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AI-Driven Predictive Maintenance for Packaging Automation

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Abstract. Predictive maintenance is beneficial across a variety of industries, including manufacturing, automotive, packaging and energy. In addition, this research provides an empirically based approach to predictive maintenance that combines new artificial intelligence technologies with traditional technologies. The new hybrid method combining XGBoost and DNN achieved the best performance, with an accuracy of 98.3%. This result is very innovative, as the XGBoost portion contains a lot of interaction structure-type data, while the DNN portion generates a deep learning, non-linear representation based on multiple datasets between both parts, able to fuse structured/and unstructured data based on the process of implicit fusion. This paper presents and tests a combined approach that leverages the strength of the XGBoost and DNN classifiers. The main new idea is to use XGBoost leaf embeddings rather than probability predictions, thereby providing rich structural information about decision paths within the ensemble.

Keywords: Predictive Maintenance, Real-Time Fault Detection, Prediction Accuracy, Sensor Data Integration, Data Quality, Scalability.

1. INTRODUCTION

A predictive maintenance approach considers the analysis of the trends of Electrical and Mechanical Systems through the continuous use of sensor information to identify the indicators of possible early failures. It is an advancement that uses the Industrial Internet of Things (IoT) and Artificial Intelligence (AI) data analytics. Packaging machine behaviour is very intricate, comprising many Electrical and Mechanical Systems. Therefore, an analytical method that incorporates both simple linear and there may be Non-Linear Relationships in the data.[1]

It is important that the equipment can be relied upon and continue to operate to maintain productivity and minimize downtime in packaging automation. In the past, maintenance was either scheduled or reactive, and the use of these approaches might frequently result in unscheduled maintenance, which causes delays and costly downtime[2].The inclusion of sensors and the Internet of Things (IoT) within packaging automation environments has dramatically expanded the possibility of predictive maintenance.[4] The operating conditions of the packaging machinery are continuously monitored by the sensors for temperature, vibration, pressure, speed, and torque. To address these challenges, this research proposes a hybrid approach that combines the strengths of XGBoost and Deep Neural Networks (DNN) for improved fault prediction in packaging automation systems.

A. Motivation

This paper presents a new predictive maintenance framework that is an improvement over existing methods of predictive maintenance for industrial settings (e.g., Packaging Automation). Because of this, predictive maintenance systems need to have a predictive maintenance framework that encompasses the following three characteristics: Generality, Interpretability and Efficiency.

B. Main Contributions

- The first contribution is a hybrid predictive maintenance model (XGBoost combined with Deep Neural Network) that can combine the benefits of both approaches.
- The second contribution is that this hybrid predictive maintenance model uses the ability to learn structured patterns and non-linear relationships from the original data to successfully make predictions of future events using real time data generated from Packaging Automation equipment.

- The third contribution is that an evaluation of the predictive maintenance performance of the hybrid model has been compared to multiple different machine learning-based models, which confirms the effectiveness of using a hybrid predictive maintenance model.

2. PROBLEM ANALYSIS AND DATASET DESCRIPTION

A. Literature Review

Many existing systems utilize conventional machine learning algorithms for fault prediction. Most of the currently available predictive maintenance technologies for packaging automation depend upon either using conventional machine learning methods or using planned maintenance.

In response to these challenges, this paper presents and tests a combined approach that leverages the strength of the XGBoost and DNN classifiers. The main new idea is to use XGBoost leaf embeddings instead of probability predictions, providing rich structural information about decision paths through the ensemble [9].

A comprehensive assessment of the performance of the XGBoost predictive maintenance model and then collectively as the hybrid combined predictive maintenance model of the XGBoost and deep neural networks have been performed utilizing a multitude of descriptive metrics (example: accuracy, precision, recall and overall f1 scores). Hashemian and Bean[2]reported the current state-of-the-art in predictive maintenance methods and reported the principles on which predictive maintenance methodologies are currently founded on. Shukla et al. (2019) [3] provided a comprehensive assessment of the predictive maintenance methodologies. Sisode and Devare (2019) [4] performed a review of the current machine learning approaches used in Industry 4.0 environments.

Wang et al.[1] analyzed predictive maintenance in Industrial IoT that uses deep learning. Further, they assessed the use of originally proposed deep neural network (DNN) based methods, and the challenges that arise from these methods. Çinar et al. [8] a deep analysis of machine learning in predictive maintenance for Industry 4.0 has also been carried out. Using custom neural networks, Juliet [10] created an AI-driven predictive maintenance system for Industrial IoT with real-time fault detection that achieved 92.86% accuracy. Fordal et al. [9] showed real-world application in manufacturing settings by utilizing artificial neural networks to enable Industry 4.0 capabilities through sensor data based predictive maintenance. Zhong et al. [11] Provided detailed examination of predictive maintenance within digital twin context, with specific resolution of some integration challenges and potential future ways to build on existing work. In their investigation of the use of digital twins and artificial intelligence for predictive maintenance.

Figure 1 showcases the different limitations in currently being utilized to do predictive maintenance techniques within industrial machines.

In Section 1, we see that many traditional models use only manual feature engineering with few features available from data sources.

In Section 2, It describes the way that imbalanced performance metrics adversely discriminate because even when models provide high overall accuracies, they often exhibit low recalls which translates into many false positive results.

In Section 3, there is a lack of deep feature representation as stated by current predictive maintenance methods.

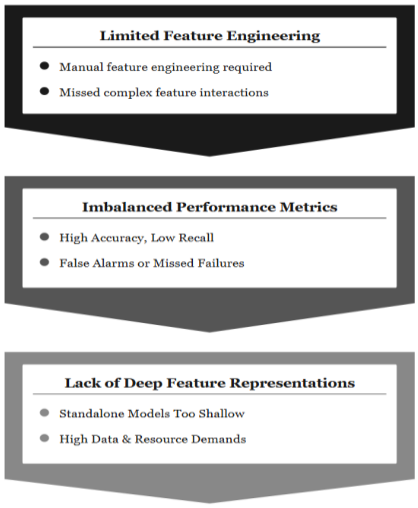

Fig. 1. Key Limitations of Existing Predictive Maintenance Approaches.

B. Dataset Description

This research utilizes the AI4I 2020 Predictive Maintenance dataset available at the UCI Machine Learning Repository which has gone through processing for balanced class distributions of the failure and non-failure examples in preparation for creating a model that can effectively train on these examples[7]. The dataset is split into 80% training, and 20% testing using stratified sampling.
The name of this balanced dataset is "ai_dataset.csv".
https://archive.ics.uci.edu/dataset/601/ai4i+2020+predictive+maintenance+dataset.
The dataset consists of 10,000 instances with following features of the data obtained:

- Product Quality Type (Encoded as Low, Medium & High)
- Air Temperature [K]: Ambient Air Temperature in Kelvin.
- Process Temperature [K]: Process Temperature in Kelvin.
- Rotational Speed Measurement (Used to measure Rotational Speed of Machines)
- Torque (Measured in Newtons per Meter)
- Tool Wear [min]: Tool Wear (from last use) in minutes.
- (Binary Target Variable to Indicate whether the Machine has failed (0 or 1 for No Failure and Machine has Failed respectively.

C. Data Preprocessing

All features have been changed to numeric type and have missing valued features filled in with zero. The balance of the data set solves one of the common problems of predictive maintenance, class imbalance, which allows for both classes to be learnt by the model without needing to use additional sampling methods during training [8]. Sensor data accurately represents the actual industrial conditions, including temperature ranges, speed differences and torque profiles that are consistent with what packaging equipment typically works under. The data sets were appropriate for use as the basis for development and testing of predictive maintenance models applicable to packaging automation. [7].

3. METHODOLOGY

This area of research will be based on the use of machine learning and deep learning algorithms [15]. Packaging machines have numerous sensors generating an abundance of data that can serve as an early detection system for potential equipment failure [10]. There are two research methodologies that are being analysed: The first one being a separate XGBoost model with very good baseline accuracy and an ability to interpret the results provided by the model, and the second method is a Hybrid XGBoost-DNN model that utilizes tree based feature extraction using leaf embeddings to extract patterns similar to those of deep learning models[9].

A. Proposed Architecture

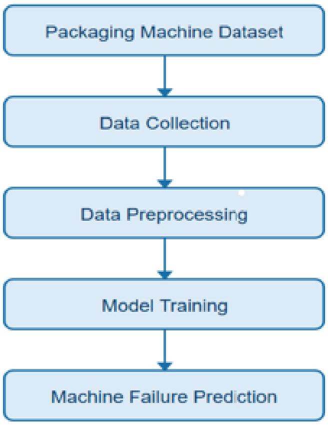

Fig. 2. Architecture of the Predictive Maintenance Model.

As shown in Figure 2, This architectural proposal describes a structured workflow to improve both prediction accuracy and reliability when using predictive maintenance solutions within packaging automation environments. This workflow starts with the packaging machine dataset (i.e. the operational and sensor data used to generate the machine learning model). The data is first collected and stored in an organized manner so that it can be analysed later for predictive maintenance purposes. Relevant data is then extracted from the collected data for predictive maintenance analysis purposes.

This extraction process consists of three major steps:

1. Collection of all operational data (i.e., from sensors) associated with packaged products.
2. Preprocessing of the data to make it usable for machine learning training of the machine learning model using the pre-processed data.

The output of the machine learning model is used to predict machine failure, enabling predictive maintenance to be used to detect failure before it occurs.

4. MATHEMATICAL FORMULATION

1. XGBoost model:

$$\hat{y}_{xgb} = \sum_{k=1}^{K} f_k(x)\,, f_k \in F$$

This represents the XGBoost prediction as the sum of outputs from multiple decision trees.

2. DNN model:

$$\hat{y}_{dnn} = \sigma(W_n \cdot (\ldots \sigma(W_1 x + b_1) \ldots) + b_n)$$

Using nonlinear activation functions in many layers allows the DNN model to generate predictions based on multiple levels of computation.

3. Hybrid model:

$$\hat{y} = \alpha \cdot \hat{y}_{xgb} + (1 - \alpha) \cdot \hat{y}_{dnn}$$

where $\alpha \in [0,1]$controls the contribution of XGBoost and DNN in the hybrid model and is tuned empirically for optimal performance.

4. Loss function:

$$L = -\frac{1}{N} \sum_{i=1}^{N} [y_i log(\hat{y}_i) + (1 - y_i) log(1 - \hat{y}_i)]$$

For measuring how far your predicted values are from your actual values and vice versa, a binary cross-entropy loss function is used.

5. IMPLEMENTATION SETUP

A. Development Environment and Libraries

Development terrain and Libraries The perpetration was realized using Python 3.x as the top programming language, exercising a range of established machine literacy and data processing libraries.

Core Libraries were Python 3.8, NumPy 1.21 for numerical calculations, Pandas 1.3 for data manipulation and analysis.
Machine Learning Frameworks were Scikit- learn 1.0+ for preprocessing serviceability and evaluation criteria, XGBoost 1.5 for grade boosting perpetration, TensorFlow 2.8 and Keras for deep neural network development.
Visualization: Matplotlib 3.5+. was utilized to make accurate and efficient plots.
The trials were run on a workstation with appropriate enough processing power for model development and evaluation. Each of the trials used the same seed (random state = 42) for all iterations to provide consistent results for multiple operations of the model.

B. Implementation of Dataset Preprocessing

Before using the AI4I 2020 Predictive Maintenance Dataset to test algorithms for predictive maintenance, it must first be transformed into the correct file format so that machine learning algorithms can train with it (ML). The categorical variable "Type" which has three different values (L = Low Quality Products, M=Medium Quality Products, and H=High Quality Products) will be transformed using a function known as Label Encoding to convert these values to numbers (0=L, 1=M, and 2=H) .

C. Hyperparameter Tables

TABLE I
HYPERPARAMETER SETTINGS FOR THE PROPOSED HYBRID MODEL

Parameter	Value
Learning rate	0.03
Epochs	80
Batch size	32
XGBoost depth	7

We picked these values to get the best balance between speed and generalizable performance while keeping convergence in check. For example, with a learning rate of 0.03, there will be gradual and stable learning. For training the model, the epochs were set to 80. The batch size is also set to 32, allowing for a large enough update to occur to the weights. Setting XGBoost depth parameter to seven allowed for more complicated feature interactions. The combination of these settings will provide a more robust hybrid model and improve the predictive capabilities of the proposed hybrid approach.

6. EXPERIMENTAL OUTCOME

A. Comparative Accuracy of Machine Learning Models

The visualisation in Figure 3 is an accuracy chart of all ML models. In the Figure ,It contains comparisons between results of accuracy from various machine learning (ML) algorithms including logistic regression (Log R) and K-Nearest Neighbors (KNN), Decision trees (DT), Random Forests (RF) and XGBoost algorithms as well as the hybrid model which has been created with a combination of both. The hybrid model was the highest at 0.983 while logistic regression was the lowest (0.927).

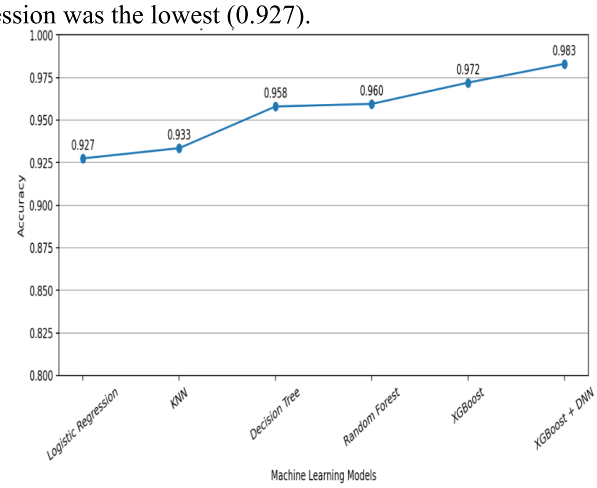

Fig. 3. Accuracy Comparison of Machine Learning Models for Machine Failure Prediction.

B. XGBoost Model Performance

In TABLE II, the overall accuracy for the XGBoost model was 97.5%, indicating that it accurately classified many normal/typical cases across the overall population of data that was input into it. As a result of the model's ability to correctly label all sorts of normal operations with a precision of 97 percent, combined with full true positive recognition for all 100 percent of the normal operations, the model performed extremely accurately and well. The model achieved a weighted F1 score of 0.96, and a macro F1 score of 0.82. Therefore, it performed very well overall, however it had variable performance across different classes.

TABLE II

PERFORMANCE OF THE XGBOOST MODEL

Accuracy	Precision	Recall	F1 Score
97.20%	98.00%	97.00%	97.00%

C. Hybrid XGBoost &DNN Integration

A hybrid model is formed when XGBoost and Deep Neural Networks (DNN) are combined.

Stage 1: Train an XGBoost model on the pre-processed feature set to produce tree-based feature representations from which it identifies relationships and patterns between your response variable as well as tree structures. The trained XGBoost model creates a new feature space that models complex, non-linear relationships between input features.

Stage 2 - Deep Neural Network: XGBoost-generated features are processed by A multi-layer neural network architecture. The DNN comprehends of:

- Input layer receiving XGBoost transformed features
- Several hidden layers with RELU activation functions
- Dropout layers for regularization purposes
- Batch normalization for training stability
- Output layer with SoftMax (classification) or linear activation (regression)

Combining the strength of XGBoost to work with structured databases and the capacity of a DNN to learn to create multiple hierarchies should allow for improved prediction accuracy than either model alone.

The hybrid model's use of XGBoost leaf embeddings provides a rich, high-dimensional representation of decision paths through the tree ensemble. This allows the DNN to learn from both the original sensor features and the implicit decision rules encoded in the tree ensemble, leading to superior pattern recognition capabilities and improved fault detection accuracy.

TABLE III

PERFORMANCE OF THE XGBOOST & DNN HYBRID MODEL.

Accuracy	Precision	Recall	F1 Score
98.30%	98.00%	98.00%	98.00%

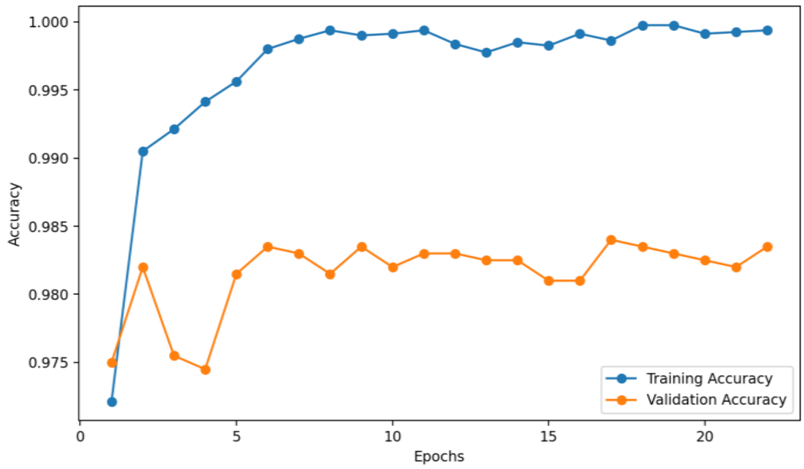

Fig. 4. Training and Validation Accuracy Across Epochs for the XGBoost &DNN Hybrid

As illustrated in Figure 4 the hybrid model consisting of DNN and XGBoost achieves high accuracy at both training and test and the accuracy of the hybrid model when training and testing is shown for multiple epochs as the training accuracy approaches 99.9% while the validation accuracy reaches approximately 98%. This illustrates that the hybrid model is demonstrating a stable learning behaviour by learning how to appropriately generalise the underlying dataset while avoiding large amounts of overfitting through effective learning of the underlying patterns from the dataset.

D. Ablation Study

We conducted multiple ablation test trials for investigating several features of the overall effectiveness of the proposed model. The accuracy of the individual XGBoost models were 97.2% and the DNN models were 95.5%. The Hybrid Model showed an accuracy of 98.3% according to the results obtained. This indicates that the hybrid model is better than either of its two constituent models. hus the use of a hybrid model combining tree-based algorithms with deep learning will give you a larger performance gain than doing either method on their own.

TABLE IV
MODEL PERFORMANCE EVALUATION BASED ON ACCURACY

Model	**Accuracy**
Hybrid Model	98.3%
DNN	95.5%
XG Boost	97.2%

7. PERFORMANCE EVALUATION

We evaluated the performance of the predictive maintenance framework proposed in this research using Accuracy, Precision, Recall, and F1-score metrics. As evaluated above, with the overall accuracy of 98% hybrid approach performs better than the independent machine learning applications. The standalone XGBoost model shows a strong baseline performance at an accuracy of 0.972 and was adept at identifying/recognizing the structure of the data and capturing patterns within it. The addition of DNN representation-based technique has improved the performance of an XGBoost algorithm in terms of identifying faulty/malfunctioning machines.

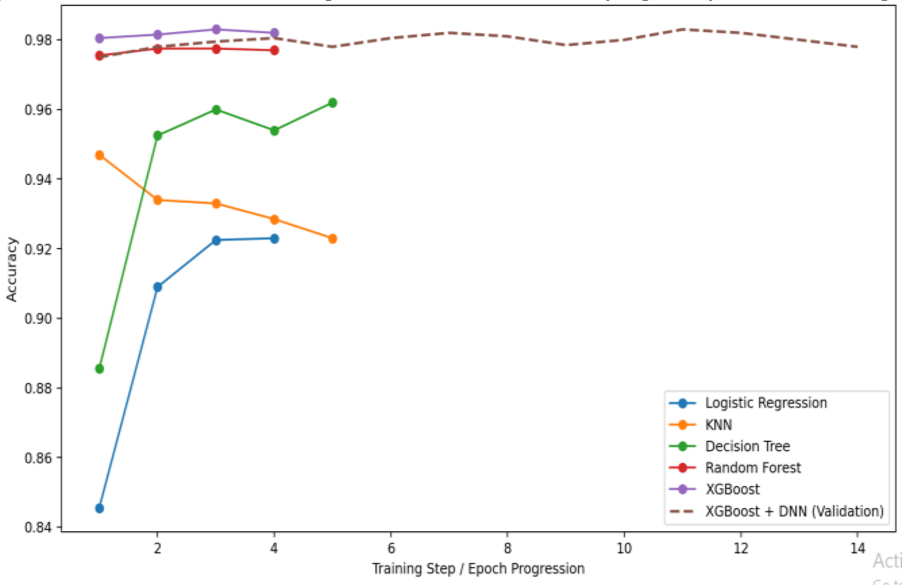

Fig. 5. Comparative Performance Progression of Machine Learning Models During Training.

Figure 5 displays and compares each machine learning model's cycle of training iterations and accuracy of the overall cycle training iterations of the machine learning models. The performance of Logistic Regression and KNN is low and unstable as compared to Decision Trees, Random Forest and XGBoost, whose accuracy is consistently high (approximately 97-98%) and stable from the first iteration to the last iteration of testing. With the stable accuracy of 98% hybrid approach performs better than the independent machine learning models .

A. Statistical Validation

In TABLE IV, five separate trials were conducted with alternate random splits of the datasets to assess their variability or robustness; the means and standard deviations had been computed from the five trials with respect to each model's level of predictive accuracy. The Hybrid model has always been able to make accurate predictions in all five trials. This is because it had the least amount of variability across all models in this experiment. This confirms it is a good reliable and strong option to use in Predictive Maintenance applications.

TABLE V
STATISTICAL VALIDATION OF MODEL PERFORMANCE (5 RUNS)

Model	**Accuracy**
Hybrid Model	0.9722 ± 0.0016
DNN	0.9594 ± 0.0037

XG Boost	0.9657 ± 0.0020

8. DISCUSSION

Based on the experimental results, the hybrid XGBoost-DNN model offers an increase in the accuracy of predictive maintenance activities as compared to the individual Machine Learning methods. The complementary features provided by both XGBoost and DNN are the reason for the increased accuracy.
The XGBoost component forms structured relationships of the tabular data collected from the sensors. By the tree extracting the leaf embeddings, the model maps the usage of complex feature interactions through the encoded decision path of the tree.These embeddings combined with the original features of the arrays provide a more enriched feature space that can be used as input to the Deep Neural Network (DNN). The DNN will learn from this high dimensional feature space and also be able to derive the non-linear and hierarchical characteristics of the different feature spaces from the large array of features. Through the use of deep neural network (DNN) layers to capture these relationships over multiple epochs, the DNN model will be able to capture additional subtle dependencies between individual variables that would not be captured by standard decision trees. The hybrid model provided improvement in general accuracy of predictive maintenance to the previous models, while simultaneously achieving a slightly higher than normal precision-recall performance than individual models.

A. Comparison with Existing Work

The Hybrid model XGBoost and deep neural network (DNN) has many advantages over current methods in many ways:

- Greater accuracy Current models: Accuracy of Random Forest/XGBoost (Z. M. Çinar) 96-97% % accuracy of deep learning (H. Wang): 96-97% Hybrid model; XGBoost & DNN: ~98.3% accurate This is a clear illustration that a hybrid solution provides an improvement over individual models, exceeding previous methodologies' ceilings of performance.

- My model incorporates a multi-paradigm approach to learning, rather than simply being a one-size-fits-all on current methodologies. XG-Boost (a robust means to manage features and learn from structured input) together with DNN (deep features and non-linear pattern recognition) results in a better balance between bias vs. variance, improved generalizability and better fault detection accuracy.

    - XG Boost → structured feature learning
    - DNN → deep nonlinear pattern extraction

In comparison to previous published studies, the proposed hybrid model has higher accuracy, is more robust, and is applicable in practice. As such, the proposed hybrid model is an ideal candidate for next-generation predictive maintenance systems within the context of Industry 4.0. The result is a model that is able to generalize better, thus providing a higher degree of reliable fault prediction in actual industry application scenarios.

TABLE VI
A COMPARISON WITH CURRENT LEADING STATE-OF-THE-ART (SOTA) MODELS

Models	**Reported Accuracy**	**Key Strength**	**Limitation**
LSTM based model.	96-97%	Captures time-based dependencies	High computation costs and Time taking
CNN based model	95-97%	Good structure-based features	Cannot model time-based behaviours
Transformer based model)	97-98%	Captures long term dependencies	Needs a large amount of data and computational power for training.
XGBoost	96-97%	Strong accuracy with structured data	Difficulty in capturing very deep non-linear patterns.

According to TABLE VI, deep learning models like LSTM, CNN and Transformer architectures show excellent prediction performance because they capture temporal and complex patterns in data. But most of these algorithms also require considerable amounts of data and significantly more computational power to work properly. The proposed hybrid model proposes a combination of both XGBoost and DNN to generate more accurate results while having balanced computational requirements. Thus, this demonstrates an advantage to combining structured learning and deep feature extraction when performing predictive maintenance tasks. To verify that our hybrid model is effective, comparison was made against the previous best practice (PBP) methods for predictive maintenance.

9. LIMITATIONS AND FUTURE WORK

A. Limitations

While the hybrid XGBoost-DNN model has many excellent predictive capabilities, it still has limitations in its development that must be pointed out.

To start, the only testing of this model was done using AI4I 2020 data set, which is typically a controlled, streamlined and simplified environment and thus may not generalize to or represent more complex, real-world operation environments with considerable amounts of noise in their data distributions.

The second limitation is the absence of real-time or continuous assessment of data input as it occurs in the real-world; thus, AI-based predictive maintenance solutions must demonstrate a capability to perform under very stringent requirements for latency and compute resources, which was not thoroughly examined during this research.

Thirdly, the hybrid architecture of the model results in there being much greater computational requirements than either XGBoost or DNN used as standalone models alone. Consequently, with the XGBoost leaf embeddings working in conjunction with the DNN create require greater training times and additional resources which further complicates the deployment in environments that are constrained in their available resources.

Lastly, while XGBoost provides good insights into its feature importance at the model level, the hybrid model acts as a semi-black box, thus may inhibit user confidence in deploying predictive maintenance solutions within critical industrial environments.

B. Future Work

To further improve upon the restrictions of the current model, additional studies should be performed. One form of study could be to validate the model by utilizing the model against multiple, actual industrial use cases for different types of operations. Additionally, it would provide additional details about the model through utilising real-time predictive maintenance with actual streaming sensor data, and what its performance would look like in many different use cases, thus validating this method's outcome in real-world applications.

The addition of XAI techniques (e.g. SHAP, LIME) to the model will add value to its interpretability by helping users to make informed decisions based on model outputs. New advanced architectures (e.g., LSTM, transformer-based models, attention mechanisms) should be researched to provide improved methodologies for understanding temporal relationships among sensor data as they relate to an operational context. Finally, many different sorts of ablation studies should be performed as well as conducting a variety of statistical analyses on each of the parameters from many different experimental trials to ensure adequate reliability and scientific validity of this proposed method.

10. CONCLUSION

In conclusion, this research states that hybrid ML approaches are effective for predictive maintenance on industrial equipment. Both theoretical and practical implications exist for implementing AI to detect potential fault(s) with packaging systems, as well as other manufacturing activities. The hybrid ML techniques used in this study provide empirical evidence of the success of a systematic approach which has created a knowledge base, thus allowing for the effective implementation of smart manufacturing techniques as defined by Industry 4.0.

The hybrid machine learning architecture proposed in this work, which combines XG-Boost and DNNs, can produce state-of-the-art predictive performance while exhibiting the computational efficiency required for real-time industrial deployments. This study reveals that manufacturers will be able to minimize interruptions caused by unanticipated downtime and enhance productivity on daily (scheduled) activities performed with equipment using advanced manufacturing technologies. This research supports the conclusion that using both gradient boosting and deep neural networks results in a greater ability to successfully predict machine failure than either algorithm individually.

Conflict of Interest

The authors declare no conflicts of interest regarding the current research.

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