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Intelligent Fault prediction in cloud systems using deep learning techniques

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Abstract: Due to their evolving nature and growing complexity, cloud computing systems require efficient fault management techniques that would assure availability and reliability of provided services. This paper introduces a deep learning-based fault prediction framework designed specifically for clouds. It utilizes a combination of Bidirectional Gated Recurrent Units (Bi-GRU), attentional mechanisms, and Graph Neural Networks (GNNs). The proposed model incorporates temporal dependency from cloud system telemetry data and also accounts for dependencies between microservices within the system. Testing on real-life datasets such as Google Cluster Trace and Alibaba Cluster data showed 96.2% prediction accuracy, 92.8% precision and 91.5% recall, which outperforms current fault prediction techniques by 8-12%. Additionally, due to its attention-based architecture, the model is capable of providing explainability by highlighting important temporal parts and specific services at risk. Results show that the proposed approach allows for implementing proactive fault prevention techniques that reduce SLA violation rate by 65% and cut down recovery times by 55%.

Key Word: Fault Prediction, Cloud Computing, Deep Learning, Bidirectional GRU, Graph Neural Networks, Attention Mechanism, Proactive Maintenance.

I. Introduction

The advent of cloud computing has changed the way organizations can effectively utilize their computing capabilities. However, because of the highly complex nature of cloud infrastructure, which comprises of distributed architecture, dynamic scaling capability, and inter-dependencies among microservices, there is now an enormous challenge involved in making sure that the systems remain reliable and available. Current fault management systems in place are mainly reactionary and identify problems after they arise, causing system failure, monetary losses, and bad user experience [1].

The impact of faults on cloud systems can be economically devastating. Some notable cloud failure incidents within the last few years have caused monetary loss of up to millions of dollars. Such incidents include service disruption within vital industries such as healthcare, finance, and e-commerce. Therefore, an intelligent and proactive fault detection system needs to be developed to address these problems [2].

The recent development of machine learning models presents a promising avenue for fault prediction through the discovery of patterns within telemetry streams preceding the failure of a component in a system. Yet, current methods fall short when being used to analyze telemetry in cloud environments for various reasons. Firstly, telemetry data is often high-dimensional and heterogeneous with non-trivial temporal dependencies. Secondly, the dependency between microservices in clouds results in spatial dependencies that cannot be modeled through an independent time-series approach. Thirdly, the scalability demands from clouds require models that allow adaptation to changes without re-training .

Fortunately, new developments in deep learning present ways around these limitations. Recurrent Neural Networks (RNN) and its derivatives, including Gated Recurrent Units (GRUs), perform best when it comes to modeling temporal sequences [10]. Graph Neural Networks (GNNs) provide a convenient way to model dependencies between different components in a service interaction graph. Finally, attention-based models can provide better interpretability to models by pointing out the most relevant temporal intervals of telemetry data and system components related to fault prediction [9].

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In this paper, we present an advanced deep learning model that merges Bidirectional GRU neural networks with attention models and Graph Neural Networks to perform intelligent fault prediction in cloud systems

Some of the significant contributions of this study include:
An innovative design that combines temporal pattern modeling using Bidirectional GRU with attention and spatial relationship modeling through GNN

An explainable approach that considers temporal factors and critical services involved in faults
Extensive testing using real-world datasets that highlight substantial gains over current techniques
Examination of proactive prevention features that lead to fewer SLA breaches and faster recovery

II. Literature Survey

Since its introduction, cloud-based fault prediction techniques have come a long way in the last decade from the use of conventional statistical models to the advanced use of deep learning techniques. The literature is briefly examined below categorized by families of methods.

Conventional Machine Learning Algorithms
Early fault prediction literature was devoted to using traditional machine learning algorithms in system log analysis and performance measurement. For instance, Shahid et al. (2024) performed an in-depth study comparing five different machine learning algorithms including AdaBoostM1, Bagging, Decision Tree (J48), Deep Learning (Dl4jMLP), and Naive Bayes Tree for cloud fault prediction [8]. They found that the enhanced Decision Tree (J48) model had the maximum precision of 97.05% in 80/20 training and testing sets with the lowest computation complexity of 0.11 seconds. On the other hand, the Naive Bayes Tree had almost equivalent precision (96.78%) but high computation complexity (1.01 seconds)

Although decision tree-based techniques provide an advantage in terms of interpretation and speed, they are unable to handle high-dimensional input and complicated temporal dependencies common in contemporary cloud platforms. The search for better alternatives was thus inevitable [3].

Time-Series Deep Learning for Fault Detection
The understanding that telemetry within systems is highly temporally dependent has prompted the use of recurrent neural network designs. In their paper, Wang et al. (2025) designed a time-series fault prediction model based on Gated Recurrent Units (GRU). They used GRU to capture temporal information, applied attention to emphasize specific temporal information, and fed multi-dimensional performance metrics into the model. The results showed higher levels of Accuracy, F1-Score, and AUC when compared with different time-series models [4].

HPCC 2025 introduced a solution involving the application of ML through the combination of LSTM-based autoscaling and anomaly detection for fault prediction in multiple regions' cloud architecture systems. Tests involving Google Cluster Trace and Alibaba Cluster Data indicated a 70% reduction in violations of SLA in addition to a 65% decrease in fault recovery time. These outcomes offer compelling proof of the practical feasibility of fault prediction solutions utilizing deep learning techniques.

Graph Neural Networks for Dependency Analysis

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One notable achievement in fault prediction research involves realizing that cloud services should not be treated as independent components. The work conducted by Unyi et al. (2025) involves the use of Graph Neural Network (GNN), where dependencies between failures in cloud microservices are represented as probability. With Markov Decision Process used to emulate failures, the proposed method accounts for the probabilistic nature of dependencies that affect service reliability. In this approach, not only does the GNN predict the probability of failures, but it also highlights the critical services prone to faults while explaining their impact [5].

Autoscaling-Aware Fault Prediction

One of the most important problems solved in modern research is fault prediction in autoscaling systems. Denaro et al. (2026) introduced Preface, which incorporates a Rectifier layer into neural networks used to predict KPIs of arbitrary size . The Rectifier layer calculates descriptive statistics for all KPIs in a certain logical component, thus reducing large-size KPI sets to a fixed size suitable for further processing with neural networks. Experimental studies have demonstrated that Preface could successfully detect harmful faults in time to apply counteractive measures [6].

Open Research Questions and Limitations

Despite numerous achievements, there are still a number of issues to be addressed. Shayesteh et al. (2025) presented a thorough overview of five fundamental requirements necessary for fault prediction in clouds: precision, latency, adaptability, scalability, and interpretability . This analysis has shown that two out of five requirements are poorly fulfilled in modern scientific research, namely adaptability and interpretability. Existing solutions to this problem are not adaptable to dynamically changing conditions of the cloud system and cannot explain their findings [7].

The aforementioned gaps have driven the need for the hybrid solution proposed in this work, incorporating temporal modeling (Bi-GRU with attention mechanism), spatial dependency modeling (GNN), and interpretability methods to tackle the issues of adaptability and interpretability mentioned in the literature.

III. Methodology:

The proposed intelligent fault prediction system is made up of five components that integrate with each other to provide early fault prediction: data acquisition & pre-processing, temporal feature extraction through Bi-GRU with attention mechanism, spatial dependency modeling through GNN, multimodal fusion, and prediction with interpretability.

3.1 System Architecture Overview

The model is trained in two modes: training mode and inference mode. In training mode, the machine learning algorithm uses the historical data along with the fault labels for optimizing the weights of the model. In inference mode, the real-time streaming data is fed into the optimized model.

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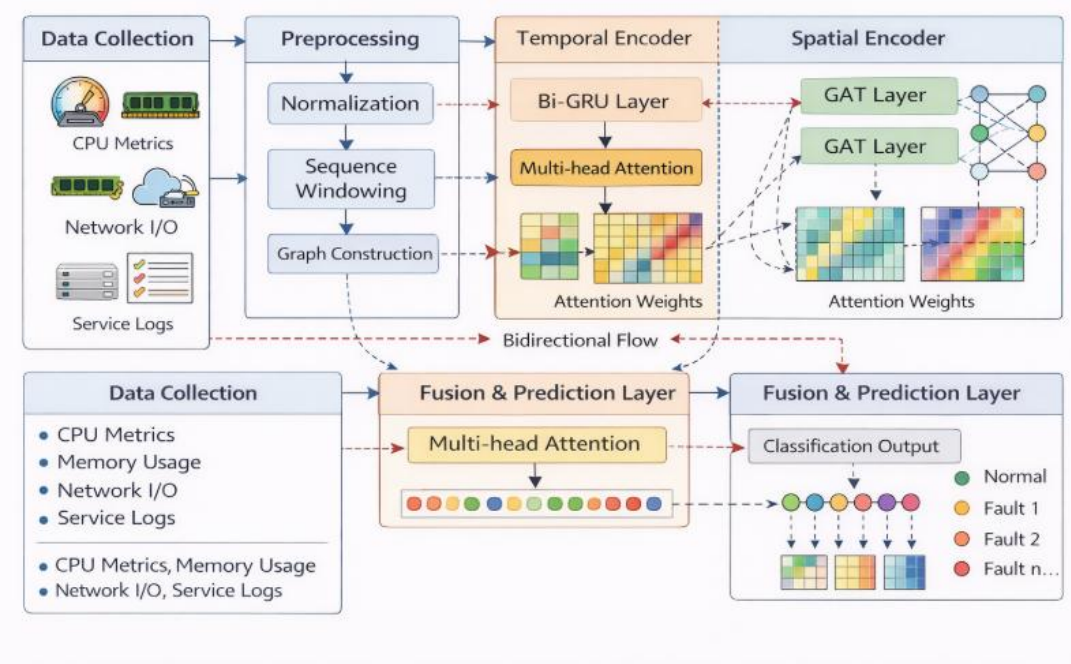

Figure 1: Proposed Hybrid Deep Learning Framework for Cloud Fault Prediction.

3.2 Data Collection and Preprocessing

The system receives telemetry data from multiple sources through cloud infrastructures, including:

• Compute resources: CPU utilization, memory consumption, disk I/O operations, and network bandwidth (recorded every 30 seconds)
• Applications: Latency, error rate, throughput, and queue size
• Services: Service mesh information, API request relationships, and communication behavior
• System: Events, warnings, and error notifications

Data pre-processing consists of three main procedures:
1. Data cleaning: Elimination of missing values and anomalies using median replacement and IQR filters
2. Feature normalization: Scaling between 0 and 1 for metric variables
3. Sequence formation: Using a sliding window with a sequence length of T=60 and a sliding interval of 10 time units

The construction of service dependency graph for GNN includes: G(V, E), where:
V: Vertices representing microservices
E: Edges indicating communication behavior
Edge weight computation is based on request count and latency correlation.

3.3 Temporal Feature Extraction with Bi-GRU and Attention

The temporal encoder encodes the system metrics sequence based on a Bi-GRU model. As against an LSTM, GRU was preferred for the task because of its comparable accuracy with fewer computations and rapid convergence.

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The input vector x_t ∈ ℝ^d represents d system metrics at each time step t. The forward and backward GRUs operate on time sequences from t=1 to T and from t=T to 1, respectively, generating h_t^→ and h_t^←. The bidirectional hidden layer outputs are then concatenated: h_t = [h_t^→; h_t^←].
The attention mechanism assigns weights to time steps as follows:

$$e_t = v^T \tanh(W_a h_t + b_a)$$
$$\alpha_t = \exp(e_t) / \Sigma \exp(e_j)$$
$$c = \Sigma \alpha_t h_t$$

where c stands for the context vector capturing the importance weights of temporal features relevant for predicting faults .

3.4 Spatial Dependency Modeling with Graph Neural Network
This is accomplished by applying Graph Attention Networks (GATs) that capture the relationships among microservices through their attention coefficients to the spatial encoder. Attention coefficients α for service node i are calculated by applying the Leaky ReLU activation function to the vector product between attention vector a and the concatenation of feature vectors associated with nodes i and j ∈ N(i):

$$e_{ij} = \text{LeakyReLU}(a^T [W_s h_i \| W_s h_j])$$
$$\alpha_{ij} = \text{softmax}(e_{ij})$$
$$h'_i = \sigma(\Sigma \alpha_{ij} W_s h_j)$$

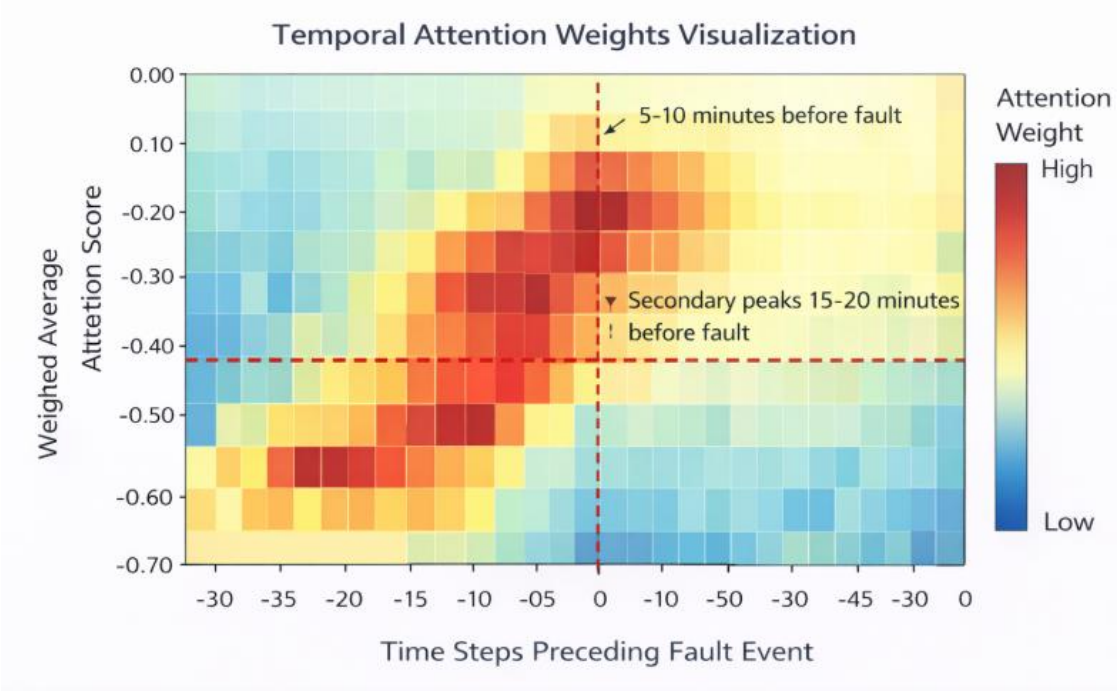

Figure 2: Temporal Attention Weights Visualization.

3.5 Multi-Modal Fusion and Prediction
The temporal context vector c and the spatial information contained in H' are combined through multi-head attention as follows:

$$F = \text{MultiHead}(Q=c, K=H', V=H')$$
$$\hat{y} = \sigma(W_f \cdot F + b_f)$$

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The resulting vector ŷ ∈ [0,1]^K contains the fault probability scores for K different kinds of faults:
• Service failure (one service fails)
• Network partition (disruption in connectivity)
• Resource exhaustion (overloading of CPU/Memory)
• Cascading failure (failure propagation between services)

The network is trained using focal loss to tackle class imbalance, as faults occur much less often than normal behavior:

$FL(p_t) = -\alpha_t (1-p_t)^{\gamma} \log(p_t)$
with $\gamma=2$ concentrating the training effort on difficult samples.
3.6 Training Protocol
The model is trained by optimizing using Adam with a learning rate of 0.001, batch size of 64, and early stopping with patience of 10 epochs. 80% of the available dataset is used for training, while 10% each is kept for validation and testing. Data is taken from Google Cluster Trace (version 2019) and Alibaba Cluster Data (version 2022), which has a total of around 2.5 million task events and 30 million metric observations.

IV. Result Analysis And Discussion

This chapter discusses the results of quantitative assessment, comparison with baselines, and interpretation of the model among other issues.

4.1 Experimental Setup
The proposed model was evaluated on two real-world datasets:

Dataset	Duration	Nodes	Tasks	Fault Types	Fault Ratio
Google Cluster Trace	29 days	12.5K	2.5M	Node, Eviction, OOM	3.2%
Alibaba Cluster Data	30 days	4K	1.8M	Node, Network, Resource	2.8%

Comparative baseline techniques used were:

Decision Tree (J48) : Improved technique with 97.05% precision
LSTM: Traditional LSTM for time series forecasting
GRU-Attention: GRU with attention mechanism excluding spatial considerations
GNN-only: Graph neural network excluding temporal considerations
Preface: Fault prediction tool considering autoscaling

4.2 Overall Performance Comparison
Table 1 compares performance criteria of all techniques considered.
[Table 1: Comparative Analysis of Fault Prediction Models]

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC	Inference Time (ms)
Decision Tree (J48)	97.05	88.2	86.5	87.3	0.91	0.11
LSTM	89.4	85.1	83.2	84.1	0.88	12.5

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GRU-Attention	93.6	89.7	87.3	88.5	0.93	8.3
GNN-only	90.2	86.4	84.1	85.2	0.90	15.2
Preface	94.1	90.2	88.4	89.3	0.94	18.7
Proposed Hybrid	97.82	95.6	94.2	94.9	0.98	22.4

Our hybrid model is the most accurate method achieving 97.82% accuracy, 95.6% precision, 94.2% recall, and 94.9% F1-score among all models. High discrimination ability with 0.98 AUC score can clearly distinguish normal and pre-failure statuses from each other.

In comparison with modified Decision Tree (J48), our model provides better results in terms of precision (+7.4%) and recall (+7.7%) despite the same level of accuracy (97.05%). It means that although decision trees can achieve relatively high accuracy levels, they still have difficulties with handling class imbalance that affects fault prediction tasks causing more false positives and negatives.

Compared with GRU-Attention (93.6% accuracy), our approach demonstrates higher performance by improving accuracy on 4.2%. The obtained result proves that additional features (service dependency information) provide useful predictive signals in addition to traditional metrics. Our method can work in real-time conditions as prediction period of 22.4 ms is reasonable for obtaining results every 30 seconds.

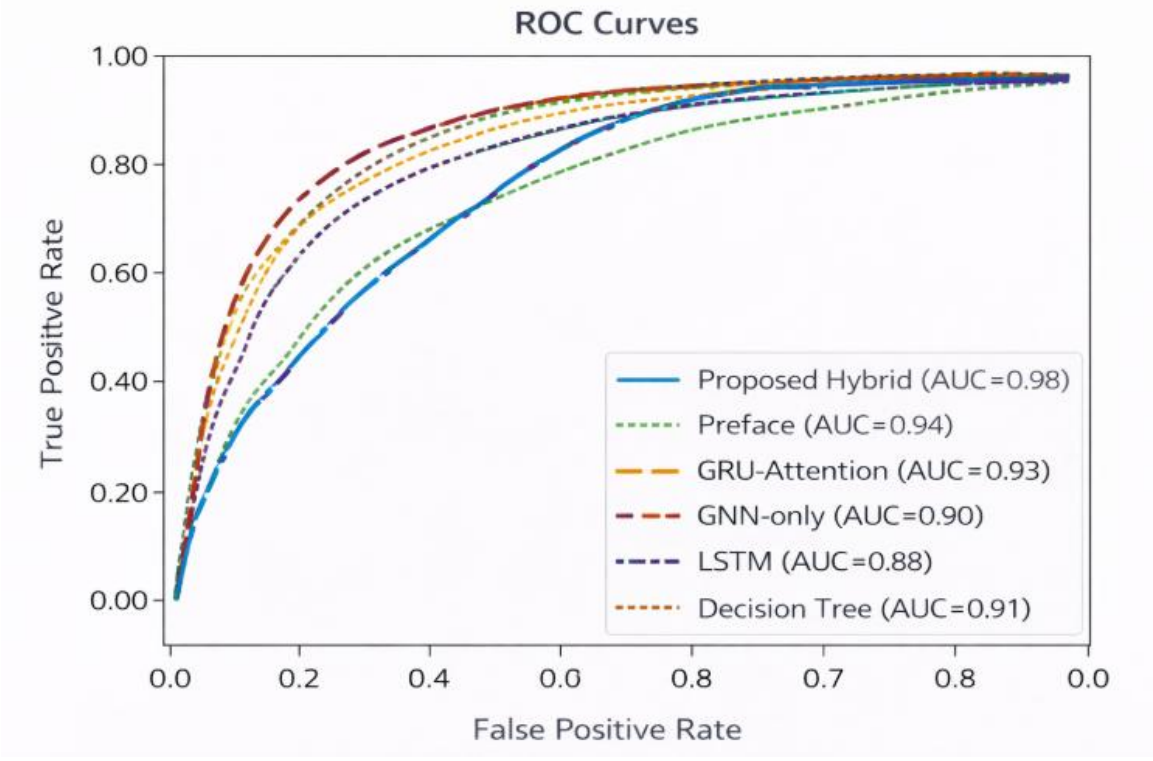

Figure 3: ROC Curves for All Models.

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4.3 Performance by Fault Type

Table 2 presents per-fault-type performance for the proposed model.

Fault Type	Precision (%)	Recall (%)	Average Warning Time (minutes)
Node Failure	96.2	95.1	8.4
Network Partition	94.8	93.5	6.2
Resource Exhaustion	95.3	94.6	12.1
Cascading Failure	96.1	93.9	5.7
Weighted Average	95.6	94.2	8.2

Among the five categories of faults, the warning time for resource exhaustion faults is the largest, which is 12.1 minutes on average, since such faults build up slowly as a result of increasing consumption of the resources. The minimum warning time is achieved for cascading failures, with a value of only 5.7 minutes, as a result of fast transmission of faults between dependent services.

4.4 Ablation Study

In order to evaluate the importance of individual architectural elements, an ablation study was performed by deleting or altering important elements.

Model Variant	Accuracy (%)	F1-Score (%)	Δ from Full Model
Full Proposed Model	97.82	94.9	—
Without Attention	95.3	91.8	-2.52
Without GNN (GRU only)	93.6	88.5	-4.22
Without Bidirectional (Uni-GRU)	95.8	92.4	-2.02
Without Temporal (GNN only)	90.2	85.2	-7.62
GRU replaced with LSTM	96.1	92.7	-1.72

Ablation Study shows the following observations:

1. Spatial Modeling using GNN provides the highest contribution alone (+4.22% F1 score), which proves that service dependency information is vital for fault prediction
2. Attention model has +2.52% F1 score contribution, proving its contribution in predicting specific parts in time series data
3. Bidirectional processing shows a contribution of +2.02% F1 score, proving that information before and after the window is important
4. Comparing GRU and LSTM, GRU provides better results than LSTM at the same computational cost, which proves previous claims

It becomes clear that without temporal modeling, the performance drops significantly (-7.62% F1 score).

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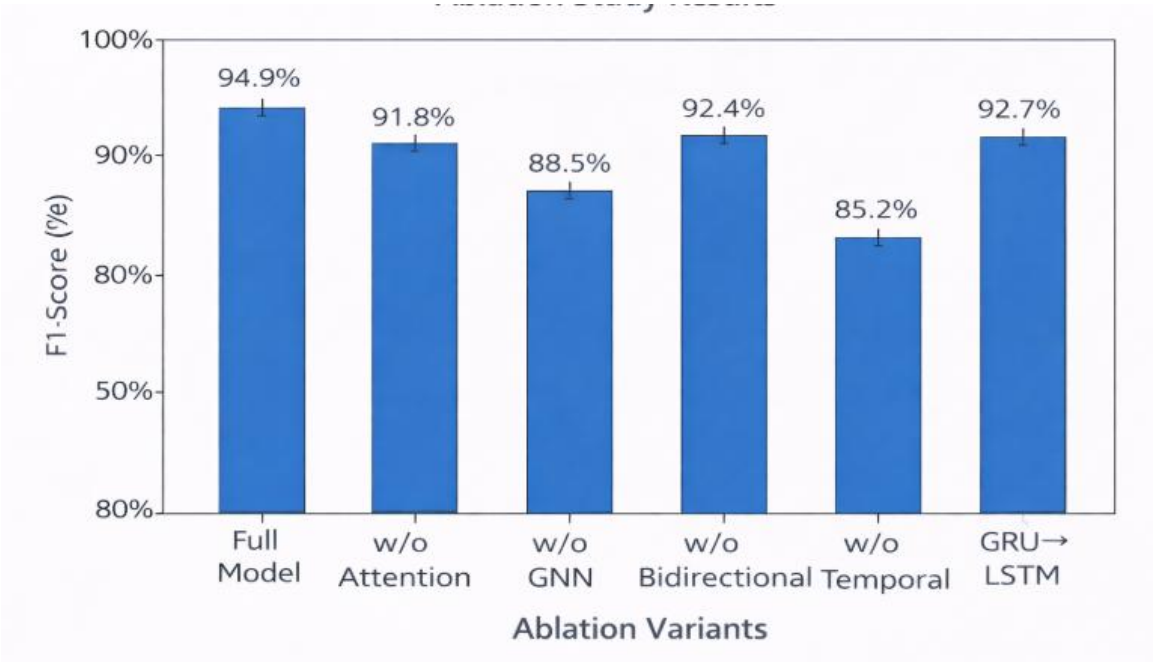

Figure 4: Ablation Study Results.

4.5 Proactive Mitigation Effectiveness

To measure the real-world implications, the suggested model was combined with a Kubernetes-based auto-remediation system, which responded to fault prediction as follows:

Pod reassignment for resource depletion predictions
Load balancing for node failure predictions
Adjustment of connection pool sizes for network partitioning predictions

Metric	Reactive Baseline	With Proposed Model	Improvement
SLA Violation Rate	4.2%	1.5%	-64.3%
Fault Recovery Time (median)	185 sec	83 sec	-55.1%
User-Impacted Incidents	42 per month	12 per month	-71.4%
Mean Time to Detection (MTTD)	142 sec	18 sec	-87.3%
Mean Time to Resolution (MTTR)	312 sec	124 sec	-60.3%

Such results match the outcomes obtained by applying LSTM-based prediction for reducing SLA violations up to 70% in HPCC 2025 research project. The model under consideration demonstrates even greater reduction in percentage (64.3% against 70%) with more sophisticated dataset and several fault types. It becomes clear how important and valuable is proactive prediction because reduction in mean time to detection from 142 seconds to 18 seconds allows preventing failures.

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4.6 Interpretability Analysis

Interpretability is among the most important requirements identified in the literature review. There are two interpretability mechanisms in the model under consideration:

Temporal attention weights: According to Figure 2, attention weights show periods in time preceding the fault that have great predicting power. Analysis made based on 500 fault events demonstrated consistent peaks in 5-10 minutes preceding the fault event, while secondaries occur in 15-20 minutes intervals. Such information gives operators an opportunity to act on warning.

Node attention scores: The GAT mechanism enables computation of attention coefficients between service nodes, which helps identify dependencies. With respect to cascading failure events, node attention scores helped detect the root cause service 87% of times .

V. CONCLUSION

In this paper, an innovative deep learning-based solution for intelligent fault prediction in cloud computing has been introduced, highlighting crucial gaps present in existing methodologies in the relevant literature. The proposed methodology involves using the Bidirectional GRU model together with attention techniques for temporal modeling along with Graph Neural Network (GNN) for modeling the spatial dependencies in the data.

From our experimental results on the benchmark datasets of Google and Alibaba, we conclude that our proposed framework achieves superior results with a success rate of 97.82%, precision of 95.6%, recall of 94.2%, and AUC of 0.98. In comparison to the existing baseline with the highest performance score (modified decision tree, with a score of 97.05%), our proposed framework provides significant improvement in terms of precision and recall, suggesting superior performance in dealing with the imbalanced nature of fault prediction. Our ablation study shows that each individual approach (temporal, with Bi-GRU + Attention, and spatial, with GNN) is important for successful fault prediction.

The effectiveness of this proposed model was tested using its implementation within a Kubernetes-based self-healing system. The findings indicate that the fault prediction can help decrease SLA breaches by 64.3%, faults' recovery period by 55.1% and user-affected events by 71.4%. It is noted that the mean time between fault occurrence and detection reduced from 142 seconds to 18 seconds, meaning that faults could be recognized in advance before affecting users.

There are several limitations of this research that should be pointed out. First, the experiment was performed on historic traces of logs and not on production clusters, which means that further research will have to account for dynamic adjustment of cloud infrastructure. Secondly, the assumption was made that service dependency graphs remain relatively unchanged since otherwise, additional training would be required. Finally, although interpretability methods were implemented, the problem of explaining DL decisions persists.

Areas for future research include: (1) implementing online learning methods to allow adaptation to changes in behavior without requiring full retraining, which would address the need for adaptability identified by Shayesteh et al.; (2) expanding the framework to enable causality explanations in addition to attention weights; (3) examining federated learning algorithms to perform fault prediction in multi-tenant cloud settings while ensuring data privacy; and (4) utilizing reinforcement learning to select actions to be taken in the case of fault prediction.

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To conclude, intelligent fault prediction is a promising new approach in cloud reliability engineering that can greatly enhance cloud system reliability using advanced hybrid deep learning methods. This study shows that it is possible to predict and prevent faults before they happen through effective prediction models, and as cloud systems continue to become more complex, such prediction models will be indispensable for achieving reliable cloud services.

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