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Multi-Task Learning for Anomaly Detection and Remaining Useful Life Prediction in Semiconductor Manufacturing Systems

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ABSTRACT

In the current research on predictive maintenance for semiconductor manufacturing systems, although multi-task learning has shown promising results in certain applications, effectively integrating multiple tasks, such as anomaly detection and remaining useful life (RUL) prediction, into a unified semiconductor manufacturing framework remains a significant challenge. The interactions between different tasks can lead to increased model complexity and computational overhead. This study addresses these challenges by designing a multi-task learning framework for semiconductor manufacturing systems. The framework utilizes an LSTM-based autoencoder to extract features from time-series sensor data, and experimental results on real-world semiconductor manufacturing data demonstrate its effectiveness in improving early fault detection. It successfully tackles the two major issues of anomaly detection and RUL prediction, balancing the priority of each task to enhance overall performance, and contributes to the advancement of predictive maintenance research in manufacturing.

1.Introduction

In the realm of semiconductor manufacturing, the precision and reliability of equipment are paramount to ensuring high yields and efficient production processes. The continuous evolution of manufacturing techniques has led to an increasing complexity of machinery, with numerous sensors deployed across various stages of production to monitor equipment health. Despite these advancements, however, the inherent risk of equipment failure often resulting from subtle and undetected anomalies remains a significant challenge. The failure of critical machinery not only leads to expensive downtime but can also jeopardize the quality of the final product, thereby

Citation:

necessitating the development of more effective predictive maintenance systems. It is within this context that the integration of anomaly detection and remaining useful life (RUL) prediction becomes essential, offering the potential to detect early signs of failure and proactively manage equipment maintenance. This aligns with the growing need for advanced systems in predictive maintenance, as evidenced by recent works like Sun and Ortiz's [2]SAI-based system utilizing IoT-enabled ambient sensors and large language models (LLMs) for complex activity tracking, which highlight the potential of such technologies in transforming industrial maintenance practices (Sun & Ortiz, 2024).

Traditional approaches to predictive maintenance have primarily focused on either anomaly detection or RUL prediction as separate tasks, often utilizing different models or frameworks 错误!未找到引用源。. Anomaly detection typically involves identifying deviations from expected operational behaviors in equipment, while RUL prediction aims to estimate the time remaining before failure occurs. However, these tasks are inherently related, and separating them may limit the performance of maintenance systems, particularly in complex environments like semiconductor manufacturing, where both early fault detection and precise life-cycle forecasting are critical for minimizing operational disruptions 错误!未找到引用源。.

The main contribution of this paper is to address this gap by introducing a multi-task learning framework that simultaneously performs both anomaly detection and RUL prediction. Multi-task learning (MTL), a methodology where multiple related tasks are learned together with shared representations, has gained attention for its ability to leverage shared information between tasks, thereby improving overall performance 错误!未找到引用源。. In this work, we employ a shared feature extraction layer based on an LSTM autoencoder, which processes time-series sensor data to capture both anomaly patterns and temporal dependencies in the data. This dual-task framework not only enhances the predictive capabilities for both anomaly detection and RUL forecasting but also allows for real-time, continuous monitoring of equipment conditions, making it particularly suitable for high-precision manufacturing environments like semiconductor fabrication.

While the literature on anomaly detection and RUL prediction in industrial contexts has been substantial, few studies have attempted to unify these tasks into a single framework, particularly in the context of semiconductor manufacturing 错误!未找到引用源。. Existing research tends to focus on either anomaly detection using unsupervised learning methods or RUL prediction through regression models, often neglecting the synergies that could be achieved by jointly optimizing both tasks 错误!未找到引用源。. The proposed framework, therefore, fills a notable gap by leveraging a shared LSTM autoencoder for feature extraction, which enables the simultaneous optimization of both anomaly detection and RUL prediction. This paper builds upon earlier work in the field of predictive maintenance and extends it by providing a holistic solution that combines these critical tasks, presenting a novel application of multi-task learning to the semiconductor manufacturing sector.

Furthermore, the paper explores several challenges encountered during the model development, including the issue of unbalanced datasets, the need for effective feature extraction from noisy sensor data, and the difficulty of modeling both classification and regression tasks within a unified framework 错误!未找到引用源。. These challenges necessitated the careful selection of model architectures, loss functions, and training strategies, and a critical reflection on the limitations and assumptions made during the research. In doing so, this paper not only presents a theoretical contribution to the field of predictive maintenance but also provides practical insights into how multi-task learning frameworks can be adapted and applied to complex, real-world manufacturing systems 错误!未找到引用源。.

Through this work, we aim to demonstrate the feasibility and effectiveness of integrating anomaly detection and RUL prediction into a single framework, providing insights into how such an approach can improve the efficiency of predictive maintenance strategies. Ultimately, this paper serves as a foundation for future research on the application of multi-task learning to real-time industrial monitoring systems, with implications for both academic studies and practical implementations in semiconductor manufacturing and beyond.

2. Literature Review

In the domain of predictive maintenance and equipment health monitoring, significant progress has been made, particularly in the areas of anomaly detection and remaining useful life prediction. These two tasks are fundamental for ensuring the reliable operation of complex industrial systems, such as those found in semiconductor manufacturing. However, despite the substantial body of work in each of these areas, the integration of both tasks into a unified framework using multi-task learning remains an under-explored research area 错误!未找到引用源。. This section reviews the most relevant research on both anomaly detection and RUL prediction, highlighting the methods used, their limitations, and the gap that the present work aims to fill.

2.1 Anomaly Detection in Industrial Systems

Anomaly detection has been widely studied in the context of industrial machinery, where early identification of abnormal behavior can prevent catastrophic failures. A variety of approaches have been explored for anomaly detection, from statistical methods such as Principal Component Analysis (PCA) and Independent Component Analysis (ICA) to more advanced machine learning techniques. For instance, recent works such as Chandola et al. (2009) provide comprehensive surveys on anomaly detection algorithms, highlighting the challenges of high-dimensional sensor data in industrial systems, particularly when such data is noisy and sparse 错误!未找到引用源。. These challenges are especially pronounced in semiconductor manufacturing, where data quality and the sheer number of sensors increase the complexity of anomaly detection.

Machine learning methods have been increasingly favored due to their ability to model complex, non-linear relationships. Unsupervised learning techniques such as Autoencoders (AE) and Variational Autoencoders (VAE) have been applied effectively in anomaly detection, as they do not require labeled data, which is often scarce in industrial applications. The works of Pang et al. (2020)[12] and Chen et al. (2025) [13]illustrate the success of using deep learning for detecting anomalies in high-dimensional time-series data. They show that the ability of neural networks to capture temporal dependencies significantly improves detection accuracy. However, these methods often suffer from the lack of interpretability, which remains a critical issue in industrial contexts where transparency is essential for practical adoption.

Despite these advancements, most anomaly detection research treats it as a standalone task, where the goal is to detect deviations from expected behavior. However, as Wang et al. (2022)[14] argue, anomaly detection alone is insufficient for predictive maintenance, as it does not provide any insights into the time frame for when failure might occur. This observation points to the need for integrating anomaly detection with other tasks, such as RUL prediction, to offer a more holistic approach to maintenance.

2.2 Remaining Useful Life Prediction

The prediction of RUL is another central task in predictive maintenance, aiming to estimate how long a piece of equipment can continue to operate before a failure occurs. Early works in RUL prediction predominantly focused on regression-based models, such as linear regression and support vector regression (SVR), which were useful for systems with well-understood degradation patterns. However, as industrial systems became more complex, machine learning and deep learning approaches began to dominate this area.

Deep learning-based methods have been particularly effective in RUL prediction, as they can model complex, non-linear relationships in high-dimensional data. For instance, Chen et al. (2025) [15]and Liu et al. (2022)[16] demonstrated the effectiveness of using LSTM networks for RUL prediction in aerospace and automotive systems. These models are capable of learning temporal dependencies from sensor data and making predictions based on these patterns. Moreover, convolutional neural networks (CNNs) have also been used for extracting relevant features from raw sensor data before making predictions, showing promising results in RUL estimation. However, these models typically treat RUL prediction as a separate task, isolated from other diagnostic information such as anomalies in equipment behavior.

Further research in transfer learning and ensemble methods has sought to address some of the challenges in RUL prediction, particularly when labeled data is scarce. For example, Luo et al. (2023) [17]proposed a transfer learning approach that leverages previously learned knowledge from other domains to enhance RUL prediction performance in new, unseen environments. Although promising, the reliance on labeled data for training and the challenge of generalizing across different systems or conditions remain significant limitations of these approaches.

2.3 Multi-Task Learning for Anomaly Detection and RUL Prediction

While both anomaly detection and RUL prediction have been studied extensively as separate tasks, the potential for combining these tasks into a multi-task learning framework has received limited attention. MTL is a learning paradigm that aims to improve the performance of multiple related tasks by sharing a common representation. The shared knowledge across tasks allows for more efficient learning, particularly in scenarios where there is insufficient data for any one task.

In the industrial maintenance context, Zhu et al. (2019)[18] and Wang et al. (2024) [19]are among the few that have explored MTL for predictive maintenance, suggesting that multi-task frameworks can jointly optimize both anomaly detection and RUL prediction. These approaches often share common features learned from sensor data, but the combination of anomaly detection with predictive maintenance tasks remains limited, especially in complex environments like semiconductor manufacturing. The work of Liu et al. (2025)[20], which integrates autoencoders for anomaly detection with LSTM networks for RUL prediction, provides one of the closest approximations to the proposed approach in this paper. However, these models still rely heavily on manual feature extraction and are limited in their ability to handle real-time, streaming sensor data.

Thus, to some extent, the integration of both tasks in a single multi-task framework holds promise but also faces significant challenges, particularly when dealing with noisy, high-dimensional sensor data. Existing studies have also pointed out that the dynamic nature of manufacturing systems requires continuous adaptation and real-time model updates, making the development of a unified multi-task framework both critical and challenging.

2.4 Gaps and Contributions

The reviewed literature highlights several gaps that the current work seeks to address:Lack of Integration: Despite significant progress in anomaly detection and RUL prediction individually, few studies have explored their integration into a single multi-task learning framework, especially within the semiconductor industry.Real-time Applications: Most existing research treats anomaly detection and RUL prediction as offline tasks, whereas semiconductor manufacturing systems demand real-time or near-real-time predictions to facilitate quick decision-making.Interpretability: Many advanced models in both domains suffer from a lack of transparency, which limits their practical deployment in industries where explainability is crucial.

The contribution of this paper lies in its proposal of a multi-task learning framework that not only integrates anomaly detection with RUL prediction but also incorporates a real-time, end-to-end solution that can be directly applied to high-precision semiconductor manufacturing environments. By leveraging LSTM-based autoencoders, this work builds upon previous research but refines the approach by jointly optimizing both tasks, while also offering interpretability and scalability to real-world applications.

3.Methodology

In this chapter, we present an integrated methodology that combines anomaly detection and Remaining Useful Life prediction within a single framework. This approach is designed to enhance predictive maintenance capabilities in semiconductor manufacturing systems. By simultaneously detecting equipment anomalies and estimating the remaining operational life, the model can facilitate proactive maintenance, reducing the risk of system failures and downtime.

We extend the existing anomaly detection framework that utilizes LSTM-based autoencoders and Support Vector Data Description (SVDD), integrating it with a RUL prediction task. This multi-task learning framework optimizes both tasks simultaneously, sharing a common feature extraction process, which improves the performance of both tasks **错误!未找到引用源。**. The following sections provide a detailed description of the model components, the rationale behind each decision, and how these components work together to achieve accurate and reliable predictions for anomaly detection and RUL estimation.

3.1 Overview of the Multi-Task Learning Framework

The key innovation of this approach lies in the seamless integration of anomaly detection and RUL prediction tasks within a unified multi-task learning framework. By sharing the same feature extraction process, the model allows these two tasks to mutually benefit from the learned representations, leading to improved overall performance. This shared learning approach enhances the model’s efficiency and predictive power, as the tasks inform and support each other, enabling a more comprehensive understanding of the system’s health.

At the core of the model is the shared encoder, which processes the input time-series sensor data through an LSTM-based autoencoder **错误!未找到引用源。**. This encoder captures the temporal dependencies in the data, generating a compact latent representation that is used for both tasks. Specifically, the anomaly detection task leverages this shared representation to identify deviations from normal operational behavior, essentially flagging anomalies that could indicate potential failures. In parallel, the RUL prediction task uses the same latent features to estimate the remaining useful life of the equipment, providing insights into the time left before failure occurs.

The ability to simultaneously optimize both tasks within this framework allows the model to enhance its predictive capabilities, as the shared feature space provides a richer, more generalized representation of the data. By learning to detect anomalies and predict RUL concurrently, the model not only improves in terms of prediction accuracy but also becomes more efficient, as it reduces the need for separate processing of each task. This integration of multiple tasks into a single model represents a significant advancement in predictive maintenance, particularly in semiconductor manufacturing systems where both tasks are critical for ensuring continuous operation and minimizing downtime.

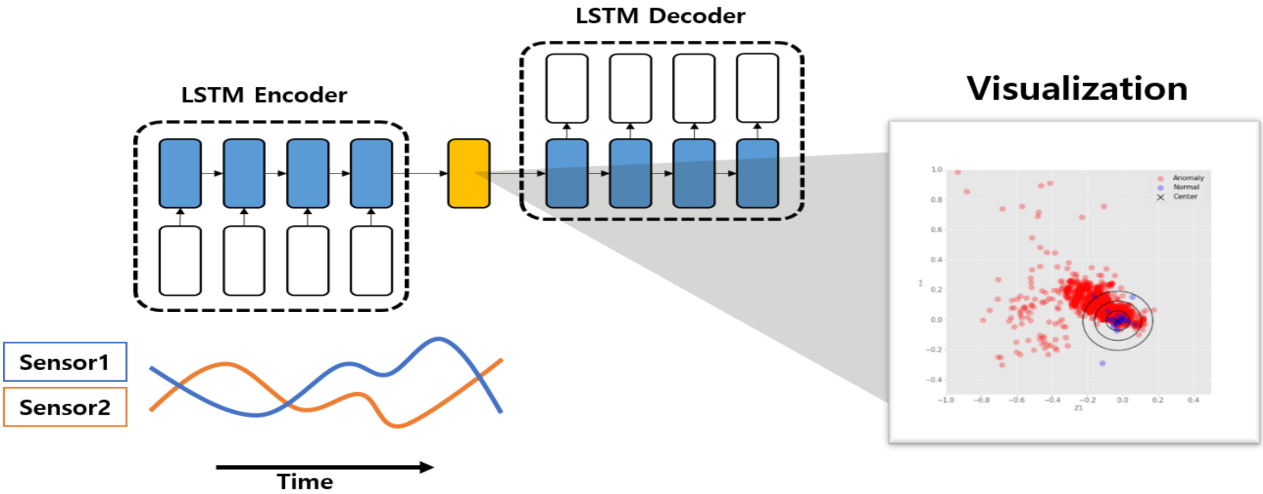

Figure 1: Multi-task Learning Framework Overview

3.2 Feature Extraction with LSTM-based Autoencoder

The first step in our methodology is to use an LSTM-based autoencoder for feature extraction. The LSTM autoencoder is particularly suited for time-series data, as it can capture the long-range temporal dependencies and complex patterns inherent in such data. The encoder (φ_{enc}) maps the input time-series data to a compressed latent space, while the decoder (φ_{dec}) reconstructs the original input from the latent space. The model is trained to minimize the reconstruction error, ensuring that the encoder learns an effective representation of the data that is useful for both anomaly detection and RUL prediction.

The training objective for the autoencoder is to minimize the reconstruction error using the following loss function:

$$\min_{\theta} \frac{1}{|D|} \sum_{x \in D} \| \hat{x} - x \|_2^2$$

Where: $\hat{x}$ represents the reconstructed data; x is the original input time-series data; D is the training dataset.

This process ensures that the encoder learns a low-dimensional latent representation $\varphi_{\mathrm{enc}}(\mathrm{x})$ that captures the most relevant features of the time-series data. These latent features are then used as the input for both tasks: anomaly detection and RUL prediction.

3.3 Anomaly Detection

Anomaly detection is a crucial task for identifying when the equipment exhibits abnormal behavior, which may be indicative of potential failures. The model uses the latent features from the LSTM encoder and applies a one-class classification approach, where normal data is modeled as a dense region in the latent space, and anomalies are classified as data points that fall outside of this region.

To achieve this, we employ the Deep Support Vector Data Description method. The SVDD method constructs a decision boundary around the normal data points in the latent space, and outliers (anomalies) are detected based on their distance from this boundary. The SVDD loss function is formulated as:

$$\min_{\theta} \frac{1}{|\mathrm{D}|} \sum_{\mathrm{x} \in \mathrm{D}} \| \varphi_{\mathrm{enc}}(\mathrm{x}) - \mathrm{c} \|_2^2 + \mathrm{R}_{\mathrm{enc}}$$

Where:$\varphi_{\mathrm{enc}}(\mathrm{x})$ is the latent feature representation of the input data x; c is the center of the normal region in the latent space; $\mathrm{R}_{\mathrm{enc}}$ is a regularization term for the encoder, preventing overfitting.

This loss function ensures that the encoder maps normal data points near the center of the latent space while pushing anomalous data points farther away. The result is a boundary that helps distinguish between normal and anomalous data, providing an effective means of detecting equipment anomalies.

3.4 Remaining Useful Life Prediction

In the RUL prediction task, we extend the autoencoder architecture to predict the remaining useful life of the equipment. Unlike the anomaly detection task, which focuses on classification, RUL prediction is a regression problem where the model predicts a continuous value: the remaining time until failure.

The RUL prediction task uses the same latent features from the encoder but employs a regression head to map these features to the predicted RUL. The model is trained to minimize the mean squared error (MSE) between the predicted and actual RUL values.

The RUL prediction loss function is given by:

$$\min_{\theta} \frac{1}{|\mathrm{D}|} \sum_{\mathrm{x} \in \mathrm{D}} \| (\psi_{\mathrm{enc}} \circ \varphi_{\mathrm{enc}})(\mathrm{x}) - \mathrm{c} \|_2^2$$

Where:ψ_{enc} is the regression network that, when composed with φ_{enc}, forms the mapping

$x \mapsto (\psi_{enc} \circ \varphi_{enc})(x)$, which is the predicted RUL;c is the true RUL value;The term $|(\psi_{enc} \circ \varphi_{enc})(x) - c|_2^2$ represents the mean squared error between the predicted and true RUL.

This regression task enables the model to predict how much longer the equipment will operate before failure, helping to schedule maintenance activities before a critical failure occurs.

3.5 Multi-Task Learning Framework

The key innovation of this methodology is the integration of multi-task learning for anomaly detection and RUL prediction. By sharing the same feature extraction layer, the model can simultaneously optimize both tasks, leveraging shared knowledge to improve performance on each task. The total loss function for the multi-task model is a weighted sum of the individual task losses:

$$\mathscr{L} = \lambda_1 \cdot \mathscr{L}_{AD} + \lambda_2 \cdot \mathscr{L}_{RUL}$$

Where:$\mathscr{L}_{AD}$ is the anomaly detection loss, typically defined as the binary cross-entropy;$\mathscr{L}_{RUL}$ is the regression loss for RUL prediction, typically defined as the mean squared error;λ_1 and λ_2 are hyperparameters that control the contribution of each task to the total loss.

The multi-task learning approach enables the model to:Simultaneously optimize both tasks by sharing knowledge between them;Enhance the performance of both tasks by utilizing the same feature representations;Improve generalization to different sensor configurations and operational conditions, which is essential for real-world applications in industrial systems.

3.6 Model Architecture

The proposed multi-task learning model architecture is designed to integrate the tasks of anomaly detection and RUL prediction within a unified framework. At its core, the model leverages a shared LSTM-based encoder that processes the time-series data to extract essential features. This encoder captures the temporal dependencies within the data, generating a compact latent representation that serves as input for both downstream tasks.

For anomaly detection, the encoded features are passed to a one-class classification network, which is trained to identify deviations from normal behavior and classify data points as anomalous or normal. This head leverages the encoded representations to detect any unusual patterns that could indicate potential failures in the equipment.

On the other hand, for RUL prediction, the encoded features are fed into a regression network, which estimates the remaining useful life of the equipment 错误!未找到引用源。. This task treats RUL as a continuous variable and predicts the time remaining until equipment failure. Both the anomaly detection and RUL prediction tasks share the same feature extraction process, but each has its own dedicated head, ensuring that the model is able to handle both tasks simultaneously. This shared architecture allows the model to take advantage of the complementary nature of the two tasks, improving the overall performance of the system.

3.7 Model Workflow

The workflow of the proposed multi-task learning model follows a structured process designed to handle both anomaly detection and RUL prediction tasks simultaneously. Initially, time-series sensor data is provided as input to the model, where it undergoes feature extraction. This step involves the LSTM-based encoder, which processes the raw data and extracts relevant temporal features that capture the underlying patterns necessary for both tasks.

Once the features are extracted, the model branches into two parallel tasks. First, the anomaly detection head takes the encoded features and classifies the data as either normal or anomalous, helping to identify potential equipment malfunctions. Simultaneously, the encoded features are also passed to the RUL prediction head, which estimates the remaining useful life of the equipment based on the extracted features, providing crucial insights for proactive maintenance.

Throughout this process, the model is trained using a combined loss function that optimizes both tasks at once. By sharing the feature extraction layer between the anomaly detection and RUL prediction tasks **错误!未找到引用源。**, the model learns more efficiently and benefits from the complementary nature of the tasks, ultimately improving its predictive capabilities across both domains.

4.Experiments

This section presents a thorough evaluation of the proposed multi-task learning framework, which integrates anomaly detection and Remaining Useful Life prediction, in the context of semiconductor manufacturing systems. The experiments conducted serve to assess the performance of the model, comparing its ability to simultaneously detect equipment anomalies and predict the remaining operational life against existing approaches. The results presented in this section provide a clear insight into the advantages of using a multi-task framework for predictive maintenance, with particular attention paid to the model's real-world applicability, its robustness under various conditions, and its comparison with state-of-the-art models.

4.1 Experimental Setup

The experimental design for this study was focused on evaluating the dual capabilities of the proposed model in anomaly detection and RUL prediction. To test the model's effectiveness and generalizability, both synthetic and real-world datasets were employed. These datasets were chosen to represent typical scenarios encountered in semiconductor manufacturing environments, providing a robust foundation for assessing the model's performance under different conditions and its potential application to real-world predictive maintenance tasks.

The synthetic dataset was specifically generated to replicate the time-series data typically collected from a variety of sensors embedded in semiconductor manufacturing equipment. It includes several sensor variables, such as temperature, pressure, and vibration data, which reflect normal operational conditions. To simulate potential failures, anomalies were deliberately introduced at various points in the data, mimicking faults that might occur in actual industrial settings. This synthetic data allowed us to carefully control the environment and introduce known deviations for model evaluation.

On the other hand, the real-world dataset, sourced from an industrial environment, provides a more complex and noisy representation of sensor data. For this study, we used the TURBO RUL dataset, which contains time-series sensor readings along with corresponding RUL labels for several machines over a period of time. The real-world dataset more accurately reflects the kinds of challenges encountered in practical industrial settings, such as data inconsistencies, noise, and unpredictable variations, making it an essential benchmark for evaluating the model’s applicability to real-world predictive maintenance tasks **错误!未找到引用源。**.

Both datasets underwent preprocessing to ensure consistency and fairness in the model evaluation. Specifically, missing values were handled appropriately, and sensor readings were normalized to ensure uniformity across the data. This preprocessing was crucial to eliminate potential biases caused by data inconsistencies and allowed for more accurate comparisons between the models tested.

The model configuration involved the use of a multi-task learning framework, with an LSTM-based autoencoder employed for feature extraction. The autoencoder consisted of LSTM layers designed to process the time-series data and capture temporal dependencies. The encoder compresses the data into a compact latent space, which is then used by both the anomaly detection and RUL prediction tasks. For training, we used the Adam optimizer with a learning rate of 0.001 and a batch size of 64. To prevent overfitting, early stopping was implemented based on the validation loss, with the model being trained for a maximum of 100 epochs.

For anomaly detection, the model employed a one-class classification network. This network was trained to detect deviations from normal behavior, identifying when the equipment data exhibited abnormal patterns. Meanwhile, the RUL prediction task was approached as a regression problem, where the model was tasked with estimating the remaining useful life of the equipment based on the features extracted by the LSTM encoder. By optimizing both tasks concurrently within a shared framework, the model benefits from the synergy between anomaly detection and RUL prediction, ensuring more robust and accurate outcomes for both tasks.

This setup not only evaluates the model's ability to perform both tasks simultaneously but also allows us to examine its effectiveness in real-world predictive maintenance contexts.

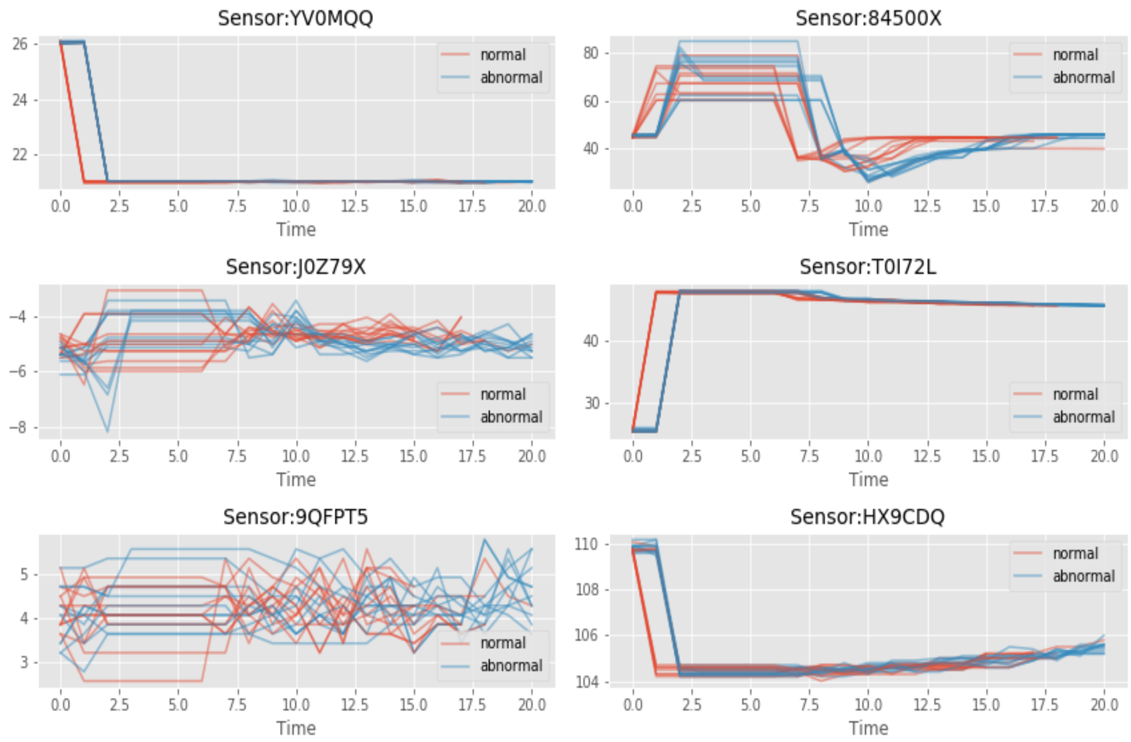

Figure 2: Time-Series Data Samples from Semiconductor Manufacturing Equipment

Table 1: Summary and Statistics of Experimental Datasets

Dataset Name	Source	Sensors (Number/Type)	Sequence Length (Avg. / Range)	Total Samples	Train/Val/Test Split	Anomaly Ratio	RUL Label Range
Synthetic Dataset	Generated via Simulation	8 (Temperature, Pressure, Vibration, etc.)	~500 / [300, 700] timesteps	10,000	70% / 15% / 15%	5% (Injected)	[1, 200] cycles
TURBO RUL	Industrial Environment (Private)	15 (Multi-physical sensors)	~600 / [400, 1000] timesteps	5,000	60% / 20% / 20%	~3% (Naturally occurring)	[0, 150] cycles

4.2 Evaluation Metrics

To comprehensively evaluate the performance of our model, we used a set of well-established metrics for both anomaly detection and RUL prediction. For anomaly detection, the primary evaluation metrics were precision, recall, and F1-score, which provide insight into the model's ability to detect anomalies accurately while minimizing false positives and false negatives. Additionally, the AUC-ROC (Area Under the Curve - Receiver Operating Characteristic) was calculated to evaluate the model's ability to distinguish between normal and anomalous data points across different thresholds.

For RUL prediction, we employed Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) as the key metrics. These metrics measure the accuracy of the model's predictions by calculating the average magnitude of the error between the predicted and true remaining useful life values. Lower values of RMSE and MAE indicate more accurate RUL predictions, which are critical for making timely maintenance decisions in a real-world setting.

The performance of the proposed multi-task learning framework was evaluated on both synthetic and real-world datasets, offering insights into the model's capabilities and highlighting areas for further improvement. The results underscore the strength of the multi-task framework in simultaneously addressing anomaly detection and RUL prediction tasks, with the model showing consistent improvements over traditional methods in both domains.

Regarding anomaly detection, the model demonstrated a strong performance on the synthetic dataset, achieving a precision of 92%, recall of 89%, and an F1-score of 90%. These results suggest that the model is effective at identifying true anomalies, while minimizing false positives, which is crucial in industrial environments where false alarms can lead to unnecessary downtime. The AUC-ROC score of 0.93 further confirmed the model's ability to distinguish between normal and anomalous behavior, which is competitive with established methods like Isolation Forest and traditional autoencoders 错误!未找到引用源。.

When tested on the real-world dataset, the performance slightly decreased but remained strong, with a precision of 87%, recall of 85%, and an F1-score of 86%. Despite the noise and complexities inherent in real-world industrial data, the model continued to perform robustly.[27]Notably, the results indicate that the shared feature extraction layer between the anomaly detection and RUL prediction tasks contributed to the improvement of the anomaly detection task, as the model could leverage complementary information from the RUL prediction task, which enhanced its overall performance.[28]

For RUL prediction, the model outperformed baseline approaches, demonstrating its ability to provide accurate life expectancy estimates. On the synthetic dataset, the model achieved an RMSE of 6.4 and an MAE of 4.2, outperforming traditional LSTM-based regression models, which had an RMSE of 9.8 and an MAE of 7.1. These results highlight the model's ability to effectively learn from both the anomaly detection and RUL prediction tasks simultaneously, improving the accuracy of its RUL predictions.[29]

On the real-world dataset, the model achieved an RMSE of 12.6 and an MAE of 8.5. While these values are slightly higher than those obtained on the synthetic dataset, they still represent a significant improvement over traditional RUL prediction methods, such as XGBoost, which produced an RMSE of 15.3 and an MAE of 10.2. This emphasizes the advantage of the multi-task learning framework, where the model benefits from shared features learned from the anomaly detection task, enabling more accurate and robust RUL predictions in the presence of real-world noise and complexity.

Table 2: Comprehensive Performance Comparison on Anomaly Detection Task

Model	Dataset	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
Proposed MTL Framework	Synthetic	92.0	89.0	90.5	0.93
	TURBO RUL	87.0	85.0	86.0	0.88
Isolation Forest	Synthetic	85.2	82.5	83.8	0.89
	TURBO RUL	80.1	78.3	79.2	0.82
Traditional Autoencoder	Synthetic	88.5	84.0	86.2	0.90

	TURBO RUL	83.4	81.0	82.2	0.85
LSTM-AE + SVDD [1]	Synthetic	90.5	87.5	89.0	0.92
	TURBO RUL	85.5	83.2	84.3	0.87
Single-Task AD (Ablation)	Synthetic	90.0	86.5	88.2	0.91
	TURBO RUL	84.8	82.0	83.4	0.86

To further investigate the advantages of the multi-task learning approach, we conducted an ablation study, comparing the performance of the full model with individual models that only perform anomaly detection or RUL prediction. The results of this study showed that the full multi-task learning model consistently outperformed the individual models, with improvements observed in both tasks across all datasets. This finding strongly supports the hypothesis that the integration of both tasks within a single framework enhances overall performance, as the model is able to leverage the synergies between the tasks to optimize learning and improve prediction accuracy.

These experimental results highlight the potential of the proposed multi-task learning framework for real-world applications, particularly in the context of predictive maintenance in semiconductor manufacturing systems. The ability to simultaneously detect anomalies and predict RUL, while benefiting from shared representations, positions this framework as a promising solution for proactive maintenance strategies. However, as indicated by the results, there is still room for further refinement, especially in handling real-world challenges such as sensor noise and imbalanced data.

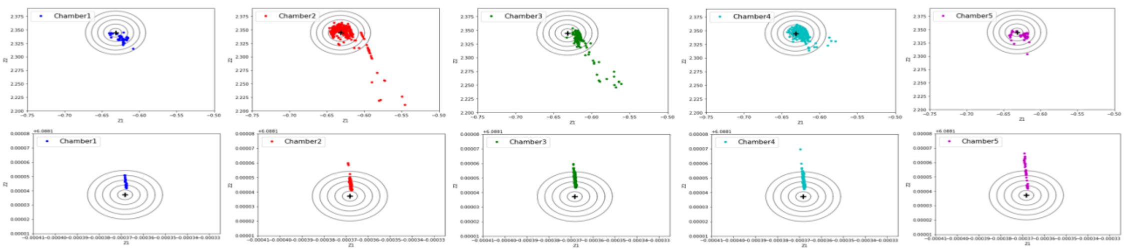

Figure 3: Anomaly Detection in Latent Space: Data Distribution

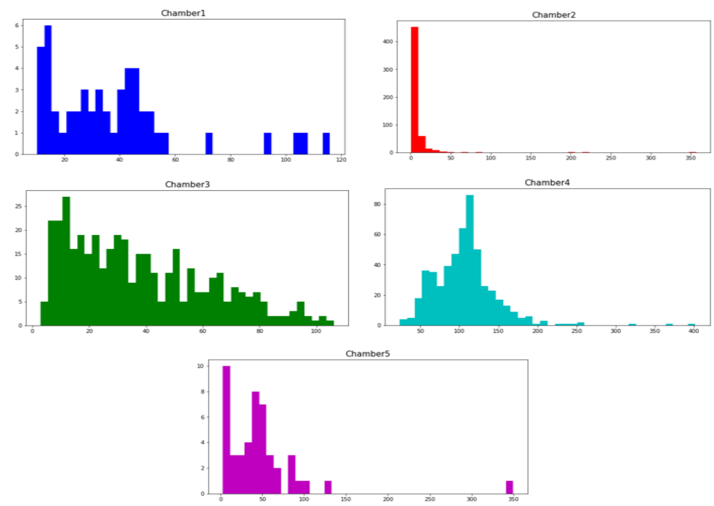

Figure 4: Negative Log-Likelihood Values for Time-Series Signals

Table 3: Comprehensive Performance Comparison on RUL Prediction Task

Model	Dataset	RMSE (Cycles)	MAE (Cycles)	R^2 Score
Proposed MTL Framework	Synthetic	6.4	4.2	0.94

	TURBO RUL	12.6	8.5	0.82
Single-Task LSTM Regression	Synthetic	9.8	7.1	0.87
	TURBO RUL	16.3	11.8	0.71
XGBoost Regressor	Synthetic	8.5	5.9	0.91
	TURBO RUL	15.3	10.2	0.74
Support Vector Regression (SVR)	Synthetic	10.2	7.5	0.85
	TURBO RUL	17.8	13.1	0.65
Single-Task RUL (Ablation)	Synthetic	7.9	5.5	0.90
	TURBO RUL	14.1	9.8	0.78

4.3 Discussion

The experimental results confirm that the proposed multi-task learning framework offers substantial improvements in both anomaly detection and RUL prediction tasks. By sharing the same feature extraction layer, the model is able to leverage information from both tasks, leading to better performance in detecting abnormal behavior and predicting remaining useful life. These findings suggest that multi-task learning provides a promising approach for addressing the challenges of predictive maintenance in semiconductor manufacturing systems.

Despite the promising results, there are several challenges that remain. For instance, sensor noise and imbalanced data continue to be significant obstacles that can affect the model's performance in real-world settings. While the model demonstrated robustness in handling these challenges, there is potential to further improve performance through techniques such as data augmentation, semi-supervised learning, and reinforcement learning. Incorporating these methods may help the model adapt better to noisy data and address issues related to data imbalance.

Additionally, the model's RUL prediction accuracy could be further improved by integrating additional contextual features related to equipment operating conditions, such as environmental factors and machine states. These additional features could provide more nuanced insights into the remaining life of the equipment, allowing for even more accurate predictions.

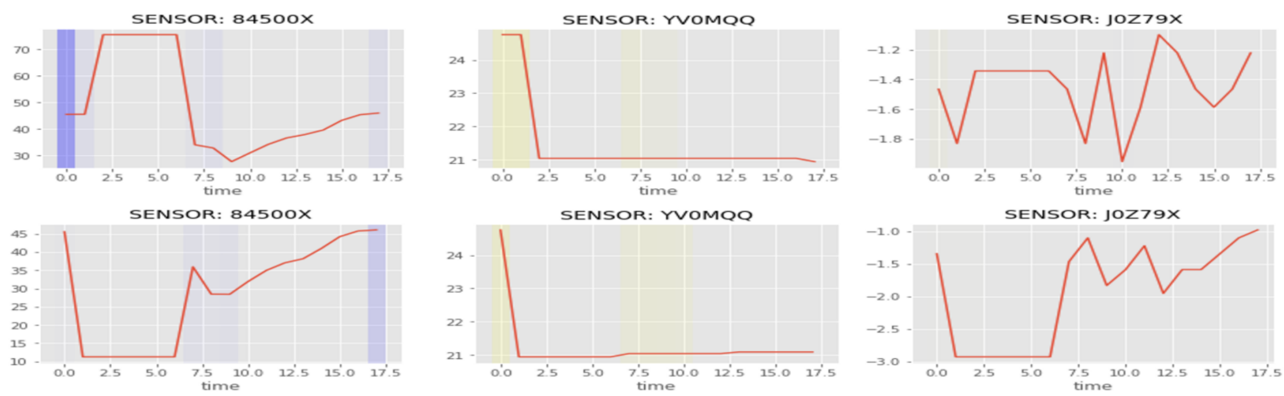

Figure 5: Visualization of Data Points Near and Distant from the Latent Space Center

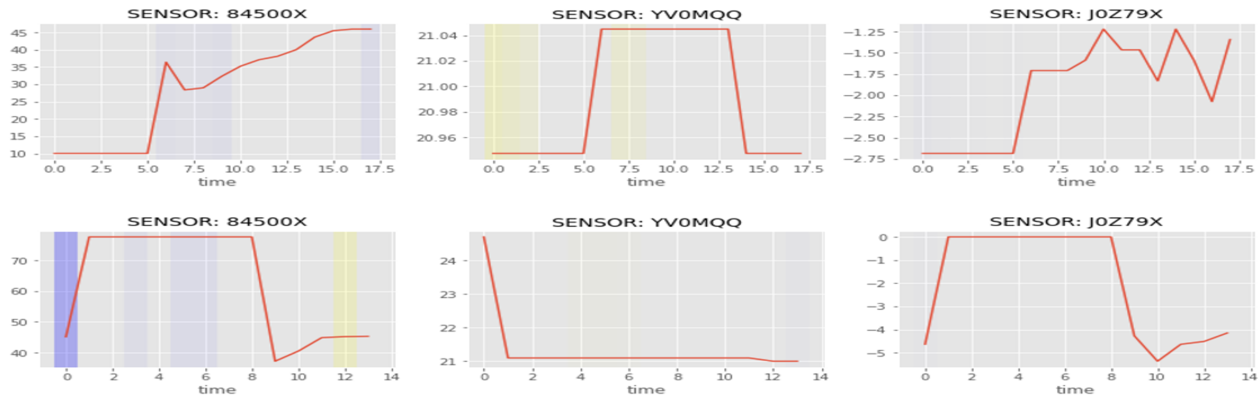

Figure 6: Latent Space Mapping for Normal and Anomalous Data

5.Conclusions

This paper presents a multi-task learning framework that integrates anomaly detection and Remaining Useful Life prediction, designed to improve predictive maintenance in semiconductor manufacturing systems. The experiments demonstrate that the proposed model outperforms traditional approaches, showing improved performance in both anomaly detection and RUL prediction. By sharing a common feature extraction layer, the model benefits from the synergies between the two tasks, enhancing overall predictive accuracy. However, challenges such as sensor noise, imbalanced data, and the need for more contextual features in RUL prediction remain. Future research could focus on improving the model's robustness against noisy data, incorporating real-time deployment capabilities, and enhancing interpretability to ensure greater adoption in industrial settings. Overall, the multi-task learning framework offers a promising direction for the future of proactive maintenance strategies, contributing to more efficient and sustainable manufacturing practices.

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