

Deep Learning for Failure Prediction and Self-Healing in Large-Scale Distributed Computing Environments

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Abstract

Large-scale distributed computing environments generate telemetry at a volume and complexity that simple thresholds and hand-built features cannot fully exploit: thousands of correlated metrics per node, millions of log lines per hour, and dense dependency graphs between services. Deep learning can learn directly from this raw, high-dimensional data. Recurrent and stochastic recurrent networks model multivariate time series, attention-based models read log sequences, and graph neural networks follow faults along service dependencies. Yet deep models also bring difficulties in production: logs change with every software release, labeled failures are scarce, inference must keep pace with streaming data, predictions are opaque, and models go stale. This article proposes a deep learning framework for failure prediction and self-healing that addresses these difficulties. Telemetry flows through a high-volume event stream into an ensemble of deep models for metrics, logs, and dependency graphs. Their outputs are fused, localized to a probable root component, and explained. A recovery orchestrator acts on them through a risk-governed workflow, and models are retrained and released without downtime. Using a design-oriented approach grounded in eleven studies published between 1997 and 2023, the article maps the evidence base, compares deep architectures, sets out production challenges and responses, and maps deep model outputs to recovery. It illustrates the design with a multi-tenant GPU cluster used for training machine learning models. It argues that deep learning's value for self-healing lies in localizing failures across complex systems, provided its outputs are robust, explained, and governed.

Keywords: deep learning, failure prediction, self-healing systems, large-scale distributed computing, anomaly detection, long short-term memory, Transformer, graph neural networks, log analysis, multivariate time series, explainable AI, event streaming, zero-downtime deployment, GPU clusters

1. Introduction

A single large data center may contain hundreds of thousands of servers running thousands of interdependent services. Each server reports hundreds of metrics, each service writes continuous logs, and each request passes through many services. Failures in such

environments rarely announce themselves through a single metric crossing a threshold. They appear as subtle, correlated changes across many signals, often in components far from where users notice the effect.

Deep learning is designed for exactly this kind of data. It learns layered representations directly from raw inputs, without hand-built features (LeCun et al., 2015). Long short-term memory (LSTM) networks capture long-range patterns in sequences (Hochreiter & Schmidhuber, 1997). Attention-based Transformers relate every element of a sequence to every other (Vaswani et al., 2017). Graph convolutional networks learn from data structured as graphs (Kipf & Welling, 2017), such as service dependency maps. Applied to operations, deep models have detected anomalies in multivariate time series through stochastic recurrent networks (Su et al., 2019) and in logs through attention-based models robust to changing log formats (Zhang et al., 2019).

Deployment at scale raises further requirements. Deep models are opaque, and operators need to know why a failure was predicted before acting on it; model-agnostic explanation methods such as LIME can help (Ribeiro et al., 2016). Telemetry must be streamed at high volume (*Event Streaming Architectures for High-Volume Transaction Processing*, 2022). Models must be retrained and replaced frequently, which Sannidhanam (2023) addresses through zero-downtime AI model updates in real-time inference systems. And recovery actions based on deep model outputs must be governed by their risk, for which Basireddy (2022) provides configurable enterprise workflow architecture with approval and escalation.

Large clusters for training machine learning models themselves show why this matters. Analysis of a large multi-tenant GPU cluster found that failures and scheduling effects significantly affect long-running training jobs (Jeon et al., 2019). Predicting and healing failures in such environments saves substantial compute and time.

This article asks: *How can deep learning be used for failure prediction and self-healing in large-scale distributed environments, in a way that is robust, explainable, and governed in production?* It contributes an evidence map (Figures 1 and 2), a comparison of deep architectures, a set of production challenges and responses, an integrated framework, a mapping of model outputs to recovery, and an illustrative case.

2. Related Work

2.1 Deep learning foundations

LeCun et al. (2015) review deep learning, which learns multiple levels of representation from raw data and has transformed perception and sequence tasks. Hochreiter and Schmidhuber (1997) introduced LSTM networks, which use gated memory cells to learn dependencies over

long time spans. Vaswani et al. (2017) introduced the Transformer, which relies entirely on attention and processes sequences in parallel.

2.2 Deep anomaly detection in operations

Su et al. (2019) propose OmniAnomaly, a stochastic recurrent neural network that learns normal patterns of multivariate time series, detects anomalies from reconstruction probability, and indicates which metrics contributed. Zhang et al. (2019) propose LogRobust, which represents log events by their semantic meaning and uses an attention-based bidirectional LSTM, making detection robust to log statements that change as software evolves.

2.3 Graph learning and explanation

Kipf and Welling (2017) propose graph convolutional networks, which learn node representations by aggregating information from neighbors. Ribeiro et al. (2016) propose LIME, which explains any classifier's prediction by fitting a simple model around it.

2.4 Large-scale clusters

Jeon et al. (2019) analyze a large multi-tenant GPU cluster used for deep learning training and report how locality, job interference, and failures affect utilization and job completion.

2.5 Streaming, model updates, and governance

The 2022 study of event streaming architectures addresses high-volume transaction processing on streaming platforms. Sannidhanam (2023) addresses zero-downtime updates of models in real-time inference systems. Basireddy (2022) proposes configurable enterprise workflow architecture for risk management, with configurable approval, escalation, and audit trails.

2.6 Research gap

Deep anomaly detection studies usually evaluate one model on one data type offline. Few designs combine deep models for metrics, logs, and dependency graphs into a self-healing system, or address the production issues of changing logs, scarce labels, explanation, model updating, and governed recovery together. This article addresses that gap.

3. Research Methodology

The study follows a design-oriented research approach. The problem, the difficulty of predicting and localizing failures in complex, high-volume telemetry, and of using deep models safely in production, was identified from the literature. Requirements were derived from the reviewed studies: learning from multiple telemetry types, robustness to change,

localization of root components, explanation, scalable inference, continuous updating, and governed recovery. The framework was designed from eleven studies published between 1997 and 2023 and demonstrated through an illustrative case.

To make the evidence base transparent, each study was assigned to the theme it primarily supports. Figure 1 shows the distribution across themes, and Figure 2 shows the studies by publication year. These figures describe the literature used in this article. They are not performance measurements. The framework has not been evaluated empirically, which is left to future work.

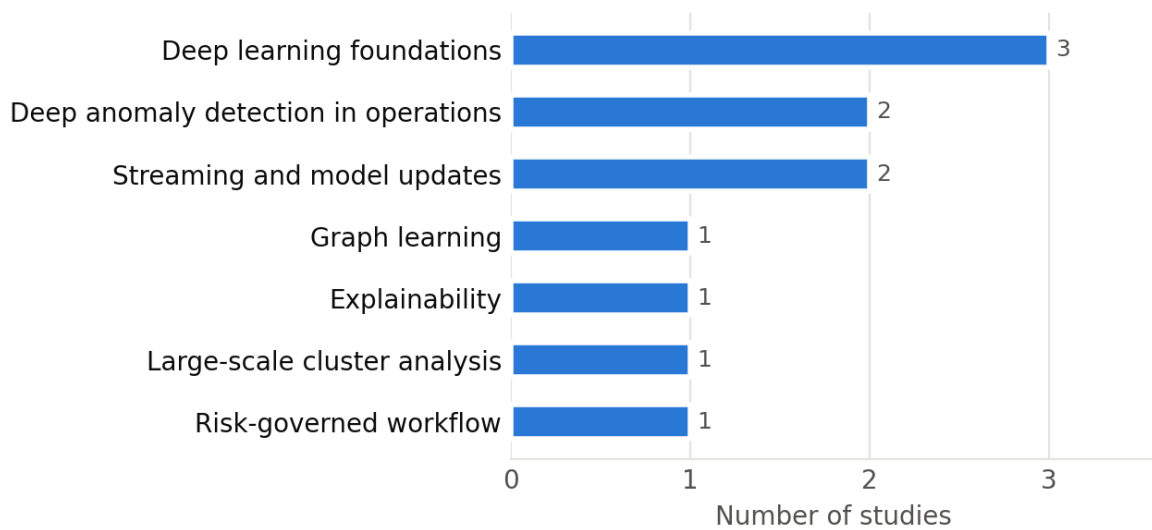


Figure 1. Number of reviewed studies primarily supporting each theme (n = 11)

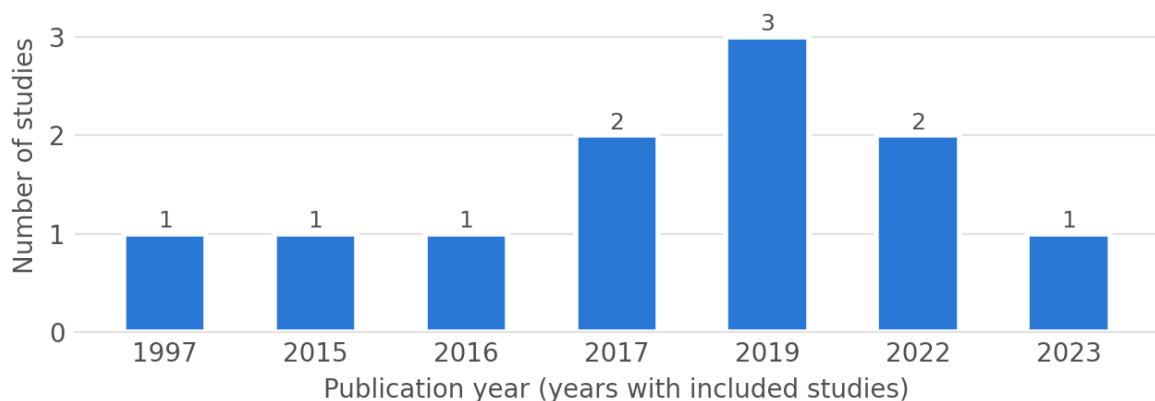


Figure 2. Reviewed studies by publication year (n = 11)

Deep learning foundations have the most studies, with three. Deep anomaly detection in operations and streaming with model updates have two each. Graph learning, explanation, large-scale cluster analysis, and risk-governed workflow have one each. The studies span 1997 to 2023, with most published from 2015 onward.

4. Deep Architectures for Failure Prediction

Table 1 compares deep architectures by the telemetry they consume and the failure patterns they capture.

Table 1. Deep learning architectures for failure prediction

Architecture	Input	What it captures	Self-healing use	Supporting studies
LSTM	Metric or event sequences	Long-range temporal patterns	Predict failure from trends	Hochreiter & Schmidhuber (1997)
Stochastic recurrent network	Multivariate metrics	Normal joint behavior of many metrics; contributing metrics	Detect anomalies and point to affected metrics	Su et al. (2019)
Attention-based log model	Log event sequences	Semantics of log events; robust to changed log statements	Detect abnormal execution despite software updates	Zhang et al. (2019)
Transformer	Long sequences of metrics or logs	Relations across distant events, in parallel	Model long incident build-ups efficiently	Vaswani et al. (2017)
Graph convolutional network	Service or node dependency graph	How problems spread across dependencies	Localize the root component	Kipf & Welling (2017)

The architectures are complementary. Metric and log models detect that something is wrong; the graph model helps find where. In large environments, localization is often the hardest and most valuable step, because an anomaly in one service may be a symptom of a fault several dependencies away.

5. Production Challenges and Responses

Deep models that perform well offline often struggle in production. Table 2 sets out the main challenges and the framework's responses.

Table 2. Production challenges of deep failure prediction

Challenge	Why it arises	Framework response	Supporting studies
Changing logs	Software updates alter log statements	Semantic log representations; attention models	Zhang et al. (2019)
Scarce labels	Failures are rare and poorly recorded	Unsupervised learning of normal behavior	Su et al. (2019); LeCun et al. (2015)
Inference volume	Millions of events per	Stream processing; batched	Event streaming

Challenge	Why it arises	Framework response	Supporting studies
	minute	inference on partitions	architectures (2022)
Opacity	Deep models do not explain themselves	Contributing metrics; local explanations	Su et al. (2019); Ribeiro et al. (2016)
Model staleness	Workloads and hardware change	Frequent retraining; zero-downtime release	Sannidhanam (2023)
Overreaction	Confident but wrong predictions trigger harmful actions	Risk-governed recovery with approval	Basireddy (2022)

Two responses are particularly important. First, learning normal behavior without labels avoids dependence on the few failures that are recorded, while still detecting new failure types (Su et al., 2019). Second, explanation turns a score into an actionable finding: knowing which metrics or log events drove a prediction tells operators, and the recovery orchestrator, what to do (Ribeiro et al., 2016).

6. Integrated Framework

6.1 Architecture

Figure 3 shows the framework.

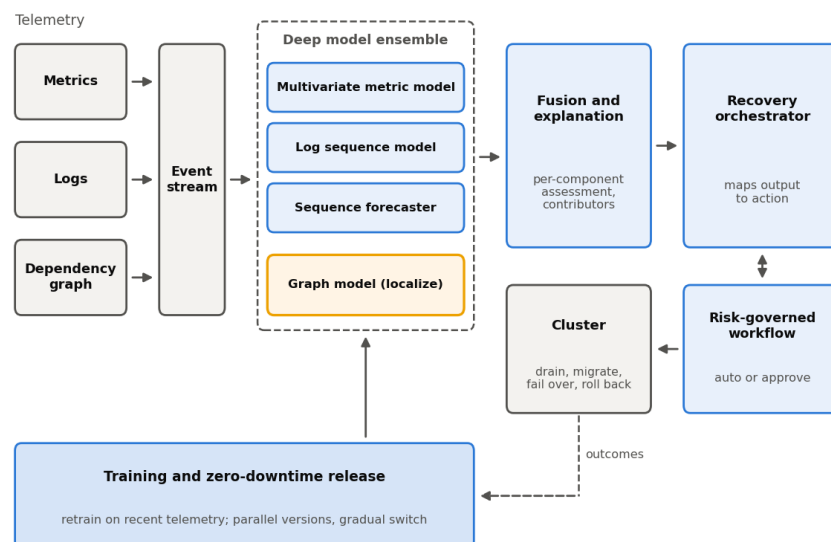


Figure 3. Deep learning framework for failure prediction and self-healing

Telemetry and streaming. Metrics, logs, and a continuously updated dependency graph are published to the event stream (Event streaming architectures, 2022).

Deep model ensemble. A multivariate time-series model detects metric anomalies (Su et al., 2019). A log model detects abnormal execution (Zhang et al., 2019). An LSTM or Transformer forecasts failure from longer histories (Hochreiter & Schmidhuber, 1997; Vaswani et al., 2017). A graph model combines anomaly signals across the dependency graph to localize the likely root component (Kipf & Welling, 2017).

Fusion and explanation. Outputs are fused into a single assessment per component, with an explanation of the contributing metrics and log events (Ribeiro et al., 2016).

Recovery orchestrator and workflow. The orchestrator maps the assessment to a recovery action (Table 3). Low-risk actions run automatically; higher-risk actions require approval (Basireddy, 2022).

Training and release. Models are retrained on recent telemetry and released alongside current versions, switching gradually without interrupting inference (Sannidhanam, 2023).

6.2 From model outputs to recovery

Table 3 maps model outputs to recovery actions.

Table 3. Mapping deep model outputs to recovery

Model output	Example	Recovery action	Governance
Metric anomaly on one node	Memory and error metrics diverge from normal	Drain and restart node	Automatic
Abnormal log sequence	Repeated driver reset events	Isolate node; schedule hardware check	Automatic; recorded
Forecast failure with lead time	Rising correctable memory errors	Migrate workloads before failure	Automatic within capacity limits
Localized root component	Shared storage service causing anomalies in many nodes	Fail over storage; do not restart the symptomatic nodes	Engineer approves
Widespread anomaly after release	Many services affected together	Roll back release	Owner approves unless error budget exhausted

The fourth row shows why localization matters. Without it, a self-healing system might restart dozens of healthy nodes that only show symptoms, making the incident worse.

6.3 Self-healing pipeline

Figure 4 shows the pipeline.

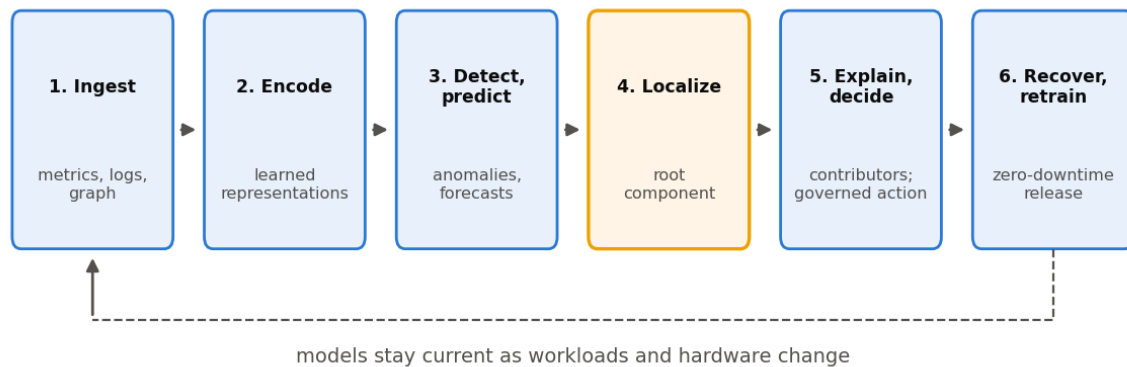


Figure 4. Deep learning self-healing pipeline

Telemetry is ingested from the stream and encoded into representations suitable for each model. The models detect anomalies and predict failures. The graph model then localizes the root component; this step is highlighted because it prevents recovery from being aimed at symptoms. Outputs are explained and a recovery is decided under governance. Finally, the system recovers, and outcomes feed retraining, with new models released without downtime (Sannidhanam, 2023).

7. Illustrative Case: A Multi-Tenant GPU Training Cluster

Consider a research organization operating a cluster of several thousand GPUs shared by many teams training machine learning models. Training jobs may run for days across many nodes, and a single node failure can stop an entire job. As Jeon et al. (2019) observed in a similar environment, failures and interference between jobs strongly affect how much useful work the cluster completes. The case is illustrative and reports no measured results.

Detection. The multivariate model learns normal patterns of GPU temperature, memory errors, power, and network throughput for each node (Su et al., 2019). The log model reads driver and kernel logs; because it represents log events by meaning, it continues to work after a driver update changes log wording (Zhang et al., 2019).

Prediction. An LSTM on the history of correctable memory errors forecasts that one node is likely to fail within a few hours (Hochreiter & Schmidhuber, 1997). The recovery orchestrator asks the job scheduler to save a checkpoint of the training job and move it to healthy nodes, then drains the suspect node for inspection (Table 3). The job loses minutes rather than hours of work.

Localization. One afternoon, dozens of nodes show slow training steps at once. Restarting them would waste the progress of many jobs. The graph model, using the dependency graph linking nodes to shared storage and network switches, localizes the problem to one storage

server (Kipf & Welling, 2017). The explanation shows rising read latency on that server as the main contributor (Ribeiro et al., 2016). Failover of the storage server is a high-risk action, so the workflow routes it to the storage engineer, who approves it (Basireddy, 2022).

Updating. New GPU models join the cluster, with different normal behavior. The models are retrained on recent telemetry and released alongside the current versions without interrupting detection (Sannidhanam, 2023). All telemetry, from thousands of nodes, flows through the event streaming platform (Event streaming architectures, 2022).

The case shows deep learning predicting failures early enough to save work, localizing a shared cause instead of treating symptoms, and staying current as hardware changes.

8. Discussion

8.1 Implications

For research, the article combines deep models for metrics, logs, and dependency graphs into a self-healing framework and emphasizes localization and production robustness over offline accuracy. For practitioners, the lessons are to use deep models where telemetry is high-dimensional and hand-built features fall short; to learn normal behavior rather than depend on scarce failure labels; to use semantic log representations that survive software updates; to localize before recovering; to explain every prediction; to govern disruptive actions; and to retrain and release models continuously without downtime.

8.2 Limitations and future work

The framework was demonstrated through an illustrative case and draws on eleven studies, so the evidence base is focused rather than comprehensive. Several descriptions of the studies are based on their stated scope. Deep models carry costs in computation and expertise, and simpler methods may suffice in smaller environments. Future work should implement the framework and measure detection quality, localization accuracy, lead time, compute saved, and inference cost. Keeping dependency graphs accurate, and explaining graph model outputs, also need further study.

9. Conclusion

Deep learning can read the complex, high-volume telemetry of large distributed environments in ways that simpler methods cannot. This article proposed a framework in which deep models for metrics, logs, and dependency graphs detect, predict, and localize failures from streamed telemetry; their outputs are explained and acted on through risk-governed recovery; and models are retrained and released without downtime. The GPU cluster case showed

failures predicted in time to save work and a shared cause found instead of symptoms treated. The central conclusion is that deep learning's value for self-healing lies in localizing failures across complex systems, provided its outputs are robust, explained, and governed.

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