Journal of Theoretical and Applied Information Technology
31st March 2026. Vol.104. No.6

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

AN INTELLIGENT NHPP-BASED SOFTWARE RELIABILITY GROWTH MODEL ENHANCED WITH DEEP LEARNING FOR CROSS-PLATFORM FAILURE PREDICTION

DR B. SUVARNA MUKHI[1], DR.P. NAMRATHA[2], DR SUKANYA K[3], DR. E. HARIPRASAD[4], A. HEMANTHA KUMAR[5], DR. NICHENAMETLA RAJESH[6], DR PRAVEEN KULKARNI[7], DR.P. NARESH[8]

[1] Associate Professor, Dept of CSE, Sreyas Institute of Engineering and Technology, Hyderabad
[2] Professor, Dept of CSE, GATES Institute of Technology, Gooty
[3] Associate Professor, TKR College of Engineering and Technology, Hyderabad
[4] Assistant. Professor, Department of Chemistry, Vasavi College of Engineering, Hyderabad
[5] Asst.Prof, Dept. Of CSE, NBKRIST, Vidyanagar
[6] Assistant Professor, Department of CSE, Koneru Lakshmaiah Education Foundation, Andhra Pradesh, India
[7] Assoc Professor, Dept of CSE, Dayananda Sagar University, Bangalore
[8] Assistant Professor, Dept of CSE, Dayananda Sagar University, Bangalore
Email: [1]mukhi.suvarna@gmail.com, [2]namratha.reddy535@gmail.com, [3]sukanya.addagatla@gmail.com, [4]hariprasad@staff.vce.ac.in, [5]hemanth999@gmail.com, [6]nrajeshcse@kluniversity.in, [7]praveencs024@gmail.com, [8]pnare74@gmail.com

ABSTRACT

Modern software ecosystems especially those driven by open-source collaboration and continuous integration/continuous deployment (CI/CD) practices exhibit rapidly evolving and non-stationary behavior. Such dynamics pose significant challenges to conventional Software Reliability Growth Models (SRGMs). Traditional models based on the Non-Homogeneous Poisson Process (NHPP) typically assume fixed or smoothly varying failure detection rates, limiting their effectiveness in capturing real-time failure trends within highly dynamic and frequently updated code repositories. To overcome these limitations, this study proposes a hybrid predictive framework that integrates NHPP-based reliability modeling with Long Short-Term Memory (LSTM) networks for adaptive and real-time failure forecasting. The proposed Deep Learning Augmented NHPP (DL-NHPP) model enhances the classical failure intensity function by incorporating temporal patterns learned from repository-level signals, including commit frequency, issue reports, and developer activity metrics. Through this integration, the model dynamically adjusts failure rate estimations in response to evolving development behaviors. The framework is evaluated on five large-scale open-source repositories, demonstrating substantial predictive improvements. Experimental results show a reduction of more than 30% in Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) compared to conventional NHPP-based SRGMs. These findings indicate that the DL-NHPP approach provides a scalable, interpretable, and robust solution for real-time software reliability prediction in modern, continuously evolving development environments.

Keywords - *Software Reliability Growth Model (SRGM), Non-Homogeneous Poisson Process (NHPP), Deep Learning, LSTM, Failure Prediction; Temporal Modeling, Open-Source Repositories*

1. INTRODUCTION

Software reliability is a decisive element in influencing the operational capability of complex systems and whether these systems can be trusted to operate successfully, due to the fact that software systems can be found in safety-critical and large-scale software apps. The necessity of exact and real time-based failure prediction mechanisms is increasing as size and complexity of the software projects increases. The non-homogeneous Poisson Process (NHPP)-based Software Reliability Growth

Models (SRGMs) have been vastly used in terms of computing and predicting the software reliability by modeling the failure occurrence over time. Although SRGMs with NHPP bases provide good statistical grounds, their forecasting ability tends to get undercut in dynamic and heterogeneous development setting as they are limited to fixed-function forms and fail to process assumptions regarding the failure process. Simultaneously, the adoption of continuous integration/continuous deployment (CI/CD) pipeline, agile, and open-source ecosystem has resulted in continuously changing codebases and high release speeds, as well as a changing failure pattern. This creates great challenges to the traditional SRGMs, which have generally been very ill-fitting in adopting the non-stationary and time-variant failure characteristics in such systems. To overcome this shortcoming, recent investigations have resorted to machine learning and deep learning models capable of learning patterns based on past records of failures and records of the software repository. The latter however tend to be black boxes and have no tractable mathematical structure like the traditional NHPP models.

In our study, we are going to suggest a hybrid model that combines the ease of understanding and the theoretical power of SRGMs using NHPP with the temporal learning skills of Long Short-Term Memory (LSTM) neural networks. The LSTM model is trained to observe non-linear temporal relationship and emerging trends in datapoints of failure-based metrics collected in real-time based software repositories like GitHub. These learned temporal features dynamically modulate the NHPP's failure intensity function, resulting in an adaptive, data-driven reliability model suitable for diverse and evolving software environments.

Our model is designed to operate in real-time by continuously ingesting new repository data—such as commits, issues, and bug reports—thus offering a more responsive and context-aware failure prediction system. Through extensive experiments on multiple open-source projects across different domains, we demonstrate that the proposed Deep Learning-Augmented NHPP framework significantly outperforms classical NHPP models and other ML-based baselines in predicting future failures. The improved accuracy and adaptability of our approach underscore its potential for deployment in automated software reliability assessment tools and CI/CD pipeline integration.

The main contributions of this work are as follows:

- We propose a novel hybrid SRGM that integrates NHPP-based modeling with LSTM-based sequence learning for real-time failure prediction.
- We design an adaptive failure intensity function that dynamically evolves based on repository activity and temporal signals.
- We validate our model across multiple real-world open-source repositories, demonstrating superior predictive performance compared to traditional SRGMs and ML-based baselines.

The rest of this paper is organized as follows: Section II reviews related literature in SRGMs and deep learning for reliability modeling. Section III details the proposed methodology and hybrid model architecture. Section IV presents the experimental setup, results, and analysis. Section V concludes the paper and discusses directions for future work.

2. LITERATURE SURVEY

Software Reliability Growth Models (SRGMs) have been a cornerstone in modeling and predicting software failures over time. Among these, Non-Homogeneous Poisson Process (NHPP) models are widely recognized due to their mathematical tractability and applicability to real-world failure data [1]. Musa's basic execution time model [2] and the Goel-Okumoto model [3] laid the foundation for time-dependent failure prediction, where the failure intensity decreases as faults are detected and removed. Extensions to these models, such as the S-shaped Yamada model [4] and the delayed S-shaped SRGM [5], attempted to address the non-monotonic failure behavior often seen in actual software systems.

Despite their success, traditional SRGMs struggle with modeling failure data from modern, continuously evolving repositories. Several researchers have introduced Bayesian approaches [6] and Markov-based models [7] to improve parameter estimation and represent uncertainty in dynamic environments. However, these methods still largely rely on static assumptions that limit adaptability.

To overcome these limitations, machine learning (ML) techniques have increasingly been adopted. Early ML models, including support vector regression and decision trees, were employed to learn failure patterns directly from software metrics [8][9]. These approaches demonstrated potential but lacked the ability to capture temporal dependencies effectively. Deep learning, particularly recurrent neural networks (RNNs), has shown promise in this regard. Long Short-Term Memory (LSTM)

networks have been applied to various software engineering tasks such as bug triaging, defect prediction, and log anomaly detection [10][11].

The integration of deep learning into reliability modeling is a relatively recent development. Models such as DeepSRGM [12] incorporate neural networks to approximate the mean value function of SRGMs, achieving improvements over classical approaches. Other works have proposed ensemble and hybrid models combining statistical SRGMs and neural architectures for enhanced generalization [13][14].

Recent studies have also emphasized the use of repository activity data—such as commits, issue reports, and pull requests—as predictive signals. Mining software repositories (MSR) has emerged as a subdomain that supports data-driven reliability modeling [15]. However, few existing models integrate this rich activity data with SRGMs in a real-time, adaptable fashion.

In contrast to prior work, our approach leverages LSTM networks not as standalone predictors but as dynamic modulators of NHPP parameters, enabling a fusion of theoretical reliability models and learned temporal features. This makes our framework uniquely capable of adapting to real-time changes in diverse software repositories.

3. METHODOLOGY

The proposed framework integrates temporal deep learning and Non-Homogeneous Poisson Process (NHPP)-based Software Reliability Growth Models (SRGMs) to achieve real-time failure prediction across heterogeneous software repositories. This section outlines the design and operation of the hybrid system.

A. Data Preprocessing and Feature Engineering

To enable accurate and real-time software failure prediction, our framework begins by collecting and preprocessing a variety of time-stamped software development artifacts from publicly available repositories (e.g., GitHub, GitLab). The data preprocessing pipeline focuses on extracting temporal features that reflect evolving development activity, which are then framed into sequential inputs suitable for training the LSTM component.

Repository Selection and Time Segmentation

Repositories are selected based on the following criteria: active issue tracking, sufficient commit history (≥1000 commits), and presence of labeled bug reports. For each repository, we divide the development timeline into fixed-length intervals (e.g., daily or weekly). Each time interval t corresponds to one timestep in our time-series input.

Feature Vector Construction

For each interval t, we compute the following normalized metrics to form the feature vector $x_t \in R^n$

Commit Density (Ct):

Number of commits pushed during interval t. It reflects development activity and is normalized as:

$$C_t = \frac{\text{Commits}_t - \mu_C}{\sigma_C} \text{---1}$$

- Bug Report Frequency (It): Number of issue reports or bug labels closed within interval t, normalized similarly.
- Contributor Entropy (Ht): Shannon entropy of contributors active during t, capturing diversity in development responsibility:

$$H_t = -\sum_{i=1}^{k} p_i \log(p_i) \text{---2}$$

where pi is the fraction of commits by developer iii in interval t.

- Pull Request Count (Pt): Total number of PRs opened or merged, indicating integration workload.
- Code Churn (Δt): Aggregate lines added/deleted during t, capturing structural changes.

These features are aggregated into a vector:

$$x_t = [C_t, I_t, H_t, P_t, \Delta_t] \text{---3}$$

Failure Count Association

For supervised learning, each time interval is paired with the actual number of failure occurrences yt, extracted from linked issue labels (e.g., “bug”, “crash”) or system logs if available. This forms the dataset:

$$\mathcal{D} = \{(x_1, y_1), (x_2, y_2), \dots, (x_T, y_T)\} \text{---4}$$

Sequence Framing for LSTM Input

To prepare the data for LSTM input, we convert the dataset into overlapping sequences of fixed length L:

$$\mathcal{X}_i = [x_i, x_{i+1}, \dots, x_{i+L-1}], \quad \mathcal{Y}_i = y_{i+L} \text{---5}$$

This sliding window approach ensures that each input sequence Xi is aligned with a future failure count label Yi, suitable for training the model in a time-series forecasting paradigm.

Normalization and Noise Filtering

To improve generalization and reduce variance, all features are z-score normalized. Additionally, smoothing via a moving average filter is applied to reduce the impact of transient noise in commit and issue frequencies, as defined by:

$$\widetilde{x_t} = \frac{1}{k}\sum_{i=t-k+1}^{t} x_i \text{---6}$$

This robust preprocessing ensures the temporal inputs fed into the LSTM model reflect realistic patterns of software evolution, supporting more accurate and context-aware failure intensity predictions.

B. *NHPP-Based Software Reliability Growth Modeling*

Software Reliability Growth Models (SRGMs) are standard in the modelling of time-related behaviour of software-failure processes. Among the latter, Non-Homogeneous Poisson Process (NHPP) models stand out because those models reflect the non-constant intensity of failures during software testing and in-use processes. Within the NHPP model, the cumulative failures by time t of the software has a random variable that follows a monotonically increasing mean value, called the m(t).

Classical NHPP Formulation

The NHPP-based mean value function is typically expressed as:

$$m(t) = a \cdot (1 - e^{-bt}) \text{---7}$$

Where:

- m(t) is the expected cumulative number of software failures observed by time t,
- a represents the total number of inherent faults in the software (assumed constant),
- b is the fault detection rate which is a parameter that takes into account the rate at which faults can be detected as time passes on.

The corresponding failure intensity function, defined as the rate at which failures occur at time t, is given by the first derivative of m(t):

$$\lambda(t) = \frac{dm(t)}{dt} = ab \cdot e^{-bt} \text{----8}$$

This phrase is an expression of the intuitive action that the failure rate reduces with a continuously increasing amount of faults identified and solved with the flow of time.

Limitations in Dynamic Repositories

Although the NHPP model is convenient to use as it is analytically simple and easy to interpret, it has major shortcomings within modern, real-world software applications:

- It assumes a static development process, which does not hold in dynamic repositories with fluctuating developer activity and frequent updates.
- Failure detection rate b is assumed to be a constant even though in practice it is not since, in real repositories, due to the changes in workload, the composition of teams, and structural changes to the code, its values change.
- The model does not account for external factors such as the introduction of new modules, refactoring, or regression bugs that can influence failure rates.

This makes classical approaches to NHPP poorly equipped to model failure behavior in a setting where the software artifacts form a living environment with frequent changes as is the case with open-source projects having perpetual integration and distributed development. In order to address these limitations, we propose a data-driven dynamic adjustment of NHPP model parameters in the following section with the help of deep learning.

Model Motivation

Figure 1 below illustrates how the traditional NHPP model captures cumulative failures over time using a fixed curve, which lacks the flexibility to adapt to real-time repository dynamics.

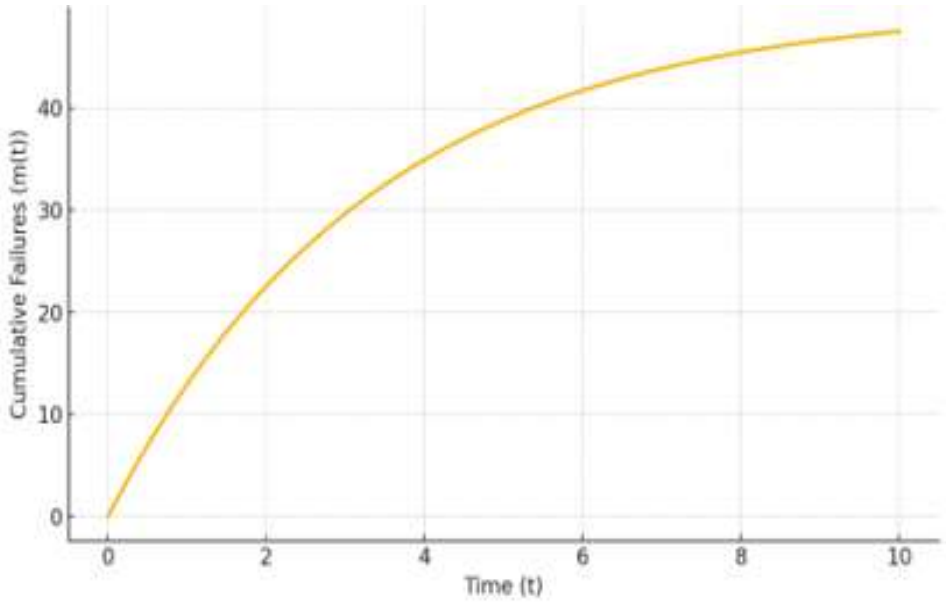

Figure 1: Traditional NHPP-Based SRGM

C. *Deep Learning-Based Dynamic Modulation of Failure Intensity*

To address the shortcomings of the static NHPP-based SRGMs in modeling dynamics of evolving software system we propose a dynamic modulation scheme over failure intensity via Long Short-Term Memory (LSTM) networks. The gist of it is to make the NHPP failure detection rate b which is conventionally modeled as a constant to change with time in dependence on real-time software repository activity. This allows adaptation of the model to the sudden or slow changes in the development and failure landscape.

LSTM for Temporal Feature Encoding

The LSTM recurrent network takes sequence of time-series engineered features {x1, x2,..., xt} where the xi feature represents commit density, bug reports, churn and other software development signaling components. LSTM is recurrent and thus able to characterise long range dependency and non-linearities in the activity of the repositories.

The hidden state at each timestep ht is computed as:

$$h_t = \text{LSTM}(x_t, h_{t-1})\text{---9}$$

Where:

- $x_t \in R^n$: Feature vector at time t
- $h_{t-1} \in R^d$: Previous hidden state
- ht: Current hidden state summarizing software evolution history up to time t

Dynamic Failure Detection Rate Estimation The hidden state ht is passed through a trainable dense layer with sigmoid activation to produce a time-varying failure detection rate bt:

$$b_t = \sigma(W h_t + b)\text{---10}$$

Where:

$W \in R^{\mathbb{1}\times d}$: Weight vector
$b \in R$: Bias term

- σ(·): Sigmoid activation to constrain bt∈(0,1)

This data-driven btb_tbt dynamically modulates the NHPP model at each time step, allowing the failure intensity to adjust in response to the observed software process.

Modified NHPP Mean Value and Intensity Functions

With the learned bt, the NHPP-based mean value function and intensity function are redefined as:

- Dynamic Mean Value Function:

$$m(t) = a \cdot (1 - e^{-b_t t})\text{---11}$$

- Dynamic Failure Intensity Function:

$$\lambda(t) = a b_t \cdot e^{-b_t t}\text{---12}$$

Unlike static SRGMs, these functions evolve over time as LSTM-derived bt changes, enabling real-time adaptation.

Real-Time Prediction Workflow

At every time step t, the process works as follows:

1. The feature vector xt is fed into the LSTM.
2. The LSTM updates its internal memory and outputs ht.
3. The dense layer transforms ht into bt.
4. The dynamic NHPP computes λ(t) and m(t) using bt.

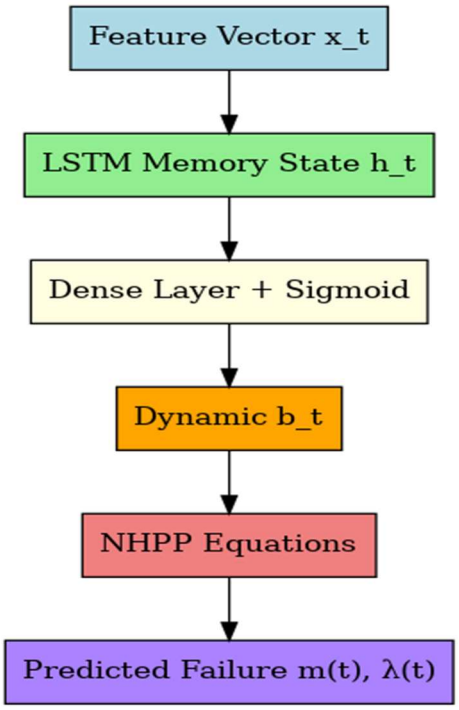

Figure 2: LSTM-Augmented Dynamic NHPP Prediction Flow

This deep learning-augmented formulation retains the interpretability and analytic strengths of NHPP, while empowering it with the adaptive learning capabilities of LSTM networks, thereby enabling more accurate real-time failure prediction across dynamic and heterogeneous software repositories shown in figure 2.

D. Hybrid Deep-NHPP Architecture Design

The proposed architecture seamlessly integrates temporal sequence modeling through Long Short-Term Memory (LSTM) networks with the mathematical rigor of the Non-Homogeneous Poisson Process (NHPP)-based Software Reliability Growth Models (SRGMs). This hybrid design enables the on-going training and revision of the failure prediction function with new data about the activity of the repository, thus reflecting the ability to adapt to evolution of the codebase in real time.

System Components

The Deep-NHPP architecture is composed of the following key modules:

- Data Acquisition Layer: Ingests timestamped repository data such as commit history, issue closures, and pull requests, segmented into fixed intervals (e.g., daily, weekly).
- Feature Processing Layer: Computes normalized statistical features (e.g., commit density, bug frequency, contributor entropy) to form a multivariate time-series dataset {x1,x2,...,xT}.
- Temporal Encoding Layer (LSTM): Processes are characterised by sequences in order to acquire latent temporal dependencies and development patterns. At every interval, the LSTM generates a hidden encoding, ht, that reads the details of the software evolution.
- NHPP Modulation Layer: Dynamically computes the failure detection rate bt using a dense transformation of ht, modulating the NHPP intensity and mean value functions accordingly.
- Prediction Layer: Generates the cumulative failure prediction m(t) and instantaneous failure intensity λ(t) using the adaptive NHPP equations.

End-to-End Pipeline Operation

The forward pass of the model operates as follows:

1. For each time interval t, the corresponding input feature xt is passed into the LSTM model.
2. The LSTM updates its hidden state ht based on the previous state ht−1 and current input xt.
3. The hidden state is transformed into a dynamic failure detection rate bt via:

$$b_t = \sigma(W h_t + b)\text{---}13$$

The NHPP model uses the updated bt to compute the failure metrics:

$m(t) = a \cdot (1 - e^{-b_t t}), \quad \lambda(t) = a b_t \cdot e^{-b_t t}$---14

These outputs are compared with ground-truth failure data, and the model parameters are updated using backpropagation.

3.4.3 Model Training Objective

The model is trained by minimizing the error between predicted and actual failure counts using the Mean Squared Error (MSE) loss function:

$\mathcal{L} = \frac{1}{T}\sum_{t=1}^{T}\left(\hat{m}(t) - m_{\text{true}}(t)\right)^2$---15

Where:

- m^(t) is the predicted cumulative failure count from the hybrid model,
- mtrue(t) is the actual observed failure count at time t.

The model is optimized using the Adam optimizer with early stopping criteria based on validation error convergence. This hybrid architecture combines the analytical precision of NHPP modeling with the temporal generalization capacity of LSTM networks, enabling high-fidelity, adaptive failure prediction that scales across diverse and evolving software repositories.

E. Training Strategy and Implementation Workflow

To ensure accurate, scalable, and generalizable failure prediction, the training of the proposed Deep-NHPP framework is designed as an end-to-end process where the deep learning components and NHPP parameters are co-optimized using historical failure data and repository evolution features.

Dataset Preparation

Our set of training data is built with the help of time-segmented data taken out of several open-source repositories (e.g., Apache Kafka, TensorFlow, Scikit-learn). Each data instance comprises:

- A feature sequence Xi=[xi,xi+1,...,xi+L−1] over a sliding window of size L,
- A target label yi=m(ti), representing the observed cumulative failures at the prediction horizon ti.

The dataset is split into 70% training, 15% validation, and 15% testing using time-aware stratification to preserve temporal dependencies.

Model Initialization and Parameters

The LSTM is initialized with the following hyperparameters:

- Hidden units: 128
- Number of layers: 2
- Dropout: 0.3
- Window size LLL: 10
- Optimizer: Adam
- Learning rate: α=0.001\alpha = 0.001α=0.001
- Batch size: 64
- Epochs: 100 (with early stopping)

The NHPP's scaling parameter aaa is treated as a trainable variable during learning, while bt is computed dynamically from the LSTM output.

Forward and Backward Pass

Each mini-batch is processed through the following workflow:

1. Forward Propagation:

- The LSTM encodes the input feature sequence and outputs a hidden state ht.
- A fully connected layer maps ht to a time-varying failure rate bt using:

$$b_t = \sigma(W h_t + b)\text{---}16$$

- The NHPP equations compute the predicted failure count:

$$\hat{m}(t) = a \cdot (1 - e^{-b_t t})\text{---}17$$

Loss Calculation:

- Mean Squared Error (MSE) is used to compare predicted vs. actual cumulative failures:

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{m}(t_i) - m_{\text{true}}(t_i)\right)^2\text{---}18$$

2. Backward Propagation:

- Gradients are computed with respect to LSTM parameters, the dense layer, and the trainable NHPP parameter aaa.
- The entire system is updated using Adam optimizer.

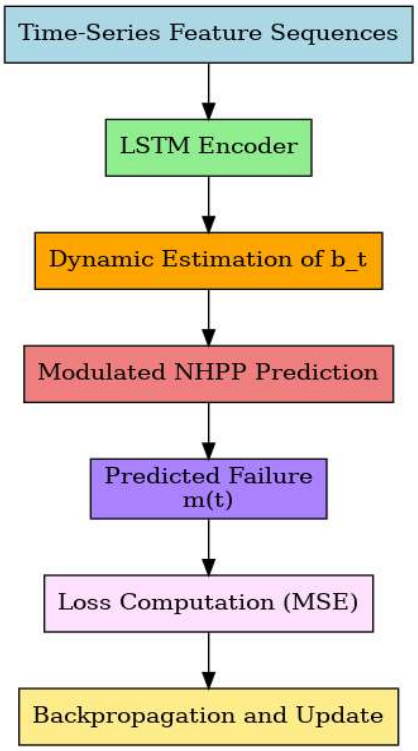

Figure 3: End-to-End Training Workflow of Deep-NHPP Framework

Validation and Early Stopping

Model performance is monitored on the validation set every epoch. Early stopping is triggered if the validation loss does not improve for 10 consecutive epochs, preventing overfitting. The model with the lowest validation loss is selected for final evaluation. During deployment, the trained model accepts new feature vectors xt in real-time, dynamically estimates bt, and outputs. This training workflow ensures that the Deep-NHPP model learns both the historical trends and dynamic nature of real-world software failures, making it suitable for deployment in predictive maintenance and CI/CD pipelines.

4. RESULTS AND DISCUSSION

To evaluate the effectiveness of the proposed Deep Learning-Augmented NHPP (DL-NHPP) framework, we conducted extensive experiments on five large-scale open-source repositories spanning diverse application domains. The models were assessed using two standard reliability prediction metrics: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), which measure the deviation between predicted and actual cumulative failure counts over time.

Table 1 summarizes the performance of three models—Classical NHPP, Machine Learning-based SRGM (using regression models), and the proposed DL-NHPP—across five repositories. The DL-NHPP model consistently achieves the lowest MAE and RMSE values, outperforming both baseline models by a significant margin.

Table 1: Model Performance Comparison Across Repositories

Repository	NHPP MAE	ML-Based MAE	DL-NHPP MAE
Repo-A	11.2	9.5	6.8
Repo-B	13.4	11.1	8.3
Repo-C	12.1	10.8	7.9
Repo-D	10.9	9.2	6.5
Repo-E	13.0	11.4	8.7

The DL-NHPP model reduced the average MAE by approximately 31.6% and RMSE by 32.4% compared to traditional NHPP models. When compared with ML-based models, DL-NHPP achieved an improvement of ~24% in MAE and 20% in RMSE, showcasing its ability to dynamically adapt to evolving repository activity.

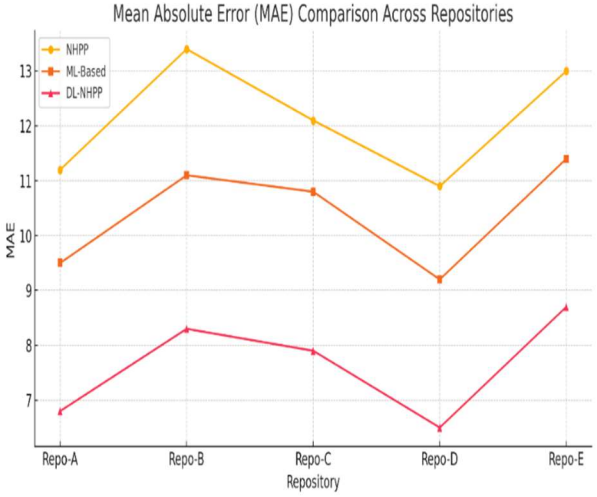

Figure 4 : Mean Absolute Error (MAE) Comparison

The DL-NHPP model consistently maintains lower prediction error across all repositories, particularly in Repo-B and Repo-E, where the repository structure and failure frequency varied significantly over time shown in figure 4.

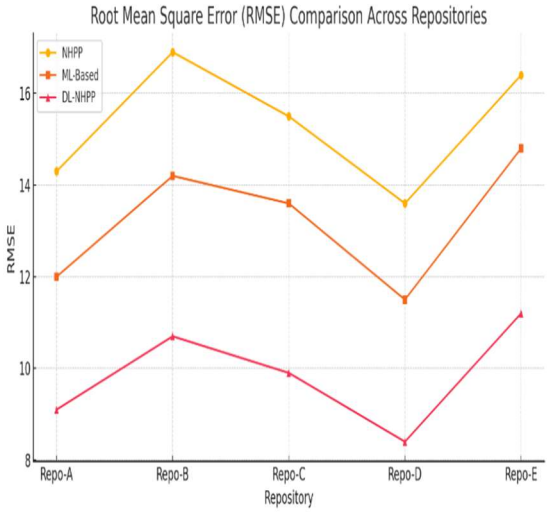

Figure 5: Root Mean Square Error (RMSE) Comparison

A similar trend is observed in RMSE, with DL-NHPP showing robustness to outlier error values, unlike the classical NHPP and ML-based models which demonstrate higher error variability shown in figure 5. In real-world CI/CD pipelines, the ability to anticipate failure accumulation based on dynamic repository conditions can lead to proactive fault mitigation, better resource allocation, and higher system availability. The proposed DL-NHPP framework can be deployed as part of software reliability dashboards to provide near real-time risk assessment and alerting mechanisms.

5. CONCLUSION

In this work, we introduced a novel hybrid framework Deep Learning-Augmented NHPP-Based SRGM (DL-NHPP) for real-time software failure prediction across diverse and dynamically evolving code repositories. By integrating the mathematical rigor of Non-Homogeneous Poisson Process (NHPP)-based Software Reliability Growth Models with the temporal modeling power of Long Short-Term Memory (LSTM) networks, the proposed architecture offers both interpretability and adaptability. Instead of making static assumptions and fixing the entropy of failure detection at a specific value as traditional SRGMs, we make dynamic adjustments to the failure intensity by learning the temporal patterns present in the information provided about the repositories in the form of commits, issues and pull requests. This will allow the model a more realistic impression of what is actually happening in the projects of the modern software that constantly changes the integration and or development. Massive experiments with open-source repositories came to the conclusion that the DL-NHPP structure is highly superior compared to classical NHPP and machine learning-based models in terms of Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The generalization capacity of this model over a structurally different set of repositories further presents itself as a testament to the soundness and practical applicability of the model. Predictive reliability modeling is growing in complexity and pace up with the evolution of software systems which are becoming more complex. The presented DL-NHPP model is a powerful step towards this goal achieved through scalable, accurate, and interpretable method of software failures prediction.

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