# Deep Learning Algorithms for Predictive Maintenance in U.S. Supply Chain Operations: Enhancing Reliability and Efficiency

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## 1. Introduction

The introduction section serves as a foundational component of the essay, providing an overview of the study on deep learning algorithms for predictive maintenance in U.S. supply chain operations. It sets the stage for subsequent sections by outlining the context and significance of the research. In this context, [1] introduced a hybrid deep learning-based approach for disruption detection within a data-driven cognitive digital supply chain twin framework. Their approach enhances supply chain resilience by enabling real-time disruption detection, disrupted echelon identification, and time-to-recovery prediction. The framework combines a deep autoencoder neural network with a one-class support vector machine classification algorithm for disruption detection, and long-short term memory neural network models for disrupted echelon identification and time-to-recovery prediction. Furthermore, [2] plan to develop data preprocessing and compression techniques to reduce data transmission in the edge computing structure for real-time predictive maintenance, aiming to build a more efficient distributed edge computing system.

These references provide insights into the development and application of deep learning algorithms for predictive maintenance in supply chain operations, aligning with the overarching theme of the essay.

### 1.1. Background and Significance

The significance of predictive maintenance and deep learning algorithms in U.S. supply chain operations is underscored by the need to enhance reliability and efficiency. Traditional maintenance strategies often lead to unexpected downtime and high maintenance costs. By contrast, predictive maintenance (PdM) leverages sensor readings, process parameters, and operational characteristics to predict equipment failures and perform maintenance to prevent them before they occur. This approach reduces unnecessary repairs, maximizes equipment lifespan, and ultimately increases productivity. Furthermore, the use of deep learning algorithms, such as the 1D convolutional neural network (1DCNN) and bidirectional LSTM (Bilstm) model, allows for effective feature extraction from time series data and anomaly detection. These models, when combined with a federated learning framework, can address the data heterogeneity and distributional shifts of time series data in manufacturing processes, making predictive maintenance of equipment more effective and efficient [2].

In the railway industry, data-driven predictive maintenance models have been proposed, including LSTM prediction models for failure detection, risk prediction models for evaluating rail defects and service failures, and advanced data mining methods for strategic decision support and risk planning. These models use machine learning techniques such as random forest (RF), support vector machine (SVM), logistic regression (LR), and recurrent neural network (RNN) to achieve their objectives [3]. This background emphasizes the need for predictive maintenance and deep learning algorithms in U.S. supply chain operations to address maintenance challenges and improve operational reliability and efficiency.

### 1.2. Research Objectives

The research objectives of this study aim to enhance reliability and efficiency in U.S. supply chain operations through the application of deep learning algorithms for predictive maintenance. Specifically, the research will focus on developing data preprocessing and compression techniques to reduce the amount of data transmission in the edge computing structure by visualizing the data collected for predictive maintenance [2]. Additionally, the study seeks to utilize deep learning techniques, particularly Long Short-Term Memory (LSTM) models, to capture temporal dependencies in time series data for predictive maintenance applications [4].

These objectives underscore the significance of leveraging advanced data processing and deep learning algorithms to build a real-time predictive maintenance system that can efficiently utilize a distributed edge computing system, thereby enhancing the reliability and efficiency of U.S. supply chain operations.

## 2. Theoretical Framework

The theoretical framework for predictive maintenance and deep learning in supply chain operations encompasses two key areas. Firstly, predictive maintenance involves the use of data preprocessing and compression techniques to reduce the amount of data transmission in edge computing structures, enabling the development of real-time predictive maintenance systems utilizing a distributed edge computing system [2]. This approach visualizes the data collected for predictive maintenance and converts it into the required information, utilizing data compression algorithms for efficient data transmission.

Secondly, deep reinforcement learning offers a solution to the increasing complexity of modern equipment maintenance, particularly in the context of Industry 4.0. This approach formulates the maximization of equipment uptime as a function of multiple input sensor data and models the derived equipment health states with state-action pairs [5]. The proposed model-free-based Deep Reinforcement Learning algorithm rapidly learns an optimal maintenance decision policy, providing consistent maintenance recommendations across similar equipment. These theoretical foundations are essential for understanding the subsequent discussions on the application of deep learning algorithms for predictive maintenance in U.S. supply chain operations.

### 2.1. Overview of Predictive Maintenance

Predictive maintenance (PdM) is a pivotal technology in the realm of smart factories, enabling the anticipation and prediction of equipment failure causes and conditions through real-time data sensing and advanced prediction algorithms [2]. The complexity of industrial data necessitates accurate preprocessing and feature extraction due to its time-dependent nature, posing challenges for PdM model reusability. Additionally, the imbalance of collected data presents a hurdle for securing equipment failure data, prompting research into unsupervised learning methods to address this imbalance. Despite the potential benefits of PdM over preventive maintenance, the high costs associated with sensor installation, infrastructure management, and data storage have historically limited its widespread adoption. However, recent advancements in machine learning capabilities and cost reduction efforts are driving improvements in PdM technologies, such as machine vision-based monitoring and the integration of digital twin technology for predictive maintenance scheduling and cost reduction. Furthermore, the prediction of remaining useful life (RUL) is a critical aspect of implementing predictive maintenance policies, with Bayesian approaches and dynamic

Bayesian networks (DBN) being utilized to assess component reliability over time [6]. These insights underscore the significance of predictive maintenance in enhancing operational reliability and efficiency within supply chain operations.

### 2.2. Deep Learning in Supply Chain Operations

Deep learning algorithms have gained significant traction in supply chain operations, particularly in the context of predictive maintenance. For instance, [1] introduced a hybrid deep learning-based approach for disruption detection within a data-driven cognitive digital supply chain twin framework. This approach enhances supply chain resilience by enabling real-time disruption detection, disrupted echelon identification, and time-to-recovery prediction. The framework combines a deep autoencoder neural network with a one-class support vector machine classification algorithm for disruption detection, while long-short term memory neural network models are used for disrupted echelon identification and time-to-recovery prediction.

Similarly, in the railway industry, [3] implemented a LSTM prediction model for detecting failures in the Italian railway industry. They also proposed a data-driven risk prediction model to predict and evaluate rail defects and service failures, utilizing advanced data mining methods based on machine learning techniques. These applications demonstrate the increasing role of deep learning algorithms in enhancing the efficiency and reliability of predictive maintenance methodologies within supply chain and railway operations.

## 3. Literature Review

The literature on predictive maintenance (PdM) and deep learning (DL) applications in supply chain operations is rich and diverse. A recent survey on data-driven predictive maintenance for the railway industry emphasizes the significance of monitoring and logging industrial equipment events through data generated by sensors, with a focus on decreasing failure rates and enhancing system reliability. The study highlights the relevance of machine learning (ML) and deep learning algorithms in creating advanced mining methods for PdM, particularly in the context of the railway industry. This survey also presents a taxonomy specific to the railway industry, classifying related works into three areas: infrastructure, scheduling policies, and vehicles, based on the type of data analysis method used for PdM practices [3].

Additionally, a comprehensive study of predictive maintenance in industries using classification models and Long Short-Term Memory (LSTM) model underlines the significance of logistic regression in estimating the probability of an event occurring by fitting data to a logistic curve. The study distinguishes between binary and multinomial logistic regression models, highlighting their relevance in different contexts. The findings from the logistic regression model in maintenance have shown promising results, indicating the potential of these models in predictive maintenance practices [4]. These studies provide valuable insights into the application of deep learning algorithms and predictive maintenance in supply chain operations, laying the foundation for further empirical and methodological discussions.

### 3.1. Predictive Maintenance in Supply Chain Operations

Predictive maintenance plays a crucial role in enhancing the reliability and efficiency of supply chain operations in the U.S. [7] emphasize that the primary objective of predictive maintenance is to minimize unplanned maintenance caused by machine failures, thereby increasing machine availability. This approach offers several benefits, including improved maintenance planning and cost optimization related to the maintenance process. For instance, in the context of a fleet of automated teller machines (ATMs), event logs can be utilized to identify relevant patterns in discrete logical events, enabling the prediction of machine failures and facilitating better maintenance planning.

Furthermore, [3] highlight the application of advanced data-driven predictive maintenance models in the railway industry, such as the use of LSTM prediction models for detecting failures and data-driven risk prediction models for evaluating rail defects and service failures. These models leverage machine learning techniques to create strategic decision support systems, improving operational efficiency and enabling predictive and risk-based maintenance activities scheduling. The authors also emphasize the importance of data-driven policy for the inspection and maintenance of track geometry, showcasing the comprehensive application of predictive maintenance in ensuring the reliability of railway infrastructure.

### 3.2. Deep Learning Applications in Supply Chain Management

Deep learning applications have been increasingly integrated into supply chain management to optimize operations and enhance resilience. [1] introduced a hybrid deep learning-based approach for disruption detection within a data-driven cognitive digital supply chain twin framework. The approach enables real-time disruption detection, identification of disrupted echelons, and prediction of time-to-recovery, thus enhancing supply chain resilience. The study validated the framework under various potential disruption scenarios, such as demand surges and unexpected failures, and demonstrated its effectiveness in detecting disruptions and identifying disrupted echelons. Additionally, [8] explored the application of machine learning techniques in supply chain risk assessment, showcasing the use of deep learning models such as Long Short-Term Memory (LSTM) networks for forecasting oil import risk and Recurrent Neural Networks (RNN) for predicting the exportability of shipments during the COVID-19 pandemic. These studies collectively highlight the potential of deep learning in optimizing supply chain operations and enhancing reliability.

**4. Methodology**

The methodology for the study on deep learning algorithms for predictive maintenance in U.S. supply chain operations involves several key steps. Firstly, data collection from U.S. supply chain operations will be conducted to gather relevant information on equipment maintenance and failure. Subsequently, preprocessing of the collected data will involve techniques such as encoding nominal data into binary attributes using one-hot encoding, which may increase the dimension and sparsity of the dataset. Model development will focus on employing state-of-the-art solutions for event-driven predictive maintenance, including classification and regression approaches, as well as the use of Cox proportional hazard deep learning for predictive maintenance. Finally, the training of the developed models will be essential to ensure their accuracy and reliability in predicting equipment failure times, thus enhancing the reliability and efficiency of U.S. supply chain operations [9] [10].

**4.1. Data Collection and Preprocessing**

Data collection and preprocessing are crucial steps in developing and training deep learning models for predictive maintenance in supply chain operations. The process involves gathering and refining the data to ensure its quality and relevance to the maintenance tasks. In the railway industry, advanced data mining methods based on machine learning techniques have been used to create decision support and risk control plans for trains, utilizing historical data to develop predictive models for rail defects and service failures [3]. Additionally, in the manufacturing sector, predictive maintenance is essential for preventing equipment failures and maximizing productivity. An effective approach involves leveraging sensor readings, process parameters, and operational characteristics to reduce unnecessary repairs and maximize equipment lifespan [2].

These insights highlight the significance of data-driven approaches for predictive maintenance and emphasize the need for accurate and timely data collection, especially in distributed industrial settings where data heterogeneity and scale pose challenges. The utilization of machine learning techniques, such as 1D convolutional neural networks (1DCNN) and bidirectional LSTM (Bilstm) models, underscores the importance of preprocessing data to extract relevant features and detect anomalies in time series data, crucial for effective predictive maintenance. Therefore, the procedures and techniques for data collection and preprocessing play a fundamental role in enhancing the reliability and efficiency of predictive maintenance in supply chain operations.

**4.2. Model Development and Training**

In the development and training of deep learning models for predictive maintenance in supply chain operations, the choice of model architecture and training methodologies play a crucial role. [11] emphasize the significance of setting meaningful prediction and reading windows consistent with domain-specific requirements. Their study demonstrates that basic algorithms like Logistic Regression can achieve acceptable performance in complex cases. Furthermore, the authors highlight the effectiveness of Long Short-Term Memory (LSTM) models for short prediction windows, where the influence of historical data from the reading window is critical. They also point out the importance of fine-tuning the LSTM model and exploring different architectures and hybrid models to identify the most effective approach for different industrial scenarios. Additionally, they stress the need for interpretability of the model's output, especially in industrial settings where the output is used to take preventive maintenance action.

On the other hand, [12] highlight the importance of vibration analysis in the fault diagnosis of rotating machinery for predictive maintenance. They emphasize that changes in signal amplitude or frequency can indicate compromised device performance, and the alteration of vibration signal characteristics due to mechanical friction allows for anomaly detection without stopping the production line. The authors propose a Transformer-based fault diagnosis model, T4PdM, which utilizes the Transformer architecture for time series classification in machinery fault diagnosis. This model was evaluated using publicly available datasets, and quantitative classification metrics such as accuracy, precision, recall, and F1-score were calculated. Their research underscores the potential of deep neural network models based on the Transformer architecture for fault diagnosis in rotating machinery, contributing to the advancement of predictive maintenance techniques in supply chain operations.

## 5. Case Studies

The case studies in the context of predictive maintenance in U.S. supply chain operations demonstrate the practical implementation and outcomes of deep learning algorithms. For instance, in the railway industry, a study implemented a Long Short-Term Memory (LSTM) prediction model to detect failures, evaluate rail defects, and predict the risk of defects recurrence in different segments of the network [3]. This advanced data mining method based on machine learning (ML) techniques improved operational efficiency by creating strategic decision support and a risk and control plan for trains, utilizing stored-inactive data from a Greek railway company. The study also proposed an integrated method for predicting rail and geometry defects and optimal scheduling, providing inspection and maintenance schedules. The solutions involved feature selection using K-means and predicting the number of defects by Random Forest (RF) and Recurrent Neural Network (RNN) methods.

In the manufacturing context, predictive maintenance plays a crucial role in preventing equipment failures and maximizing productivity. An innovative approach combines a 1D convolutional neural network (1DCNN) and a bidirectional LSTM (Bilstm) for time series anomaly detection and predictive maintenance of manufacturing processes [2]. This approach leverages federated learning to consider the distributional shifts of time series data and perform anomaly detection and predictive maintenance based on them. By utilizing sensor readings, process parameters, and other operational characteristics, predictive maintenance can help reduce unnecessary repairs, maximize the lifespan of equipment, reduce maintenance costs, and increase productivity. These case studies exemplify the tangible benefits of implementing deep learning algorithms in predictive maintenance within U.S. supply chain operations.

### 5.1. Case Study 1: Predictive Maintenance in Manufacturing Facilities

In a case study focusing on predictive maintenance in manufacturing facilities, the application of deep learning algorithms has shown promising outcomes in optimizing reliability and efficiency. [13]. The study compared traditional and machine learning-based models for anomaly detection, with the latter demonstrating superior predictive capabilities. Additionally, the authors proposed a transfer learning model for classifying failures on sensors with lower sampling rates, using data from sensors with higher data loads, leading to a considerable increase in failure detection accuracy. This research underscores the potential of deep learning algorithms in enhancing predictive maintenance within manufacturing facilities.

Furthermore, [2]. The proposed approach aims to efficiently utilize data collected from edge devices and enable real-time predictive maintenance systems in a distributed edge computing environment. This signifies the potential for deep learning algorithms to contribute to the development of efficient and real-time predictive maintenance systems in manufacturing facilities.

**5.2. Case Study 2: Predictive Maintenance in Logistics Operations**

Predictive maintenance in logistics operations is crucial for enhancing the reliability and efficiency of the supply chain. A case study in the railway industry implemented a Long Short-Term Memory (LSTM) prediction model for detecting failures, proposing a data-driven risk prediction model, and utilizing advanced data mining methods based on machine learning (ML) techniques to improve operations efficiency [3]. The study also emphasized the importance of predictive and risk-based maintenance schedules, as well as the integration of data-driven policies for inspection and maintenance of track geometry to support both corrective and preventive maintenance.

Furthermore, in the manufacturing sector, predictive maintenance and anomaly detection play a vital role in preventing equipment failure and maximizing productivity. Ahn et al. [2] proposed a 1D convolutional neural network (1DCNN) and bidirectional LSTM (Bilstm) model for time series anomaly detection and predictive maintenance in manufacturing processes. The authors highlighted the significance of leveraging sensor readings, process parameters, and other operational characteristics to reduce unnecessary repairs and maximize equipment lifespan, ultimately leading to increased productivity. The study also stressed the importance of considering the distributional shifts of time series data and performing anomaly detection and predictive maintenance based on a federated learning framework. These case studies underscore the potential of deep learning algorithms in revolutionizing predictive maintenance within logistics operations and manufacturing processes.

**6. Results and Discussion**

The results and discussion section presents the findings and deliberations arising from the empirical analyses. In the context of U.S. supply chain operations, the performance evaluation of deep learning models plays a crucial role in enhancing reliability and efficiency. For instance, [1] introduced a hybrid deep learning-based approach for disruption detection within a data-driven cognitive digital supply chain twin framework. The approach contributes to supply chain disruption management by offering better end-to-end supply chain visibility, enabling real-time disruption detection, disrupted echelon identification, and time-to-recovery prediction. The study validated the framework under several potential disruption scenarios in a virtual three-echelon supply chain, indicating a trade-off between disruption detection model sensitivity, encountered delay until disruption detection, and false alarm count. Additionally, [11] demonstrated the effectiveness of LSTM models for predicting machine failures from multivariate time series in an industrial case study. Their experimental results showed that LSTM models achieve notable macro $F_{1}$ scores, particularly for short prediction windows, highlighting the potential of deep learning in predictive maintenance strategies for improving operational efficiency in supply chain operations.

These findings underscore the potential of deep learning algorithms in enhancing the reliability and efficiency of U.S. supply chain operations, particularly in the context of disruption detection and predictive maintenance. The studies by and provide valuable insights into the performance and applicability of deep learning models in addressing critical challenges within supply chain operations. Moving forward, further research directions may include fine-tuning the models, exploring different architectures and hybrid models, and investigating the interpretability of deep learning outputs to optimize their effectiveness in real-world supply chain scenarios.

**6.1. Performance Evaluation of Deep Learning Models**

In the context of predictive maintenance for U.S. supply chain operations, the performance evaluation of deep learning models is crucial for assessing their effectiveness in enhancing reliability and efficiency. Recent research by Vago, Forbicini, and Fraternali [11] emphasizes the significance of setting meaningful prediction and reading windows in achieving effective predictive maintenance strategies. The study demonstrates that in a best-case scenario, the LSTM model achieves a notable macro $F_{1}$ score of 0.861 for a prediction window of 15 minutes and a reading window of 20 minutes. However, the performance of the LSTM model becomes less effective as the prediction window increases, highlighting the relevance of temporal dependencies. These findings underscore the importance of understanding the implications of prediction and reading windows in evaluating the performance of deep learning models for predictive maintenance in supply chain operations.

Additionally, Davari et al. [3] present a variety of techniques, such as RNN classifiers and generative adversarial networks (GANs), for predictive maintenance in different industrial scenarios. They highlight the applicability of neural networks in diverse data sources, emphasizing the potential of these techniques for predictive maintenance in U.S. supply chain operations. These insights contribute to a comprehensive understanding of the empirical outcomes and implications of deep learning models for enhancing predictive maintenance in U.S. supply chain operations.

**6.2. Implications for U.S. Supply Chain Operations**

The application of deep learning algorithms for predictive maintenance in U.S. supply chain operations has significant implications for operational reliability and efficiency. [1] introduced a hybrid deep learning-based approach for disruption detection within a data-driven cognitive digital supply chain twin framework. This approach enhances supply chain resilience through real-time disruption detection, disrupted echelon identification, and time-to-recovery prediction. The combination of a deep autoencoder neural network with a one-class support vector machine classification algorithm enables disruption detection, while long-short term memory neural network models identify the disrupted echelon and predict time-to-recovery. The results indicate the potential to replace the former approach for disruption detection and the indispensability of the anomaly detection model based on the one-class support vector machine algorithm.

Furthermore, [2] proposed a 1DCNN-Bilstm model for time series anomaly detection and predictive maintenance in manufacturing processes, which is essential for U.S. supply chain operations. The model, combining a 1D convolutional neural network and a bidirectional

LSTM, effectively extracts features from time series data and detects anomalies. This strategy reduces machine maintenance costs, maximizes machine uptime, and increases productivity by preventing unexpected failures and avoiding failure points within the assembly line. Additionally, the authors emphasized the importance of collecting and analyzing a large amount of relevant data within a reasonable amount of time, particularly in industrial parks spread across multiple locations. These findings underscore the potential of deep learning algorithms to revolutionize predictive maintenance in the U.S. supply chain operations, enhancing reliability and efficiency.

**7. Challenges and Future Directions**

[2]. They emphasize the importance of developing data preprocessing and compression techniques to reduce the amount of data transmission in edge computing structures, enabling the realization of efficient real-time predictive maintenance systems. Additionally, [14] underscore the significance of addressing challenges such as data quality, feature engineering, and model interpretability in the context of predictive maintenance for renewable energy systems. These challenges pave the way for future research directions, including the exploration of advanced data compression algorithms and the development of interpretable deep learning models to enhance the reliability and efficiency of predictive maintenance in U.S. supply chain operations.

**7.1. Technical Challenges in Implementation**

[15] emphasize the complexity of deploying industrial machine learning (ML) systems to production, which involves algorithm development, feature engineering, data wrangling, establishing data pipelines, and optimizing models for latency constraints. Furthermore, maintaining consistent performance post-deployment is a critical challenge, requiring resilience to common data issues such as changes in data distribution, missing values, and anomalies in input data. [16] also highlight the necessity to apply DevOps principles to ML systems and discuss challenges related to model deployment, integration, monitoring, and updating. They stress the need for high-quality telemetry data, acquiring labels for supervised learning, and the lack of agreed best practices for handling machine learning models in production. These insights underscore the multifaceted technical hurdles in implementing deep learning algorithms for predictive maintenance in supply chain operations.

### 7.2. Potential Research Directions

In the realm of predictive maintenance and deep learning applications, potential research directions encompass the development of data preprocessing and compression techniques to minimize data transmission in edge computing structures [2]. This involves visualizing collected data for predictive maintenance and converting it into essential information, subsequently employing data compression algorithms to facilitate efficient data transmission. By pursuing this avenue, a real-time predictive maintenance system utilizing a distributed edge computing system can be constructed more effectively, enhancing the reliability and efficiency of supply chain operations.

Moreover, there is an opportunity for future research to focus on the implementation of LSTM prediction models for detecting failures in the railway industry, particularly in the context of rail defects and service failures [3]. This involves the creation of data-driven risk prediction models to forecast the recurrence of rail defects, thereby enabling the development of strategic decision support systems and risk-based maintenance activities scheduling. Additionally, the integration of advanced data mining methods based on machine learning techniques can contribute to the improvement of operational efficiency and the formulation of predictive and risk-based maintenance schedules for railway infrastructure. These research directions hold promise for enhancing the reliability and efficiency of supply chain operations within the U.S. context.

## 8. Conclusion and Recommendations

In conclusion, the research findings underscore the potential of deep learning algorithms, particularly Long Short-Term Memory (LSTM) models, in enhancing predictive maintenance within U.S. supply chain operations. The application of LSTM models has demonstrated promising results in capturing temporal dependencies in time series data, which is crucial for predictive maintenance tasks. Additionally, the study emphasizes the significance of data-driven prognostics in industrial service business, highlighting the value of predicting upcoming failures with sufficient accuracy to aid in planning services offered to clients. This aligns with the industry's need to evaluate the value proposition of maintenance, particularly for customers with a large installed base of components and limited knowledge on maintenance requirements [17] ; [4].

Moving forward, it is recommended that industry practitioners and stakeholders in U.S. supply chain operations consider integrating LSTM models and data-driven prognostics into their maintenance planning and service offerings. This proactive approach aligns with the goal of ensuring continuous operation of machinery, preventing unexpected breakdowns, and optimizing the value of maintenance services for clients. Moreover, the application of logistic regression models, as highlighted in the literature, can further enhance the evaluation of the probability of occurrence of maintenance events, providing valuable insights for decision-makers at various levels within the supply chain operations.

**8.1. Summary of Findings**

In this section, a comprehensive summary of the key findings derived from the study on predictive maintenance and deep learning is presented. The findings encompass the development of advanced prediction models, such as LSTM for detecting failures in the railway industry, and the proposal of a 1DCNN-Bilstm model for time series anomaly detection and predictive maintenance in manufacturing processes [3]. These models aim to predict equipment failures and perform maintenance to prevent them before they occur, thereby reducing unnecessary repairs and maximizing the lifespan of equipment. Additionally, the study emphasizes the importance of data-driven risk prediction models for predicting rail defects and service failures, as well as the integration of federated learning frameworks to consider distributional shifts of time series data for anomaly detection and predictive maintenance [2].

The research also highlights the significance of predictive and risk-based maintenance activities in the railway industry, where strategic decision support and risk and control plans are developed using machine learning techniques based on stored-inactive data from railway companies. These insights contribute to the domain of predictive maintenance by providing a comprehensive overview of the contributions and implications of the research, ultimately enhancing the reliability and efficiency of supply chain operations.

**8.2. Recommendations for Industry Practitioners**

To achieve faster adoption and routine usage of deep learning algorithms for predictive maintenance in U.S. supply chain operations, the present study suggests the following recommendations for U.S. industry practitioners. Firstly, American deployment of deep learning, consolidation of cloud services, in-house or outsourced data labeling, and any data augmentation should leverage the economies of scale and learning associated with well-established deep learning industries in East Asian countries and the EU. However, uniquely, the American industry provides a trendsetter role in innovation supporting expanded adoption of deep learning, including pathway development and skill transfers that should eliminate global source bias.

Supply chain practitioners should request that equipment, spare parts, and real-time sensor and internet usage data be open to digitalization and anonymization with options that respect the confidential nature of stored and moving data, especially when near completions. Upon successful completion of training the first U.S.-based predictive maintenance model(s), important related data collected, cleaned, labeled, and merged (if not done already) could be integrated back into a Korean manufacturer's MMS software. U.S. supply chain practitioners should ensure that the sales agreements include and/or exclude the right for the sharing of data for predictive maintenance with a customer, where necessary.

Successful action planning should include timely processes to secure R&D funding, hire data science talent, integrate software to deploy a minimum viable predictive maintenance model attracting early adopters and selected quiet champions, develop strategic deployment plans, and introduce successful applications with confidence. Furthermore, over time, take advantage of regulatory relief more than one blue-ribbon commission, including learned societies, to investigate data protection challenges as well as other predictive maintenance monitoring topics.

Upon early adopter success, investment in training U.S. personnel to deliver sustainable predictive maintenance models and budgets prior for additional data science retraining, preparation for facility expansion, continuous model revisions, and talent retention. Reliability engineers who have led or been assigned to champion other successful machine learning projects, similar predictive analytics projects such as regression models, or others with building-stage model reservists should be strongly considered early transfers. Where at all possible, provide career development support with conferences or journal subscriptions, industry-recognized certificates, and the opportunity to publish predictive maintenance scholarship. Organizations should reimburse employees indicating leadership potential for the MS degree in applied statistics or AI-related discipline with an understanding that proprietary and technological learning will not be lost when an employee moves to a competitor, forming the expectation of on-the-job training and pairing of newly minted statisticians and data engineers, next-reactor AI graduates. Organize corporate curriculum invites to facilitate networking.

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