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HYBRID LSTM AUTOENCODER AND BILSTM-BASED PREDICTIVE MAINTENANCE FOR BEARING FAILURE IN ELECTRICAL MOTORS

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***ABSTRACT*:**

Unexpected failures of electric motors can lead to significant operational downtime and maintenance costs in industrial systems. This paper proposes a hybrid predictive maintenance framework combining a Long Short-Term Memory Autoencoder and a Bidirectional Long Short-Term Memory network to detect anomalies and predict degradation stages in electric motor bearings. Vibration and temperature signals are processed using feature extraction and sliding window segmentation to capture temporal patterns. The Long Short-Term Memory Autoencoder learns normal operational behavior through sequence reconstruction and identifies anomalies using reconstruction error. The encoded latent features are then used by a Bidirectional Long Short-Term Memory classifier to predict degradation stages categorized as Safe, Warning, and Danger. Experimental results demonstrate the effectiveness of the proposed approach in detecting abnormal behavior and forecasting failure progression, enabling proactive maintenance and improved equipment reliability.

Keywords: *Anomaly Detection, Bearing Monitoring, Bilstm, Electrical Motors, Lstm Autoencoder, Predictive Maintenance*

INTRODUCTION

Electric motors are essential components in industrial environments, and their unexpected failure can cause costly downtime and operational disruptions. Predictive maintenance aims to identify early signs of degradation using sensor data so that main-tenance can be scheduled before catastrophic failure occurs. However, traditional strategies such as reactive maintenance and fixed-interval maintenance often fail to capture early fault development and may either delay intervention or result in unnecessary replacement of components.

Recent advances in machine learning and deep learning have enabled automated analysis of industrial sensor data for predictive maintenance applications. In particular, Long Short-Term Memory networks are well suited for modeling sequential time-series signals because they can capture temporal dependencies in vibration and temperature measurements. Existing approaches have shown that anomaly detection models can identify deviations from normal behavior, whereas classification models can estimate degradation stages. However, many studies focus on only one of these tasks and do not integrate early anomaly sensitivity with structured stage-level forecasting.

To address this limitation, this study proposes a hybrid predictive maintenance framework that combines a Long Short-Term Memory Autoencoder for anomaly detection and a Bidirectional Long Short-Term Memory classifier for degradation stage prediction. Using fused vibration and temperature features, the proposed system detects abnormal behavior through reconstruction error and predicts degradation stages categorized as Safe, Warning, and Danger. This layered design aims to improve both fault sensitivity and interpretability for bearing failure monitoring in electric motors.

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RELATED WORK

Predictive maintenance for rotating machinery commonly relies on vibration analysis, as vibration signals capture mechanical fault signatures such as bearing defects, imbalance, and misalignment. Frequency-domain features, particularly Fast Fourier Transform-based representations, have been widely used for fault diagnosis and integrate effectively with machine learning models [1, 2]. Temperature monitoring is also utilized to detect thermal anomalies, although it often requires normalization to address baseline drift [3–5]. Recent studies show that combining multiple sensor modalities improves robustness and diagnostic accuracy compared with single-sensor approaches [6–9].

Deep learning methods, particularly autoencoder-based approaches, have become prominent for anomaly detection by learning normal system behavior and identifying deviations through reconstruction error [10, 11]. Long Short-Term Memory Autoencoders are well suited for sequential industrial data due to their ability to capture temporal dependencies [12–15]. Reconstruction-error analysis can further enhance interpretability by identifying modality-specific contributions to anomalies [16, 17].

For degradation forecasting, recurrent models such as Long Short-Term Memory and Bidirectional Long Short-Term Memory networks have demonstrated strong performance in modeling temporal degradation patterns. Bidirectional Long Short-Term Memory models capture bidirectional context, improving classification of health states and degradation transitions [18–20]. Hybrid architectures that combine deep learning models and multimodal features have also shown improved performance in complex predictive maintenance scenarios [21]. Motivated by these advances, this study integrates a Long Short-Term Memory Autoencoder for anomaly detection with a Bidirectional Long Short-Term Memory classifier for degradation stage prediction using fused vibration and temperature data.

PROPOSED METHODOLOGY

A. Dataset and Data Acquisition

This study uses the public run-to-failure ball-bearing dataset released by Jung et al. [22]. The dataset contains synchronized vibration and temperature measurements collected during an accelerated life test from normal operation until failure. According to the source study, the bearing operated at approximately 1770 to 1780 RPM under axial and vertical loads of 2.94 kN and 5.88 kN, respectively, and the signals were acquired at a sampling frequency of 25.6 kHz. The dataset spans 128 working hours and is stored in hourly CSV files containing vibration measurements in the x- and y-directions and temperature readings from the bearing housing. In this work, the vibration and bearing-temperature channels are used as inputs for predictive maintenance modeling.

B. Signal Processing and Feature Extraction

Raw vibration and temperature signals were transformed into fused feature sequences for model training. The vibration signal was segmented into 1-second windows and multiplied by a Hanning window to reduce spectral leakage. Each 1-second window was divided into 50 overlapping segments of 512 samples. A 512-point Fast Fourier Transform was applied to each segment, and the resulting magnitude spectra were averaged element-wise to produce a 512-dimensional vibration feature vector:

$$\mathrm{VibFeat}_{avg}[\square] = \frac{1}{N}\sum^{N} |\square_i[\square]|, \qquad \square = 0, \dots, 511$$

i=1

where N is the number of overlapping segments.

Temperature values were normalized to reduce slow thermal drift. For each 1-second temperature reading $T[t]$, a rolling median $m[t]$ and interquartile range $q[t]$ were computed over a 5-second window:

$$Z[t] = \frac{T[t] - m[t]}{q[t]} \qquad (2)$$

The 512-dimensional vibration feature vector and the 1-dimensional normalized temperature score were concatenated to form a 513-dimensional fused feature vector:

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$f[t] = [\mathrm{VibFeat}t\ [0:511], Z\ [t]] \in R513$ (3) Each feature dimension was standardized using the training-set mean and standard deviation. The resulting fused vectors were grouped into non-overlapping 5-second windows, producing input sequences of shape 5 × 513 for the Long Short-Term

Memory Autoencoder.

C. Long Short-Term Memory Autoencoder for Anomaly Detection

A Long Short-Term Memory Autoencoder was used to model normal operating behavior from fused vibration and temperature sequences. The model follows a sequence-to-sequence architecture in which two stacked Long Short-Term Memory encoder layers compress each input sequence of shape 5 × 513 into a 32-dimensional latent representation. A symmetric decoder reconstructs the original sequence from this latent code.

The autoencoder was trained exclusively on Safe data so that it could learn the temporal structure of normal motor behavior. During inference, anomalies were identified through reconstruction error, computed as the mean-squared error between the input sequence and its reconstruction. A higher reconstruction error indicates a greater deviation from learned normal patterns and therefore a higher likelihood of anomalous behavior.

To improve interpretability, reconstruction error was decomposed into vibration and temperature components. This allows the system to determine whether abnormal behavior is primarily associated with mechanical or thermal deviations. A decision threshold was selected using Youden's J statistic on validation data, and sequences whose global reconstruction error exceeded this threshold were flagged as anomalous.

D. Bidirectional Long Short-Term Memory Classifier for Degradation Prediction

The latent representations produced by the trained Long Short-Term Memory Autoencoder were used as inputs to a Bidirectional Long Short-Term Memory classifier for degradation stage prediction. After the autoencoder was trained on Safe sequences, its encoder was frozen and used to transform each fused input window into a 32-dimensional latent vector. These latent vectors were then used to train a supervised classifier that predicts the degradation stage of the motor.

Each latent vector was assigned one of three labels based on its temporal position in the run-to-failure sequence: Safe, Warning, or Danger. Safe corresponds to normal operation, Warning indicates an intermediate degradation stage, and Danger represents late-stage behavior close to failure. By processing the latent sequence in both forward and backward directions during training, the Bidirectional Long Short-Term Memory classifier captures richer temporal context and improves recognition of transitions between degradation stages.

Because the dataset is imbalanced, with Safe samples outnumbering Warning and Danger samples, the classifier was trained using Focal Loss to emphasize harder and minority-class examples. The classifier outputs a stage label for each 5-second input window, enabling structured degradation forecasting that complements the anomaly detection capability of the Long Short-Term Memory Autoencoder.

EXPERIMENTAL SETUP

The dataset was divided chronologically to preserve the natural degradation progression of the run-to-failure sequence. The majority of the data was used for model development, where sequences were organized to ensure that all degradation stages were represented during training and validation while maintaining temporal consistency. A final portion of the timeline was reserved as a fully held-out test set for evaluation. This setup simulates a realistic deployment scenario in which models are applied to unseen late-stage degradation data.

For anomaly detection, only Safe sequences from the development portion were used to train the Long Short-Term Memory Autoencoder. Five-fold cross-validation was applied within this Safe subset to improve robustness and reduce overfitting. Re-construction errors obtained from the validation folds were used to determine the anomaly threshold through Youden's J statistic. During inference, anomalies were identified using mean-squared reconstruction error, and both global and modality-specific error components were recorded.

For degradation stage prediction, all fused windows in the development portion were encoded into 32-dimensional latent vectors using the frozen encoder. These latent vectors were labeled as Safe, Warning, or Danger based on their temporal position in the run-to-failure sequence and were then split into training, validation, and internal test

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sets using a 70/15/15 ratio. The classifier was trained with Focal Loss to address class imbalance and was evaluated using accuracy, precision, recall, F1-score, and macro-F1. Final evaluation on the held-out 20% segment assessed both the anomaly detection capability of the Long Short-Term Memory Autoencoder and the stage forecasting performance of the Bidirectional Long Short-Term Memory classifier.

RESULTS AND DISCUSSION

This section presents the results of the proposed hybrid predictive maintenance framework evaluated on the held-out 20% of the run-to-failure sequence. The analysis focuses on the behavior of the Long Short-Term Memory Autoencoder for anomaly detection, the performance of the Bidirectional Long Short-Term Memory classifier for degradation stage forecasting, and the combined behavior of both models in the hybrid framework.

A. Long Short-Term Memory Autoencoder Anomaly Detection Performance

The anomaly detection capability of the Long Short-Term Memory Autoencoder was evaluated on the held-out 20% of the run-to-failure sequence. Reconstruction error was used as the anomaly score, and the detection threshold was determined using Youden's J statistic on the validation set. Table I summarizes the anomaly detection performance.

TABLE I: LOng ShORT-TERM MEMORY AUTOEnCODER AnOMALY DETECTIOn PERfORMAnCEL

Metric	Value
Accuracy	85.07%
Precision	83.40%
Recall (Sensitivity)	100%
F1-score	90.95%
Specificity	40.27%
False Positive Rate	59.73%
ROC-AUC	0.796

The results in Table I show that the Long Short-Term Memory Autoencoder achieved perfect recall on the held-out test set, indicating strong sensitivity to anomalous behavior. However, the model still misclassified some Safe windows as anomalous, resulting in a high false positive rate and limited specificity. This suggests that the model tends to generate conservative alerts rather than risk missing anomalies.

Despite this limitation, the ROC-AUC indicates that reconstruction errors still provide useful separation between normal and anomalous windows. Overall, the Long Short-Term Memory Autoencoder functions effectively as a sensitive first-layer anomaly detector within the proposed hybrid framework.

B. Per-Modality Reconstruction Error Analysis

To analyze the contribution of each sensor modality, reconstruction errors were decomposed into vibration and temperature components. Fig. 1 illustrates the evolution of reconstruction error over the run-to-failure timeline.

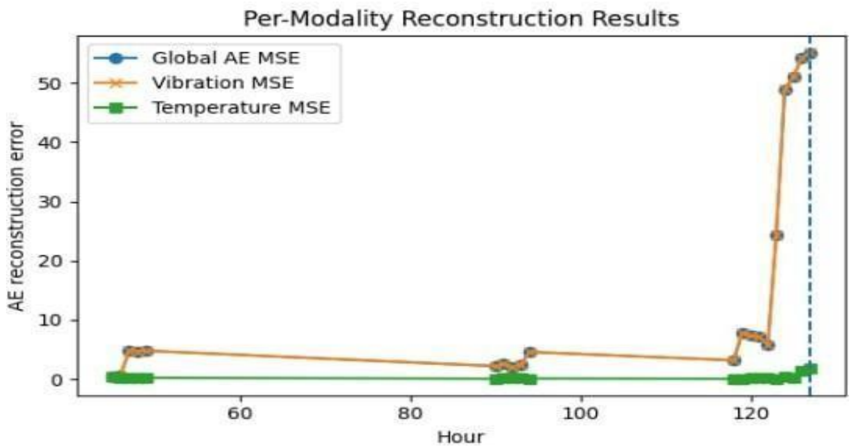

Fig. 1 Per-Modality Reconstruction Error Over the Run-to-Failure Timeline

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The results show that vibration reconstruction error closely follows the global reconstruction error and increases steadily as the system approaches failure. In contrast, temperature error remains relatively stable for most of the timeline and rises only near the final stage of degradation. This difference is partly due to feature dimensionality, as the model uses 512 vibration features and a single temperature feature per timestep.

Consequently, the global reconstruction error is dominated by vibration behavior. Nevertheless, temperature information remains valuable for capturing gradual thermal changes associated with prolonged system stress.

C. Bidirectional Long Short-Term Memory Stage Classification Performance

The Bidirectional Long Short-Term Memory classifier was trained to predict degradation stages from the 32-dimensional latent vectors generated by the frozen Long Short-Term Memory Autoencoder encoder. Focal Loss was used during training to mitigate class imbalance and emphasize minority Warning and Danger samples. Table II summarizes the stage classification performance.

TABLE II: BIDIRECTIOnaL LOng ShORT-TERM MEMORY STAgE CLAssIfICATIOn PERfORMAnCE

Metric	Value
Accuracy	79.23%
Macro F1-score	0.736
Safe Recall	0.390
Warning Recall	0.995
Danger Recall	0.892

The Bidirectional Long Short-Term Memory classifier demonstrates strong detection of Warning and Danger stages, particu-larly during the degradation transition preceding failure. However, Safe recall is relatively low, indicating that some Safe windows were conservatively classified as Warning. In predictive maintenance settings, such conservative predictions can be beneficial because early Warning signals provide additional time for inspection and maintenance planning.

Using an hour-level majority rule, failure onset was defined as the first hour in which at least 50% of window predictions were classified as Danger. Based on this criterion, the model predicted failure at Hour 118, providing a lead time of approximately 9 hours before the true terminal hour, which occurred at Hour 127.

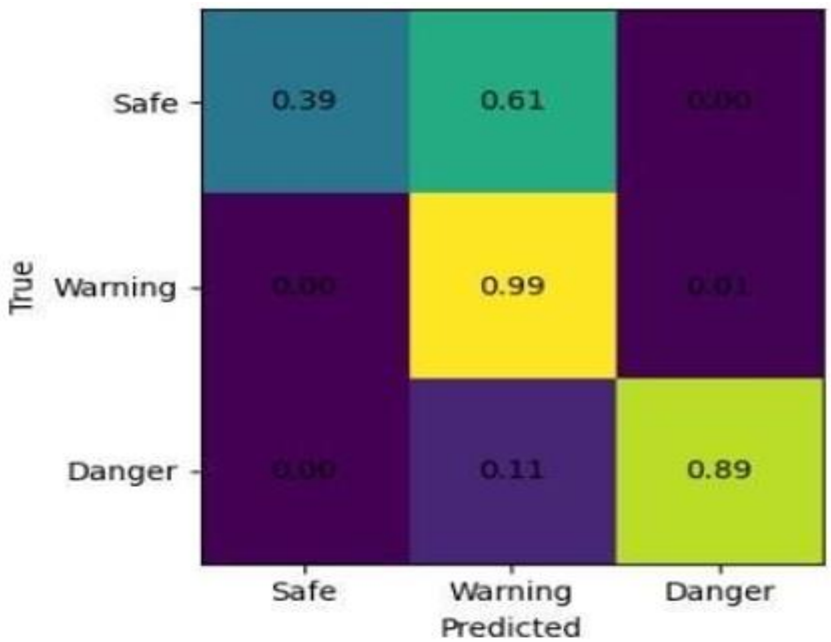

Fig. 2 Confusion Matrix for Bidirectional Long Short-Term Memory Stage Classification

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Stage transition consistency was also analyzed at the hour level. Fig. 3 shows the dominant predicted stage across the run-to-failure timeline.

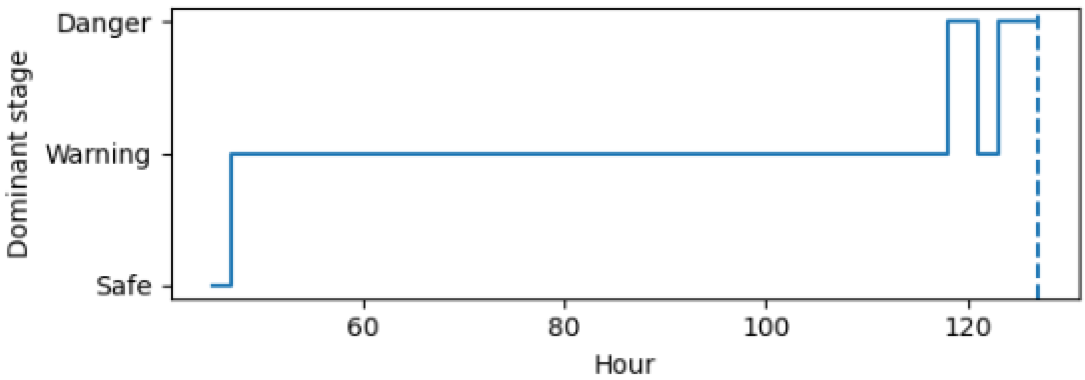

Fig. 3 Predicted Degradation Stage Across the Run-to-Failure Sequence

The dominant stage transitions from Safe to Warning and eventually to Danger as the system approaches failure. Minor fluctuations between Warning and Danger near the terminal phase reflect short-term prediction variability rather than recovery behavior.

D. Hybrid System Evaluation

This section evaluates the trained Long Short-Term Memory Autoencoder and Bidirectional Long Short-Term Memory models on the same held-out test hours from the run-to-failure sequence. The analysis focuses on the hour-level behavior of both models during the late degradation period and compares their alert responses across the shared evaluation timeline.

TABLE III: ALERT TIMIng COMPARIsOn ACROss MODELs

Model	Alert Hour	Lead Time
Long Short-Term Memory Autoencoder	47	80 hrs
Bidirectional Long Short-Term Memory	118	9 hrs

The Long Short-Term Memory Autoencoder produced an early alert at Hour 47 due to its high sensitivity to reconstruction deviations. However, earlier anomaly detection results indicate that the autoencoder also exhibits a relatively high false positive rate, meaning early anomaly flags should be interpreted cautiously.

In contrast, the Bidirectional Long Short-Term Memory stage classifier produced a later but more stable risk signal. The first sustained Danger prediction occurred at Hour 118, providing a lead time of approximately 9 hours before the terminal failure point at Hour 127.

The synchronized evaluation highlights the different behaviors of the two models during degradation. The Long Short-Term Memory Autoencoder functions as a highly sensitive anomaly detector capable of identifying early deviations from normal behavior, whereas the Bidirectional Long Short-Term Memory classifier provides a more selective stage-based warning closer to failure. These results suggest that the two models capture different aspects of the degradation process rather than producing identical alert responses across time.

E. Comparative Evaluation Against Baselines

To validate the architectural design choices of the proposed hybrid framework, two baseline models were evaluated under matched experimental conditions. The first baseline was a standalone Bidirectional Long Short-Term Memory classifier trained directly on fused feature windows without the Long Short-Term Memory Autoencoder encoder. The second baseline was a Vanilla Autoencoder evaluated on the same anomaly detection task as the proposed Long Short-Term Memory Autoencoder. Both baselines used the same dataset partitions, evaluation timeline, and random seed as the proposed models.

Anomaly Detection Comparison: The Vanilla Autoencoder baseline follows the same experimental protocol as the proposed Long Short-Term Memory Autoencoder. The baseline uses a feedforward encoder-decoder architecture, whereas the proposed model uses stacked Long Short-Term Memory layers to capture temporal dependencies across the five-second input sequence.

Both models achieved perfect recall and nearly identical performance across most anomaly detection metrics. The Vanilla Autoencoder achieved a higher ROC-AUC, indicating stronger threshold-independent separability between normal and anomalous windows. However, the proposed Long Short-Term Memory Autoencoder produced a slightly lower false positive rate at the selected operating threshold. These results suggest that while the Vanilla Autoencoder is a strong anomaly detection baseline, the proposed model remains competitive while also providing latent representations for downstream degradation forecasting.

TABLE IV: AnOMALY DETECTIOn PERfORMAnCE COMPARIsOn

Metric	LSTM-AE	Vanilla AE
Accuracy	85.07%	84.93%
Precision	83.40%	83.27%
Recall	100%	100%
F1-score	90.95%	90.87%
Specificity	40.27%	39.73%
False Positive Rate	59.73%	60.27%
ROC-AUC	0.796	1.000

Stage Classification Comparison: The standalone Bidirectional Long Short-Term Memory baseline was trained using the same architecture, loss function, and hyperparameters as the proposed model. The only difference was the input representation. The proposed model used latent vectors extracted from the Long Short-Term Memory Autoencoder encoder, whereas the baseline used directly fused feature windows.

TABLE V: STAgE CLAssIfICATIOn PERfORMAnCE COMPARIsOn

Metric	Proposed Hybrid	BiLSTM-only
Accuracy	79.23%	69.49%
Macro F1-score	0.736	0.710
Warning Recall	0.995	1.000
Danger Recall	0.892	0.490
Safe Recall	0.390	0.800
First Danger Hour	118	118
Lead Time	9 hrs	9 hrs
Danger Stability	Predominantly Maintained	Unstable

The proposed hybrid framework substantially improved degradation-stage forecasting performance. Accuracy increased from 69.49% to 79.23%, while Macro F1-score improved from 0.710 to 0.736. Most importantly, Danger Recall increased from 0.490 to 0.892, indicating a significantly stronger ability to identify critical late-stage degradation.

Although both models produced the first Danger prediction at Hour 118 and achieved the same 9-hour lead time, the standalone Bidirectional Long Short-Term Memory baseline failed to maintain a consistent danger signal near terminal failure. In contrast, the proposed hybrid framework maintained predominantly Danger-stage predictions throughout the critical pre-failure period, despite occasional temporary transitions back to Warning. While the standalone baseline achieved higher Safe Recall, predictive maintenance systems generally prioritize reliable detection of dangerous operating conditions over maximizing Safe classifications.

Fig. 4 compares hour-level stage predictions across the true labels, the proposed hybrid model, and the standalone baseline. The proposed model maintains a more stable Danger-stage signal after the first Danger hour, while the baseline reverts to Safe near the terminal period. This supports the improved Danger Recall and the value of the LSTM-Autoencoder latent representation for stage forecasting.

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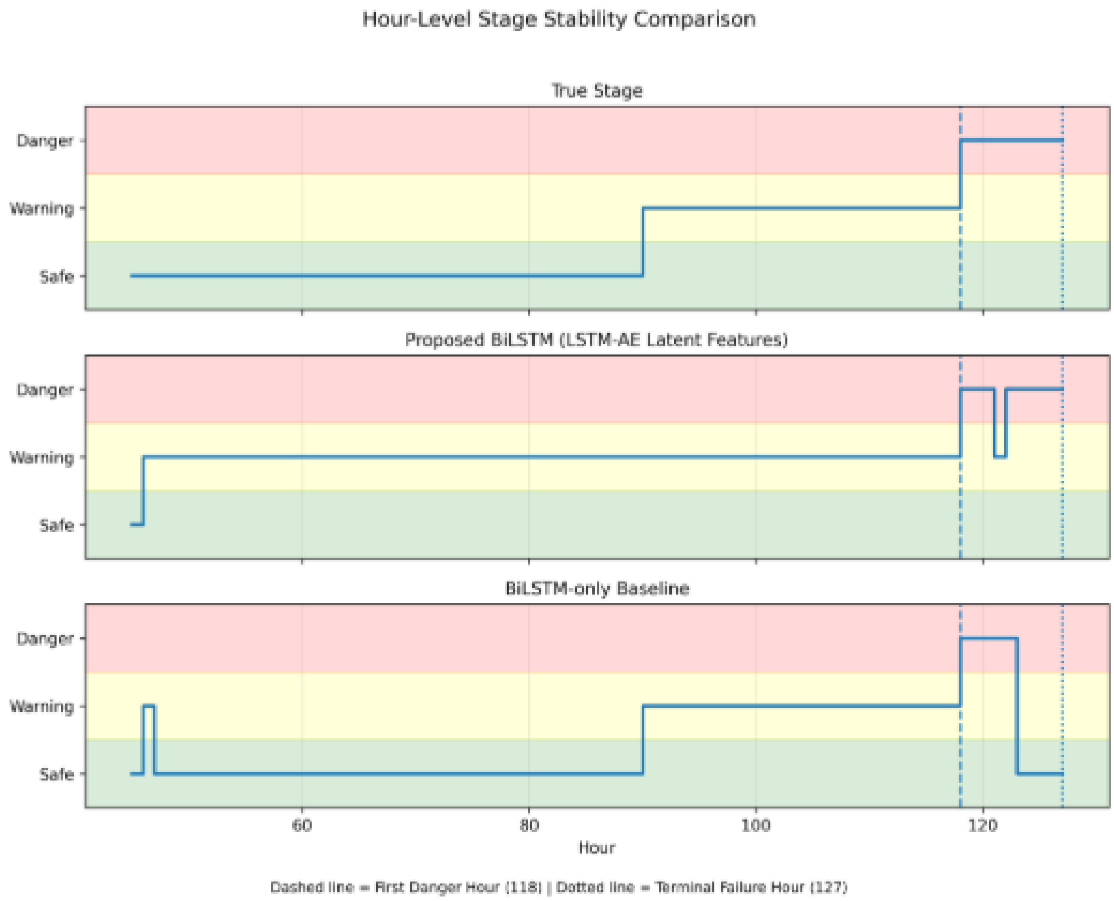

Fig. 4 Hour-Level Stage Stability Comparison

Overall, the comparative evaluation suggests that the primary benefit of the Long Short-Term Memory Autoencoder lies not in superior standalone anomaly detection performance, but in generating compact latent representations that improve downstream degradation-stage forecasting. The resulting hybrid framework provides more reliable identification of critical failure states and more stable warning behavior, which are highly desirable characteristics in predictive maintenance applications.

CONCLUSION

This study proposed a hybrid predictive maintenance framework that combines a Long Short-Term Memory Autoencoder and a Bidirectional Long Short-Term Memory classifier for anomaly detection and degradation-stage forecasting in electrical motor bearings. Using fused vibration and temperature features, the system successfully identified abnormal behavior through reconstruction error and predicted degradation stages categorized as Safe, Warning, and Danger.

Experimental results demonstrated that the Long Short-Term Memory Autoencoder achieved 85.07% accuracy, 100% recall, and a ROC-AUC of 0.796 for anomaly detection. However, its high false positive rate indicates that reconstruction-based anomaly detection alone is not sufficient for reliable failure prediction. The Bidirectional Long Short-Term Memory classifier achieved 79.23% accuracy and a macro F1-score of 0.736 while providing approximately 9 hours of lead time before failure. Comparative evaluation further showed that the hybrid framework substantially outperformed a standalone Bidirectional Long Short-Term Memory classifier in identifying critical Danger-stage conditions.

Despite the promising results, this study is limited by the use of a single run-to-failure trajectory and a single bearing operating condition. Future work should evaluate the framework across multiple operating conditions, fault types, and industrial datasets to improve generalizability. Additional sensor modalities, adaptive thresholding

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methods, and continuous remaining useful life estimation may also be explored to further enhance predictive maintenance performance.

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