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Original Article

Machine Learning-Driven Predictive Maintenance for Early Fault Prediction and Detection in Smart Manufacturing Systems

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Abstract: *Numerous pieces of equipment have been introduced as a result of the increase in industrialization and digitization. Nonetheless, the equipment has to be carefully maintained and watched after. Any deviation results in the occurrence of fault. The stability and effectiveness of the system depend heavily on the discovery of faults at the outset. By implementing the suggested fault diagnostic method, the shortcomings of the traditional systems are addressed. This study presents a robust fault detection methodology for smart manufacturing, leveraging the Dense Net deep learning model on the CWRU bearing dataset. Through comprehensive data preprocessing, including noise filtering, normalization, and outlier removal, the model achieved an impressive accuracy of 98.57%, outperforming traditional ML models like MLP, CNN, and Bi-LSTM. The high precision (98.54%) and recall (98.55%) demonstrate the model's effectiveness in minimizing false positives and accurately detecting faulty conditions. Training and validation performance trends indicate strong generalization, with minor overfitting but stable loss values. Comparative analysis highlights Dense Net's superior capability in capturing complex fault patterns, surpassing MobileNetv2, which achieved 97.9% accuracy. This research proves that the Dense Net deep learning model can accurately anticipate and detect smart manufacturing system faults at an early stage.*

Keywords: *Smart Manufacturing, Fault Detection, Failure Prediction, Industrial Automation, Maintenance Optimization, Predictive Maintenance (PDM), Machine Learning (ML), CWRU Data.*

I. INTRODUCTION

Manufacturing industries depend on a wide range of machinery and equipment to ensure efficient production, high-quality output, and minimal operational disruptions [1][2]. These machines experience multiple operational situations that combine with continuous use alongside environmental effects and mechanical degradation. The elements affecting equipment components result in long-term degradation, which means poor functioning and unforeseen hardware breakdowns. The preservation of industrial machinery reliability, together with extended lifespan, remains essential for continuous factory operations and for preventing time-consuming breakdowns.

The main obstacle for industrial operations involves machinery failures and malfunctions caused by component wear, sensor problems, misalignment problems and overheating conditions, or system operational inefficiencies [3]. Equipment breakdowns that become catastrophic occur when unnoticed problems escalate into failures, leading to unexpected downtime and financial losses, together with safety hazards [4]. Standard fault detection procedures, which include manual assessments and fixed servicing protocols, produce limited advance notifications about possible system breakdowns. Tradition-based service detection methods either trigger unjustified maintenance expenses or miss unknown equipment flaws that produce unanticipated equipment breakdowns.

Wealthy industrial systems based on automation, IoT devices, and real-time data collection have created new resource opportunities and innovation challenges regarding fault detection. Modern advanced environments require the constant collection of sensor-generated data focused on equipment health, which includes temperature, pressure, vibration as well and operational efficiency. The identification of initial fault signs from numerous sophisticated datasets demands sophisticated analytical methods. The extensive amount of data overwhelms conventional maintenance methods because it becomes impossible to detect failures as this happens and implement proactive measures when analysis lacks intelligence.

PdM implemented with ML and DL technology emerges as a revolutionary solution to handle these challenges [5]. The use of predictive models built with ML capabilities enables detection of anomalies as well as fault pattern recognition and fault prediction of equipment failures before their occurrence through historical data collection with real-time sensor inputs [6]. Unlike the previous approaches used in maintenance, the use of ML and DL promotes a preventive technique of equipment maintenance that is more efficient in terms of cost and time. It is also effective in detecting faults since it enhances the analysis of time series data, capturing dependencies in failure modes more sensitive than conventional analyses.

A. Motivation and Contribution of Study

The increasing need for smart maintenance solutions in contemporary smart industrial settings is driving this research. A lot of inefficiency, greater operating expenses, and downtime are the results of using traditional maintenance methods like reactive and preventative maintenance. PdM is approaching an ML solution to provide accurate predictive outcomes of equipment failure, thereby improving the reliability and efficacy of complex production systems. The purpose of this research is to enhance the fault prognosis and diagnostic model in smart manufacturing environments by employing advanced learning techniques. The following are the main contributions of this study:

- Utilization of the CWRU bearing dataset, which provides real-world vibration sensor data for fault detection.
- Enhances data quality through noise filtering, normalization, and outlier removal, improving model robustness.
- Implements PCA to identify critical fault indicators, reducing computational complexity while preserving essential information.
- Implement Dense Net for accurate classification of normal and faulty conditions, enhancing fault detection capabilities.
- Evaluating potential ML models side-by-side using metrics like F1score, re-call, accuracy, and precision to identify the best strategy.
- Enables predictive maintenance by detecting early fault signatures, reducing unexpected downtimes and maintenance costs.

B. Novelty of paper

This paper's original contribution is the use of dense Net on the CWRU dataset to anticipate and identify smart manufacturing system faults early on. The study enhances fault classification accuracy through comprehensive data preprocessing, including noise filtering, normalization, and outlier removal, along with Principal Component Analysis (PCA) for dimensionality reduction. Comparative analysis demonstrates Dense Net's superior performance, surpassing existing models. Additionally, this research explores real-time deployment, enabling predictive maintenance and minimizing unexpected downtimes in industrial environments.

C. Structure of paper

The framework of the article is as follows: Section II summarizes the literature on fault prediction. Section III covers methodology, including data collection and model evaluation. Results and comparative analysis are presented in Section IV, and insights and future study topics are discussed in Section V.

II. LITERATURE REVIEW

Predictive analytics and smart manufacturing fault detection are highlighted and examined in this section. Some of the reviewed works are:

Bharot et al. (2023) make use of transfer learning to modify an existing model from a relevant domain for use in the target domain, allowing for accurate prediction of product quality with sparse data. The reference architecture lays out the groundwork for using the suggested method in a production setting, allowing for prediction-based decision-making and real-time monitoring. The suggested method has the potential to increase the accuracy of defective product identification by as much as 11% when compared to conventional methods, according to experiments conducted on a real-world production dataset [7].

Albayati et al. (2023) use supervised and semi-supervised ML algorithms to field-collected OS data enables the creation of innovative FDD procedures and shows building owners the benefits of proactive maintenance. The data used in the research originated from a standard operating single-packed rooftop unit (RTU) HVAC system at a Connecticut industrial location. This study examines three distinct methods for classifying faults for a real-time functioning RTU utilizing semi-supervised learning, with few-shot learning reaching accuracies of up to 95.7% [8].

Mbey et al. (2023) validate the usefulness of their strategy using a detailed depiction of the IEEE 13-node network. Multiple metrics are used to assess the efficacy and resilience of the suggested model. These metrics include accuracy, precision-recall, F1score, ROC curve, and complexity time. The results demonstrate that the proposed DL model outperforms prior DL methods described in the literature, with a success rate of 99% in fault detection and classification [9].

Fernandes, Corchado and Marreiros (2022) plan to take stock of where things are in terms of industrial-level ML-based mechanical defect detection and fault diagnosis. A total of 44 main studies were chosen from 4549 data. A total of

37 research used either ANN (n=12), DT approaches (n=11), hybrid models (n=8), or latent variable models (n=6) to diagnose and forecast problems; one study used two types of techniques separately [6].

Shetve et al. (2022) a suggested adaptive N-step anomaly detection method, takes into account the percentage of outliers in the manufacturing process to determine the number of steps (or modules) in the method. Even with an outlier population of about 25%, the suggested adaptive method achieves >99% accuracy. A development of a Digital Twin model suitable for smart industrial environments depends on real-time anomaly detection systems with such a high degree of accuracy [10].

Khalil et al. (2020) outline a method for predicting circuit faults early. Two circuits—a comparator and an amplifier—are used to test the suggested approach and confirm that it functions in various circuits. Their research indicates that this is the first effort to predict hardware system failures at the transistor level. The suggested method incorporates aging, short-circuit, and open-circuit failures into its fault prediction accuracy; for amplifier circuits, it's 98%, and for comparator circuits, it's 98% [11].

Ang and Suandi (2019) the data were collected hourly to enable the producer to track the status of the manufacturing. The assessment of the network reveals an acceptable level of performance with 3.75% misclassification and an MSE of 0.0875. The firm would undoubtedly benefit from the ANN system's ability to forecast the production line's health and respond appropriately. This will increase productivity and optimize return on investment while requiring less work [12].

Table 1 : Summary of Reviewed Works on Machine Learning-Driven Fault Detection and Predictive Maintenance in Smart Manufacturing

Author	Methodology	Data	Key Findings	Limitation	Future Work
Bharot et al. (2023)	Transfer Learning for product quality inspection	Real-world production dataset	Improved faulty product detection accuracy by 11%	Limited generalizability across different manufacturing settings	Extending the approach to various production domains
Albayati et al. (2023)	Supervised and semi-supervised ML for HVAC fault detection	RTU HVAC system dataset	Achieved 95.7% accuracy in fault classification using few-shot learning	Limited dataset size and single equipment evaluation	Expanding methodology to multiple HVAC systems and industrial equipment
Mbey et al. (2023)	Deep learning for fault detection in power networks	IEEE 13-node network dataset	Outperformed existing models with 99% accuracy	High computational cost for large-scale deployment	Implementing the model in real-world power distribution systems
Fernandes et al. (2022)	Systematic review of ML-based fault diagnosis in manufacturing	44 selected studies on industrial case studies	Identified common ML approaches (ANN, DT, hybrid models, etc.)	Excluded non-English studies and non-peer-reviewed sources	Exploring emerging AI techniques in fault prognosis
Shetve et al. (2022)	Adaptive N-step anomaly detection using DBSCAN, IF, LOF	Manufacturing process dataset	Achieved >99% accuracy for anomaly detection at 25% outlier rate	High dependence on data quality and preprocessing	Integrating the approach into Digital Twin environments
Khalil et al. (2020)	FFT, PCA, and CNN for circuit fault prediction	Comparator and amplifier circuit datasets	Achieved 98% accuracy for comparators and 98% for amplifiers	Focused only on comparator and amplifier circuits	Extending the approach to broader circuit fault detection
Ang and Suandi (2019)	ANN-based smart production healthiness monitoring	Hourly production data from manufacturing line	Misclassification rate of 3.75% with MSE of 0.0875	Limited to available production data	Enhancing ANN models for improved prediction accuracy

The comparative analysis of background study based on their Methodology, Key Findings, Performance, Limitations, and Future work are provided in Table I.

III. METHODOLOGY

The methodology for Early Fault Prediction and Detection in Smart Manufacturing Systems involves a structured approach A first step of the process is gathering data from the CWRU bearing dataset, which includes normal and problematic vibration sensor readings. Data preprocessing techniques, including noise filtering, normalization, and outlier removal, enhance data quality. Dimensionality Reduction methods like PCA are employed to identify key fault indicators. Implement Deep Learning model like dense Net, are trained on labeled datasets to classify normal and faulty conditions. Accuracy, precision, recall, and F1score are some of the performance indicators used to test the models and guarantee their dependability. The system is then put into action for continuous monitoring, which allows for predictive maintenance through the early detection of failure signs and the avoidance of expensive downtimes in smart industrial settings.

A. Data Collection

Case Western Reserve University's Bearing Data Center makes available the widely-used CWRU bearing dataset, which is home to some of the best bearing research ever. The data is gathered from vibration sensors and includes both normal and faulty bearings, such as drive-damaged and fan-damaged bearings. The CWRU bearing dataset is often used to evaluate and contrast bearing fault diagnosis methods. Sample of data given are:

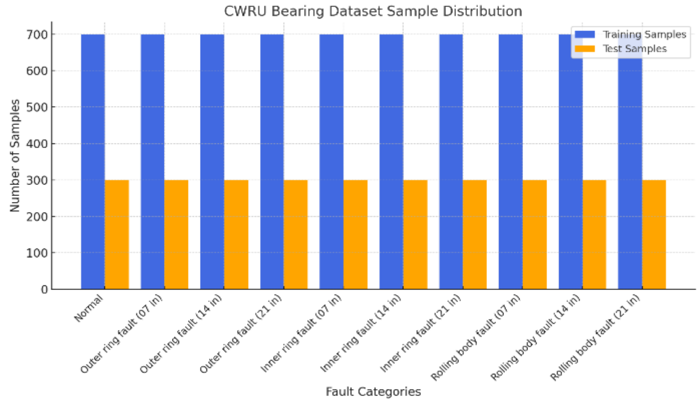

Figure 1 : Distribution of Fault Category of Dataset

Figure 1 illustrates the sample distribution in the CWRU bearing dataset, categorizing faults such as normal, outer ring faults (07, 14, 21 inches), inner ring faults (07, 14, 21 inches), and rolling body faults (07, 14, 21 inches). Each category is allocated 700 training samples and 300 test samples, ensuring a balanced dataset for model training and evaluation. This distribution supports effective fault diagnosis by providing sufficient data across all fault types, enabling machine learning models to generalize well in detecting bearing failures.

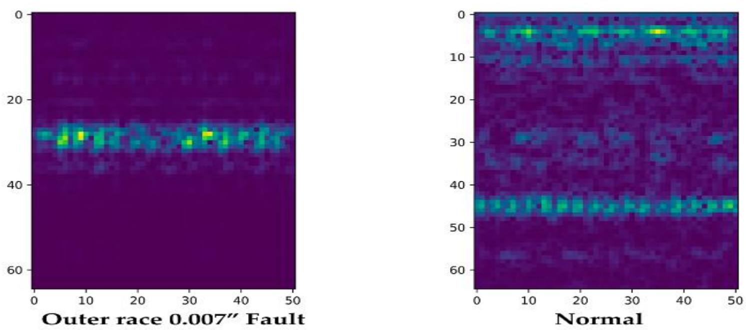

Figure 2 : Spectrograms of Bearing Damage

Figure 2 compares spectrograms of vibration patterns for damaged and normal bearing conditions. The left spectrogram, representing an Outer race 0.007 faults, exhibits a concentrated high-energy band around the 25-30 frequency range. In contrast, the right spectrogram, labeled "Normal," shows a more evenly distributed energy pattern with multiple moderate-intensity bands. The distinct spectral differences highlight the impact of outer race-bearing damage, emphasizing the focused energy concentration in faulty conditions versus the broader distribution in normal operation, a key aspect of vibration-based fault detection.

B. Data Preprocessing

Machine learning relies heavily on data preparation, the significance of which cannot be emphasized enough[13]. Digital filtering, trend term removal, outlier processing, and zero-meaning processing are the primary components of raw data pre-processing. The key pre-processing steps are provided below:

- Data Cleaning: Data from the real world tends to be incomplete, loud, and unpredictable. Data cleaning aids in identifying outsiders and precise unpredictability in the information, filling in missing numbers, and smoothing out noise.
- Remove outlier: Outliers in dataset can arise due to sensor noise, transient disturbances, or anomalous readings unrelated to actual bearing faults. Removing these outliers is essential for enhancing an accuracy and reliability of ML models used for fault detection.

C. Gray Level Normalization

Every vibration signal sample's amplitude is first normalized to fall between 0 and 255, which is the crucial pixel intensity range for a greyscale picture, as Equation (1) explains:

$$output = round\left(\frac{(255-0)^{*}\,(input-min(input))}{max(input)-min(input)}\right) \qquad (1)$$

where round (·) is the rounding function, after running the numbers through the aforementioned procedure, normalize the sample to a range from 0 to 255.

D. Dimensionality Reduction with PCA (Principal Component Analysis)

Most linear dimensionality reduction methods involve PCA. By using linear projection to transform high-dimensional data into a low-dimensional space, it may preserve the attributes of more original data points while utilizing fewer data dimensions. The goal is to anticipate the greatest variation in the projected dimension and use that knowledge to their advantage. The goal is to lessen the data's processing load or noise while being careful not to misrepresent the quantity of information.

E. Data Splitting

Data splitting is a common technique for model validation; it involves separating a dataset into a training set and a testing set. The dataset was split into sections for testing (20%) and training 80%.

F. Proposed DenseNet Model

Dense Net, a CNN architecture, has decreased the number of parameters while achieving advanced performance in visual object recognition. In contrast to Dense Net, which uses its concatenates (.) attributes to combine the output of several layers, ResNet uses an additive property (+) to combine the output of each successive layer [14][15]. To put it simply, the goal of the Dense Net architecture is to address this issue by tightly coupling all levels. What follows is information on the DenseNet-121: 2-dense blocks (1×1 and 3×3conv), 5-layers for convolution and pooling, 3-transition layers (6, 12, 24, 1). 1-classificationlayer (16)[16]. As shown in Equation (2), conventional CNNs typically compute the output layers l^{th} by applying a non-linear transformation Hl (.) on the output of the preceding layer X_{l-1}.

$$X_l = H_l(X_{l-1}) \qquad (2)$$

Dense Nets don't just sum an inputs and outputs of a layer; they concatenate them as well. Streamlined information flow across layers is made possible by Dense Net's straightforward communication paradigm: The lth layer receives inputs from all previous levels based on their characteristics. Finally, Equation (3) is modified one more to:

$$X_l = H_l([X_0, X_1, X_2, \ldots\ldots\ldots\ldots X_{l-1},]) \qquad (3)$$

Where, $[X_0, X_1, X_2, \ldots\ldots\ldots\ldots X_{l-1},]$ is a singular tensor createdby merging an output maps of earlier layers. The three primary steps of this function are convolution(CONV), activation(ReLU), and Batch Normalization (BN). The following, however, is how the l th layer may be generalized with the aid of the growth rate k: $k^{[l]} = k^{[0]} + k(l-1)$). Where $k^{[0]}$ is referred to as a five-year channel count.

G. Performance Matrix

Performance metrics are a part of every machine-learning pipeline. The experiments were evaluated based on the confusion matrix. There are four possible outcomes in the confusion matrix: TP, FP, TN, and FN. The following computation yields the matrices for recall, accuracy, precision, and f1Score:

- True Positive (TP): These cases have been properly recognized as fraud.
- False Positive (FP): Situations in which valid purchases are mistakenly marked as fraudulent.
- True Negative (TN): Instances when it is accurately determined that a transaction is not fraudulent.

- False Negative (FN): Cases where fraud goes undetected.

Accuracy: This ratio is calculated by dividing a sum of TP and TN by a total of TP, TN, FP, and FN. Total accuracy reveals how often a classification system yields correct results. as shown in Equation (4).

$$Accuracy = \frac{\mathrm{TN + TP}}{\mathrm{TP + TN + FP + FN}} \quad (4)$$

Recall: It is TP divided by a sum of TP and FN. It gauges how well the categorization algorithm recognizes the TPs. Equation (5) is used for the calculation:

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \qquad (5)$$

Precision: This is the proportion of TP to the sum of TP and FP. It shows the percentage of all cases that the classifier properly classified as positives compared to all instances that the algorithm predicted as positives. The notation for it is Equation (6):

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \quad (6)$$

F1 Score: It is TP divided by the sum of TP and FN. It gauges how well the categorization algorithm recognizes the TPs. Equation (7) provides a definition for the F1 score:

$$\mathrm{F1} = \frac{2*(\mathrm{precision}*\mathrm{recall})}{\mathrm{precision+recall}} \qquad (7)$$

These performance matrices are utilized for comparative analysis and evaluate the model performance for fault prediction.

IV. RESULTS AND DISCUSSION

The results of suggested models used for smart manufacturing problem detection are examined in this research. Experiments were conducted using Python 3 with TensorFlow and Scikit-Learn on a 64-bit Windows 10 system with an Intel i7 processor (3.60 GHz, four-core) and 16 GB RAM. The Dense Net model performance, shown in Table II, achieved outstanding performance in fault classification of vibration signals. It recorded 98.57% accuracy, ensuring precise overall classification. The precision of 98.54% indicates minimal false positives, while the recall of 98.55% confirms its ability to detect actual faults effectively. The F1-score of 98.56%, balancing precision and recall, highlights its robustness. These metrics demonstrate the model's efficiency in diagnosing faults with high reliability and consistency in real-world applications.

Table 2 : Findings of Densenet Models for Fault Detection Across Key Performance Matrix

Performance Metric	DenseNet model
Accuracy	98.57
Precision	98.54
Recall	98.55
F1-score	98.56

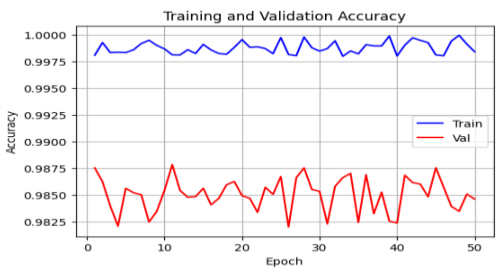

Figure 3 : Training and Validation Accuracy for DenseNet

Figure 3 displayed the training and validation accuracy trends over 50 epochs. The training accuracy remains consistently high (99.5–100%), while validation accuracy fluctuates slightly between 98.2% and 98.8%. Despite minor oscillations, both metrics indicate strong model performance with a small gap, suggesting slight overfitting but maintaining good generalization.

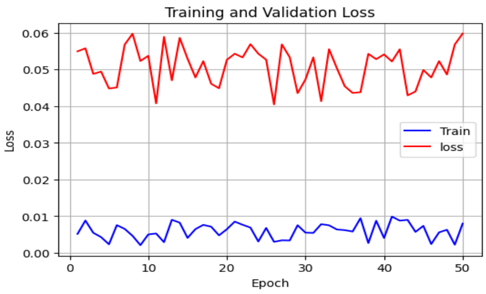

Figure 4 : Training and Validation Loss for DenseNet

Figure 4 shows the regression of the Dense Net model's training and validation losses across 50 epochs. The training loss fluctuates between 0.04 and 0.06, while the validation loss remains lower, ranging from 0.0 to 0.01. Despite noticeable oscillations, the absence of a rising validation loss suggests no overfitting, indicating stable generalization performance.

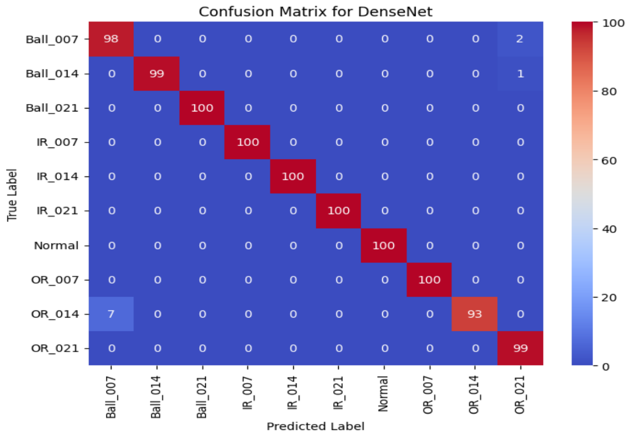

Figure 5 : Confusion Matrix of DenseNet Model

Figure 5 shows a confusion matrix that illustrates how well a classification model performed across 10 classes. The diagonal displays high values, indicating accurate predictions. However, "OR_014" shows 7 misclassified as "Ball_007," and "Ball_007" has 2 misclassified as "OR_021." The model generally performs well with high precision and recall but struggles with distinguishing between "OR_014" and "Ball_007."

A. Comparative Analysis

Table 3 shows a comparison of how well different deep learning models performed on the CWRU bearing dataset in terms of accuracy. While conventional Convolutional Neural Networks (CNN) achieve an accuracy of 96.4% and lightweight models such as MobileNetV2 reach up to 97.9%, Dense Net outperforms both with an accuracy of 98.57%. Beyond this quantitative improvement, Dense Net offers significant architectural advantages that justify its selection. The main novelty of Dense Net is its dense connection structure, in which all previous levels provide input to each layer. This design not only strengthens feature propagation and encourages feature reuse but also mitigates vanishing gradient problems commonly encountered in deep networks. In contrast, traditional CNNs suffer from information loss as depth increases, and MobileNetV2, while lightweight and efficient, sacrifices some representational power for reduced computational load. Dense Net strikes a balance by maintaining depth and performance without redundancy, making it more capable of learning subtle distinctions between fault types. Its compact yet expressive architecture enhances fault classification robustness, especially in cases with overlapping or noisy signals, making it a more suitable candidate for deployment in high-precision, real-time industrial fault diagnosis systems.

Table 3 : Comparison of the Bearing Fault Diagnosis Accuracy Performance on CWRU Data

Models	Accuracy
CNN[17]	96.4
MobileNetv2[18]	97.9
DenseNet	98.57

This approach advances the field of fault diagnosis in smart manufacturing beyond mere accuracy improvements by integrating a robust, end-to-end pipeline that combines high-quality data preprocessing, dimensionality reduction, and an advanced deep learning architecture—Dense Net—that is specifically chosen for its ability to preserve and reuse features across layers. Unlike traditional models that often struggle with feature degradation and vanishing gradients, this method ensures deeper insights into the fault characteristics by maintaining rich, hierarchical feature representations. Additionally, by deploying the trained model for continuous real-time monitoring, the system moves beyond static analysis and enables predictive maintenance, offering a scalable, intelligent solution that aligns with Industry 4.0 goals of minimizing downtime, enhancing reliability, and improving decision-making processes in smart industrial environments.

V. CONCLUSION AND FUTURE SCOPE

Equipment malfunctions in contemporary smart manufacturing systems might result in a large amount of production downtime and higher operating expenses. Predictive maintenance (PdM) developed with ML serves as a workable solution to handle these problems by identifying potential breakdowns in advance. An early identification of defects, together with their detection, forms the essential foundation for dependable operation of smart manufacturing applications. The Dense Net model reached a robust 98.57% precision rate for detecting normal and defective cases during validation through performance measurements, including recall, accuracy, precision and F1score. Different from MLP, CNN, Bi-LSTM, and Dense Net is superior in identifying complex defect patterns. Nevertheless, the model exhibits limitations in accurately distinguishing between fault types with minimal variance, and its reliance on a single dataset (CWRU) restricts generalizability across diverse industrial settings. Future research will focus on implementing domain adaptation techniques to enhance the model's transferability to different machinery and operating conditions. Additionally, incorporating multi-sensor data fusion, such as combining vibration, acoustic, and thermal signals, will provide a more comprehensive understanding of machine health. Furthermore, exploring hybrid deep learning architectures that integrate convolutional layers with recurrent or attention-based mechanisms (e.g., CNN-LSTM or Transformer-based models) may improve temporal feature extraction and fault classification accuracy in dynamic environments. These enhancements aim to make the model more robust, scalable, and applicable to real-world smart manufacturing systems. As future work, the model will be integrated into a live industrial monitoring system using IIoT-enabled sensors and edge/cloud infrastructure to enable real-time fault detection and predictive maintenance. This will involve developing low-latency data pipelines, alert mechanisms, and adaptive model retraining to ensure continuous performance in dynamic industrial environments.

VI. REFERENCES

[1] M. Abdallah, B. Joung, W. J. Lee, C. Mousoulis, J. W. Sutherland, and S. Bagchi, “Anomaly Detection and Inter-Sensor Transfer Learning on Smart Manufacturing Datasets arXiv : 2206 . 06355v1 [cs . LG] 13 Jun 2022,” pp. 1–23, 2022.

[2] K. Murugandi and R. Seetharaman, “Analysing the Role of Inventory and Warehouse Management in Supply Chain Agility : Insights from Retail and Manufacturing Industries,” Int. J. Curr. Eng. Technol., vol. 12, no. 6, pp. 583–590, 2022.

[3] N. Daurenbayeva, A. Nurlanuly, L. Atymtayeva, and M. Mendes, “Survey of Applications of Machine Learning for Fault Detection, Diagnosis and Prediction in Microclimate Control Systems,” Energies, vol. 16, no. 8, pp. 1–21, 2023, doi: 10.3390/en16083508.

[4] H. Shao, H. Jiang, X. Li, and T. Liang, “Rolling bearing fault detection using continuous deep belief network with locally linear embedding,” Comput. Ind., vol. 96, pp. 27–39, 2018, doi: https://doi.org/10.1016/j.compind.2018.01.005.

[5] A. Gogineni, “Artificial intelligence-Driven Fault Tolerance Mechanisms for Distributed Systems Using Deep Learning Model,” J. Artif. Intell. Mach. Learn. Data Sci., vol. 1, no. 4, 2023.

[6] M. Fernandes, J. M. Corchado, and G. Marreiros, “Machine learning techniques applied to mechanical fault diagnosis and fault prognosis in the context of real industrial manufacturing use-cases: a systematic literature review,” Appl. Intell., vol. 52, no. 12, pp. 14246–14280, 2022, doi: 10.1007/s10489-022-03344-3.

[7] N. Bharot, M. Soderi, P. Verma, and J. G. Breslin, “Improving Product Quality Control in Smart Manufacturing through Transfer Learning-Based Fault Detection,” in 2023 IEEE International Conference on Smart Computing (SMARTCOMP), 2023, pp. 213–215. doi: 10.1109/SMARTCOMP58114.2023.00051.

[8] M. G. Albayati, J. Faraj, A. Thompson, P. Patil, R. Gorthala, and S. Rajasekaran, “Semi-Supervised Machine Learning for Fault Detection and Diagnosis of a Rooftop Unit,” Big Data Min. Anal., vol. 6, no. 2, pp. 170–184, 2023, doi: 10.26599/BDMA.2022.9020015.

[9] C. F. Mbey, V. J. Foba Kakeu, A. T. Boum, and F. G. Y. Souhe, “Fault detection and classification using deep learning method and neuro-fuzzy algorithm in a smart distribution grid,” J. Eng., vol. 2023, no. 11, pp. 1–19, 2023, doi: 10.1049/tje2.12324.

[10] D. Shetve, I. Raju, R. V. Prasad, R. Trestian, H. Nguyen, and H. Venkataraman, “Adaptive N-Step Technique for Real-Time Anomaly Detection in Smart Manufacturing,” in 2022 IEEE 5th International Conference on Industrial Cyber-Physical Systems (ICPS), 2022, pp. 1–6. doi: 10.1109/ICPS51978.2022.9816882.

[11] K. Khalil, O. Eldash, A. Kumar, and M. Bayoumi, “Machine Learning-Based Approach for Hardware Faults Prediction,” IEEE Trans. Circuits Syst. I Regul. Pap., vol. 67, no. 11, pp. 3880–3892, Nov. 2020, doi: 10.1109/TCSI.2020.3010743.

[12] E. C. Ang and S. A. Suandi, “Smart Manufacturing with An Artificial Neural Network to Predict Manufacturing Healthiness,” in 2019 IEEE 15th International Colloquium on Signal Processing & Its Applications (CSPA), 2019, pp. 120–123. doi: 10.1109/CSPA.2019.8695975.

[13] A. Rahman, “Statistics-based data preprocessing methods and machine learning algorithms for big data analysis,” Int. J. Artif. Intell., 2019.

[14] D. C. R. Aniket Deshpande Dr. Arshey M, Ravuri Daniel, Deepak Dasaratha Rao, Dr. Emerson Raja, “Optimizing Routing in Nature-Inspired Algorithms to Improve Performance of Mobile Ad-Hoc Network,” Int. J. Intell. Syst. Appl. Eng., pp. 508–516, 2023.

[15] Y. H. Rajarshi Tarafdar, "Finding majority for integer elements," J. Comput. Sci. Coll., vol. 33, no. 5, pp. 187–191, 2018.
[16] S. Mathur and S. Gupta, "Classification and Detection of Automated Facial Mask to COVID-19 based on Deep CNN Model," in 2023 IEEE 7th Conference on Information and Communication Technology, CICT 2023, 2023. doi: 10.1109/CICT59886.2023.10455699.
[17] Y. Yoo, H. Jo, and S. Ban, "Lite and Efficient Deep Learning Model for Bearing Fault Diagnosis Using the CWRU Dataset," 2023.
[18] D. Zhang and T. Zhou, "Deep Convolutional Neural Network Using Transfer Learning for Fault Diagnosis," vol. 9, no. Dl, 2021, doi: 10.1109/ACCESS.2021.3061530.