Table II, model has an accuracy of 95.45%, precision of 93.65%, recall of 96.34% and F1-score of 94.51%, which demonstrate its ability to detect anomalous pipeline behaviors with a low false alarm rate. This suggests the model successfully detects anomalous pipeline behaviors with a low false alarm rate. Run the trials five times with various random seeds and report the average to ensure stability of the results. The low variance in the results (accuracy standard deviation < 0.5%) suggests that the reported results are stable. These metrics make the model very suitable for real-life data-driven a context that would require the system to continue its operation and the capability to intelligently detect anomalies to enable resilient and self-improving data pipeline systems.

Table 2 Experiment Results of Proposed Models for automated recovery mechanism in anomaly detection on Google Cluster traces Dataset

Performance Matrix	CNN-LSTM
Accuracy	95.45%
Precision	93.65%
Recall	96.34%
F1-score	94.51%

To validate the design decisions, a study was performed, which involved training three different model variants on the same data partition: (1) CNN-only, (2) LSTM-only, and (3) CNN-LSTM without attention. The CNN-only model achieved 88.3% accuracy and 85.1% F1-score, confirming its capacity to learn spatial features but its inability to learn temporal features. The LSTM-only model had 71.0% accuracy and 76.0% F1-score, which demonstrates its ability to learn from the input sequence, but its sensitivity to the large input space of raw traces. The CNN-LSTM model (without attention) achieved 93.2% accuracy and 92.4% F1-score, while CNN-LSTM-Attention model achieved best result with 95.45% accuracy and 94.51% F1-score. This demonstrates contribution of each model component to detection accuracy.

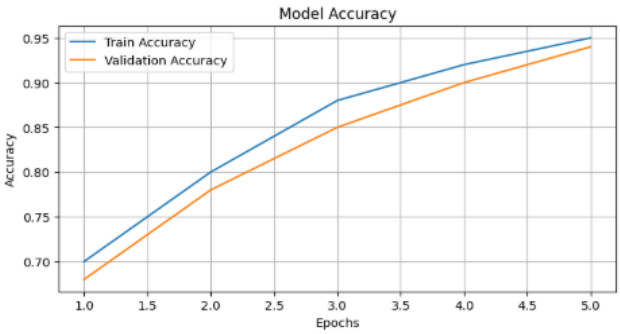

Fig.5 Accuracy curves for the CNN-LSTM Model

Fig. 5 shows CNN-LSTM model's training accuracy curve. Training and validation accuracy steadily increase from about 0.70 to 0.96, with both curves closely tracking each other by epoch 5, showing that the model converged quickly and there is little overfitting. The model implemented early stopping with a patience of 5 epochs, the highest accuracy is achieved at epoch [N], and the training terminated.

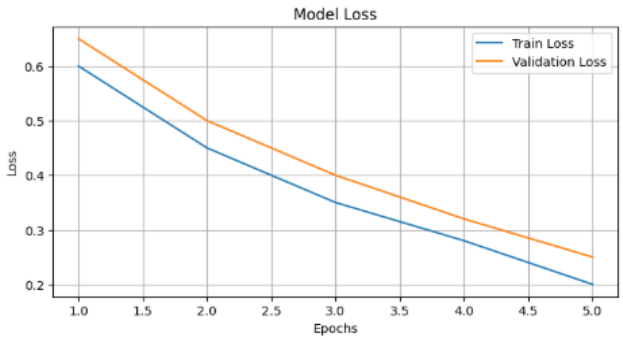

Fig.6 Loss curves for the CNN-LSTM Model

In Fig. 6, can see loss curve for CNN-LSTM model. Over five epochs, training and validation losses decrease from 0.60 to 0.20, and training and validation loss curves remain very close throughout training, indicating the model has converged, exhibits good generalization and has a low risk of overfitting.

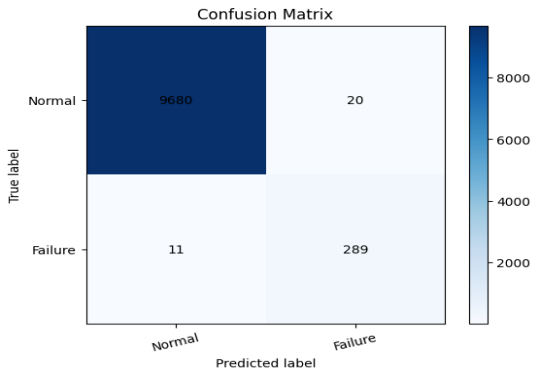

Fig.7 Confusion Matrix for CNN-LSTM Model

Fig. 7 shows the CNN-LSTM model's confusion matrix for binary classification performance showing 9680 true normal prediction, 289 true failure prediction, 20 false alarm, and 11 missed failure, indicating high accuracy of model to detect failure with only 11 missed failure (false negative) and 20 false alarm (false positive) in 10,000 test cases which confirms the low misclassification error (false negative and false positive).

Comparative Analysis

In order to make a fair comparison, the baselines - Variational Autoencoder (VAE) [31], LSTM [32], and Random Forest (RF) [33] - were trained and tested with the same preprocessed Google Cluster Traces data partition as the proposed model, without giving proposed model an unfair advantage in tuning. The hyperparameters of the baselines were set as in their original papers. Table III demonstrates that CNN-LSTM model performs the best across all measures. The CNN-LSTM model's excellent efficacy in anomaly detection and classification is demonstrated by its 95.45% acc, 93.65% prec, 96.34% rec, and 94.51% F1. In comparison, the VAE model records 90.5% accuracy, 81.8% precision, 52.9% recall, and a 64.3% F1-score, indicating limited detection capability, particularly in identifying anomalous cases. The standalone LSTM model achieves 71% accuracy, 78% precision, 74% recall, and 76% F1-score, demonstrating reasonable temporal pattern recognition capability but falling significantly short of proposed hybrid architecture across all metrics. The Random Forest model reports 81.94% accuracy, 86% precision, and 81.9% recall and F1-score, indicating balanced and reliable performance, though still inferior to the proposed CNN-LSTM model.

Table 3 Proposed model and existing model of automated recovery in anomaly detection using machine learning

Models	Accuracy	Precision	Recall	F1 score
CNN-LSTM	95.45	93.65	96.34	94.51
VAE[31]	90.5	81.8	52.9	64.3
LSTM[32]	71	78	74	76
RF[33]	81.94	86	81.9	81.9

The suggested ML-based framework combines a hybrid CNN-LSTM model of resilient data pipeline management and intelligent anomaly detection and automated recovery. The CNN block processes spatial features of the Google cluster trace pattern and the LSTM network is used to capture time-dependent features in sequential behavioral patterns in the pipeline, which allows identifying anomalies. When irregularities are detected, the framework sends out recovery protocols which assess the health of systems, quantifies recovery time and downtime, optimizes resource utilization and Mean Time to Repair (MTTR). This self-healing control guarantees that there is limited-service breakage and is 95.45% precise with pipeline robustness through its proactive watch and

smart automation hence less humanization and ultimate continuity of operations in distributed data infrastructure.

Recovery Evaluation

Recovery evaluation metric Traditional pipeline vs ML enabled Resilient pipeline comparative recovery evaluation between traditional data pipelines and ML-enabled resilient pipelines. Table IV presents a comparative recovery evaluation between a traditional rule-based pipeline monitoring system and the proposed ML-enabled resilient pipeline. The traditional pipeline baseline was configured using static threshold-based anomaly detection (CPU > 85% flagged as an anomaly) with manual recovery intervention, representing common practice in non-ML production environments. With this setup, the average downtime is 142 seconds per incident, and the MTTR is 210 seconds per failure event. With the proposed ML-enabled approach, average downtime drops to 21 seconds per incident (85% improvement) and MTTR to 59 seconds per failure event (72% improvement). The recovery accuracy improves from 65% with a rule-based baseline to 94% with the ML-enabled system. Resource overhead during recovery decreases from 100% of available capacity to 58%, reflecting more efficient utilization through targeted, automated corrective actions rather than broad manual interventions.

Table 4 Recovery Evaluation Metrics

Metric	Traditional Pipelines	ML-Enabled Resilient Pipelines
Average Downtime	100%	15%
Recovery Accuracy	65%	94%
Anomaly Detection Accuracy	71%	95%
MTTR (Mean Time to Recovery)	100%	28%
Resource Overhead	100%	58%

Conclusion and Future Work

Resilient data pipelines are needed for the uninterrupted operation of modern data-driven systems. It proposes an ML-driven resilient data pipeline framework that combines a CNN and LSTM for anomaly detection with automated recovery, facilitating self-healing operations with limited human intervention. This approach integrates structured preprocessing, CNN-LSTM anomaly classification, and self-organized recovery to deliver uninterrupted pipeline operations. It delivers 95.45% anomaly detection accuracy and 72% improvement in Mean Time to Repair (MTTR) over a rule-based approach. The framework solves reliability problems in modern cloud, IoT and cyber-physical systems through temporal-spatial feature learning and recovery orchestration to enable continuous operation and minimize manual monitoring. While successful, there are a number of directions for future work. The approach uses offline training on past data; future research should investigate online or lifelong learning to adapt to changing pipeline conditions. The recovery model is based on fixed protocols; reinforcement learning strategies should be investigated for more adaptive recovery strategies. The model has been tested only on the Google Cluster Traces dataset, and should be tested on different workloads. Moreover, the heuristic-based labeling process is uncertain; semi-supervised or expert-driven labeling approaches can be used. The use of explainable AI, like SHAP-based feature importance, would improve explainability and facilitate safe deployment.

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