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A Novel Hybrid Machine Learning Model for Defect Prediction in Industrial Manufacturing Processes

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Abstract:
The primary contribution of this study is the development of a novel hybrid machine learning model to improve defect prediction in industrial manufacturing processes. In this work, the model integrated four base models of XGBoost, LightGBM, CatBoost, and an artificial network, whose features are modeled with Random Forest (RF) as the metamodel using a stacking ensemble approach. For this study, industrial data from Kaggle were used, and through extensive and detailed hyperparameter optimization with Optuna, we significantly improved the model's prediction performance. In the context of this study, key challenges such as data imbalance and feature selection were addressed using data balancing techniques, including SMOTE, and random forest-based analysis for identifying the most critical input features. The hybrid model generated great results, which were quite better than the traditional single models, with an accuracy of 96.06% and precision, recall, and F1 scores of 95.10%, 97.32%, and 96.20%, respectively. The real-world applications of this model can be many, as it accurately and timely predicts defects in industrial environments. All results are reliable and interpretable due to the usage of robust data preprocessing methods, including feature standardization and correlation analysis. The results of this study will have a significant impact on tasks such as defect management in manufacturing, as they provide a scalable solution to enhance product quality, minimize operational costs, and improve process efficiency. This research illustrates the promise of hybrid machine learning methods in tooling manufacturing process optimization and the performance of the industry.

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1. Introduction

Manufacturing processes can now be considered vital to today's economic and industrial development. These processes often encounter numerous complex challenges in the production of components for the automotive, electronics, and chemical industries. Manufacturing defects, ranging from quality problems to defective components and system failures, can escalate manufacturing costs geometrically; they also reduce productivity and cause reputational harm to manufacturers. This necessitates the prediction of defects in these industrial processes, which are increasingly viewed as essential in today's industry. Case in point: who, under such circumstances, will use these novel machine learning and neural networks to effectively simulate and predict defects, given the turnaround constraints inherent in the enhanced complexity of systems within the changing parameters of dynamic production environments? At present, many industries rely on conventional means of predicting defects in manufacturing processes, which include a firm reliance on human experience and expertise. Such methods cannot effectively identify and predict defects accurately due to insufficient precision and flexibility [1]. Especially in complex processes and dynamic production environments, there is a pressing need for accurate and rapid defect prediction. In this regard, new models based on machine learning and neural networks are likely to solve the problem [2, 3] .Extensive prior research has been conducted on the simulation of defects in manufacturing processes with a

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view toward their prediction. Among the works conducted, one of the key articles by Liu et al. [4] demonstrates that combined optimization algorithms and neural networks substantially increase the accuracy of defect predictions in manufacturing systems. Likewise, Y. Wang et al. [5] have employed hybrid techniques to detect defects in complex systems and achieved some success in increasing detection precision. On the other hand, Lee et al. [6] simulated defects in semiconductor manufacturing processes with higher accuracy using convolutional neural networks (CNNs). Provided research makes appreciable mention of the new paradigm shift in machine learning and neural networks in the simulation and prediction of defects. However, not all of the essential advances have addressed the many remaining challenges that warrant further research. First, many models and algorithms have been applied to only limited datasets and thus cannot be generalized to other systems. Most existing models also take a massive amount of computing time, thereby eliminating their applicability to industrial contexts. Furthermore, since in most studies research is focused only on one type of defect, a multifaceted approach to predict various types of defects in manufacturing processes has not been utilized. Hence, this study aims to address these gaps by enhancing the accuracy of defect prediction in manufacturing processes through the use of hybrid and advanced machine learning models and neural networks. Although significant progress has been achieved in defect prediction for industry, there are still several significant problems with previous studies. The use of limited and narrowly defined datasets means that results from these studies may not apply to a broader range of industries. Specific approaches focus only on one type of model, which misses the variety in today's production tasks, and few handle problems with uneven data or with real-time processing. The field has not paid enough attention to methods for selecting the correct hyperparameters and features. To fill these gaps, this study proposes a model that puts together four advanced models through a random forest ensemble. Significant innovations are achieved by utilizing real industry data, carefully selecting features based on importance, applying SMOTE to address imbalanced classes, and tuning hyperparameters using Optuna. The combined approach yields more accurate predictions and enables their easier and more frequent use in complex manufacturing tasks.

The purpose of this research is to consolidate several machine learning models into a single, comprehensive model for more accurate comparison and prediction of defects in manufacturing processes. This research will propose, as its main hypothesis, that various machine learning models integrate well due to the use of neural networks; hence, defect prediction will be more accurate, yielding better results, than employing traditional methods that would reduce production costs while improving productivity in manufacturing processes. The objective of this study is a great pole of improvement in manufacturing processes, where the employment of advanced models can help minimize costs and maximize productivity and quality. This research provides on-time information to build a decision-making framework to improve the manufacturing processes with the application of advanced solutions across different industries. In this respect, with the increasing prominence of machine learning and neural network technologies, this research plays a key role in advancing the Industrial 4.0 agenda, which focuses on integrating smart technologies into manufacturing.

2. Theoretical Foundations and Research Background

2.1. Machine Learning

Machine learning is a branch of artificial intelligence that helps systems develop learning capability from data and make decisions based on what they learn, without any explicit programming [7] . The primary goal of machine learning is to produce models capable of simulating human cognitive functions, simulate the process of learning, and perform specific tasks based on data [8]. According to Ciaburro & Iannace [9], machine learning uses algorithms to detect patterns in data and make predictions. Such algorithms can generally be classified into three categories: supervised learning, unsupervised learning, and reinforcement learning [10]. Among these, supervised learning is one of the most popular forms of machine learning, where models use labeled datasets for training. Input data is fed into the model together with the correct labels that would enable the model to make predictions or classify new data accurately. Algorithms in this category would include decision trees, support vector machines (SVMs), linear regression, logistic regression, and neural networks [11]. these models have a great application in classification and regression problems [12]. SVM algorithms, in particular, are well-suited for high-dimensional and complex data classification, such as in facial recognition and natural language processing, where several applications have been developed utilizing them [13].

In contrast to supervised learning, unsupervised learning involves models that are trained on unlabeled data. The goal of unsupervised learning is to identify hidden patterns and structures in the data. The key techniques within this domain are clustering and dimensionality reduction [14]. Of these algorithms, K-means is one of the best-known approaches when it comes to clustering [15]. Additionally, dimensionality reduction algorithms based on Principal Component Analysis (PCA) compress data and isolate important features from complex datasets [16]. This form of learning is different from the rest, as it mainly learns from the interaction of the agent with its environment. In this learning paradigm, an agent learns from experience and reinforcement—over time, through rewards and punishments—while striving to achieve a goal [17]. However, this type of learning finds applications in various complex domains, ranging from games and robotics to automatic control systems [18]. Q-learning and deep neural network-based methods, such as deep Q-networks (DQN), are popular algorithms in this category, which have proven helpful in solving complex problems, including strategic games and robotic simulations [19]. Artificial Neural Networks (ANNs) remain among the most advanced and essential machine learning models in history and have a broad range of applications in problems of data processing and prediction [20]. These networks have very significant resemblances to the structure of human biological neural networks, while their objective is to simulate the processes used by the human brain in everyday information processing. The individual neurons, which are the building units of these neural networks, are set up in several layers. They are an input and output function expressed mathematically by means of an activation function [21].

3. Defects in Production Processes

The appearance of defects in manufacturing processes poses numerous challenges across nearly every industry, as they impact product quality, production line efficiency, and production costs [22]. Defects can be attributed to various sources, including poor process design and monitoring, the use of low-quality raw materials, and changing environmental conditions [23, 24]. Identifying and predicting defects at early production stages can significantly reduce production costs, enhance product quality, and guarantee customer satisfaction [25]. There are generally two significant classifications of defects: those caused by equipment and those caused by the quality of raw materials or processes of operation [22, 24]. Equipment-related defects refer to misalignment, tool wear, and machine failures, which cause defects that lead to defective products [22]. In contrast, processes-related defects are defects caused by changes in temperature, pressure, or production speed, which could lead to changes in product quality due to improper product models [26].

Therefore, the implementation of more complex fault management systems, which integrate the use of advanced statistical tools and machine learning techniques to uncover trends embedded in historical production data patterns, has become a pivotal trait of current fault management strategies [27, 28]. Such models are seen as probing through historical data of production systems and extracting information regarding failure rates, the operational parameters of equipment, and the quality of the raw materials used. Algorithms like Random Forest, XGBoost, and Deep Neural Networks have shown wonderful success in predicting any possible defects [29, 30]. Process Monitoring Systems have been recognized as a practical approach for reducing or eliminating defects by helping to collect and analyze production data while the process continues [31]. Additionally, preventive maintenance strategies can reduce equipment-related defects. These techniques are based on data mining and machine learning, forecasting equipment behavior, and recommending corrective actions to avert possible failures [32]. Defects arising within production processes have always posed a serious problem for industries, given their influence, on the one hand, on product quality and, on the other hand, on production efficiency. Intelligent identification and modeling solutions need to address these issues. In this respect, the use of advanced artificial intelligence tools presents an excellent opportunity for defect mitigation, ultimately leading to improved overall production performance.

4. Research Background

The most critical issue in manufacturing is the presence of defects, as it impacts product quality, production efficiency, and operational costs. Preventing or anticipating defects significantly reduces resource waste while creating value by increasing productivity and lowering production costs. The recent advancements in machine learning and deep learning have spearheaded the development of intelligent models for defect prediction. A summary of related studies and their objectives is presented, along with a comparison of differing approaches, further elucidating optimal solutions, as shown in Table 1.

Table 1. Research background

Authors	Article title	Goals	Model used	Dataset	Conclusion
Wang et al. [33]	Sample-Evaluation-Enhanced Machine Learning Approach for Fault Diagnosis of Hybrid Systems	This paper aims to increase the accuracy of fault detection in hybrid systems by using hybrid approaches.	Hybrid neural networks with knowledge-based expert systems	Experimental data from hybrid systems	This method significantly improves the accuracy of defect detection and demonstrates greater adaptability when handling sparse and incomplete data.
Lu et al. [34]	Machine Learning Methodologies to Predict the Results of Simulation-Based Fault Injection	Investigating the use of machine learning methods to predict defect injection results in circuit design.	Graph Neural Networks	Electronic circuit simulation data	Using GNN enhances prediction accuracy compared to traditional neural networks and delivers more precise results for defect injection.
Li et al. [35]	Enhancing LightGBM for Industrial Fault Warning: An Innovative Hybrid Algorithm	This paper aims to enhance the accuracy of defect warnings in industry by utilizing a combination of the LightGBM algorithm and optimization methods.	Improved LightGBM algorithm	Diverse industrial data	This combination significantly enhances the accuracy of fault prediction and the delivery of timely warnings in industrial systems.
Tang et al. [36]	Graph Neural Networks for Chemical Process Fault Diagnosis Based on Hybrid Variable Feature Learning	This research aims to use combinatorial feature learning to detect defects in chemical processes using neural networks.	Graph Neural Networks	Chemical process data	The use of GNN significantly improves defect detection in chemical processes by leveraging a variety of features.
Li et al. [37]	Multistage Quality Prediction Using Neural	Designing a data-driven quality control and	Long Short-Term Memory Network	Water cooler production data	The LSTM model outperformed other models

	Networks in Discrete Manufacturing Systems	prediction model for discrete manufacturing environments using deep learning and fuzzy theory			in accurately predicting and identifying defects promptly.
Liu et al. [4]	Developing a Hybrid Algorithm Based on an Equilibrium Optimizer and an Improved Backpropagation Neural Network for Fault Warning	This paper aims to enhance the prediction and warning of defects in manufacturing systems by utilizing optimization algorithms and neural networks.	Hybrid algorithm of equilibrium optimization and improved neural network	Industrial production simulation data	This model significantly enhances prediction accuracy and is well-suited for providing timely warnings of defects in manufacturing processes.
Kosim et al. [38]	Optimization of prediction and prevention of defects on metal based on AI using VGG16 architecture	Prediction and prevention of metal defects using machine learning methods, especially CNN architecture with VGG16	Convolutional neural network, VGG16	Metal defect dataset (10 classes, 17221 training data, 4311 test data)	An accuracy of 89% during training and 76% during testing was achieved, effectively interpreting the type of fault and preventing its occurrence.
Yang et al. [1]	Using Deep Learning to Detect Defects in Manufacturing: A Comprehensive Survey and Current Challenges	Investigating deep learning methods for detecting manufacturing defects across various industries, with a focus on developing real-time and high-accuracy solutions for complex environments.	Deep Learning (Various Models)	Survey-based, includes defect categories across multiple sectors (e.g., electronics, textiles, pipes).	Deep learning enhances defect detection, but challenges persist in detecting small objects and handling complex backgrounds, necessitating future improvements in manufacturing quality control.
Ma et al. [39]	Prediction of Thermal System Parameters Based on PSO-ELM Hybrid Algorithm	This research aims to predict the parameters of thermal systems using a hybrid PSO-ELM algorithm for higher accuracy.	PSO-ELM hybrid algorithm	Thermal systems data	This method achieves higher accuracy in predicting thermal parameters compared to conventional methods and proves effective in detecting defects.
Lee et al. [6]	A Convolutional Neural Network for Fault Classification and Diagnosis in Semiconductor Manufacturing Processes	This paper aims to investigate the use of convolutional neural networks to identify and classify defects in semiconductor manufacturing processes.	Convolutional neural network	Semiconductor manufacturing process data	CNN improves defect classification accuracy and pattern detection in semiconductor manufacturing.

The studies discussed above have considered several aspects of fault detection and diagnosis in manufacturing systems, producing significant advances. However, the literature survey gives a far-reaching statement of limitations and future research opportunities that reveal the need for new research and methodological enhancements. Thus, Wang et al. [33] and Ma et al. [39] used relatively little contextual data, often developed via simulation or collected from particular systems, thus causing the models to be less generalizable to other industrial areas. In this study, we attempt to bring such generalizations to reality by the use of real-time and varied industrial data. Several studies, such as those by Kosim et al. [38] and Lee et al. [6], have employed only one type of model, specifically CNNs. While highly effective in detecting specific patterns, such models can benefit from hybrid methodologies implemented in connection with optimization algorithms. The study tries to fill this gap with the hybrid stacking model. Some papers, such as Yang et al. [1], have indeed demonstrated the advantages of using deep learning in defect detection; however, they have also reported limitations related to real-time data processing in complex industrial conditions, rendering the implementation of these advantages inefficient. Current research aims to provide industry solutions with practical applicability by emphasizing speed and real-time prediction via model application.

Additionally, studies such as Liu et al. [4] and Li et al. [35] provide limited details on the data preprocessing steps and feature selection methods. The present study responds to this gap by employing correlation analysis and data balance via SMOTE to optimize the quality of input data and allow for improved model accuracy. Some studies have totally focused on chemical processes or specific datasets, such as Tang et al. [36], whereas defects could evolve from interactions of several factors in different production processes. By analyzing multidimensional and comprehensive industrial data, this investigation aims to identify defects within complex processes. In the studies by Wang et al. [33] and Ma et al. [39], optimization of model parameters has received inadequate attention. This study proposes to optimize the model parameters to deal with this limitation by using an advanced optimization framework, that is, OPTUNA, for maximizing the prediction accuracy. Thus, this study aims to close these gaps by developing a hybrid stacking model that combines the strengths of advanced machine learning models and neural networks. The proposed model eventually improves the generalization capability of defect prediction accuracy through the treatment of wide industrial data, comprehensive preprocessing models, and hyperparameter optimization. This also makes the method more effective and applicable across various industries in real-world settings, taking into account the complex nature of real-time industrial environments.

4.1. Research Methodology

This study aims to predict whether a given production day in an industrial factory will result in high or low defect levels, using a hybrid machine learning approach. The primary aim is to develop a robust hybrid model that combines an artificial neural network with other machine learning methods so that an accurate defect prediction is obtained. The data source is a Kaggle dataset containing variables such as production volume, supplier quality, costs, and defect rates. In preprocessing, correlation analysis, feature selection, and data balancing with SMOTE were done. A stack-based hybrid machine learning model was designed and optimized using the OPTUNA framework for hyperparameters to increase efficiency and robustness. Performance was evaluated in terms of Accuracy, Precision, Recall, and F1 score and compared with those of seven other models. All analyses and modelling were done using Python.

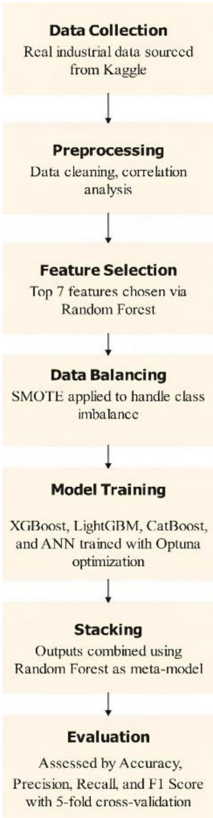

Figure 1. Workflow of the Proposed Hybrid Machine Learning Methodology for Defect Prediction

4.2. Features Description

The dataset is entirely original and unpublished, containing information on factors related to production processes and quality management in an industrial factory [40]. The dataset comprises 16 independent variables and one target variable. The target variable, DefectStatus, indicates whether a production day is classified as high-defect (1) or low-defect (0). It consists of 3,240 samples. Table 2 offers a comprehensive summary of the variables of the dataset applied in defect prediction. Each of the sixteen independent features in the dataset reflects important facets of industrial manufacturing processes; one binary target variable also exists. These characteristics encompass various operational aspects, including production volume, cost, supplier quality, delivery time, defect rate, maintenance, energy consumption, and workforce productivity. To guarantee clarity and openness in the subsequent research, every variable is enumerated together with its value range, data type, and a quick explanation.

Table 2. Features description

Value range	Data type	Description	Variable
100 to 1000 units/day	Integer	Number of units produced per day	ProductionVolume
$5000 to $20000	Float	Production cost per day	ProductionCost
80% to 100%	Float (%)	Supplier quality rating	SupplierQuality
0 to 5 days	Integer (day)	Average delivery delay	DeliveryDelay
0.5 to 5.0 defects	Float	Defect rate per thousand units produced	DefectRate
60% to 100%	Float (%)	Overall quality assessment	QualityScore
0 to 24 hours	Integer	Maintenance hours per week	MaintenanceHours
0% to 5%	Float (%)	Percentage of production downtime	DowntimePercentage

2 to 10	Float	Inventory turnover ratio	InventoryTurnover
0% to 10%	Float (%)	Inventory run-out rate	StockoutRate
80% to 100%	Float (%)	Labor productivity level	WorkerProductivity
0 to 10 incidents	Integer	Number of safety incidents per month	SafetyIncidents
1000 to 5000 kWh	Float	Energy consumed (kWh)	EnergyConsumption
0.1 to 0.5	Float	Energy efficiency ratio	EnergyEfficiency
1 to 10 hours	Integer (day)	Added production time	AdditiveProcessTime
$100 to $500	Float ($)	Cost of additives per unit	AdditiveMaterialCost
0 or 1	Binary	Defect prediction status (0: low defects, 1: high defects)	DefectStatus

As shown in Figure 2, the dataset emphasizes defective samples, which are rare but crucial to identify in production. To address this, non-defective samples were added, but the dataset remains imbalanced. This imbalance can hinder machine learning model performance by biasing predictions toward the dominant class.

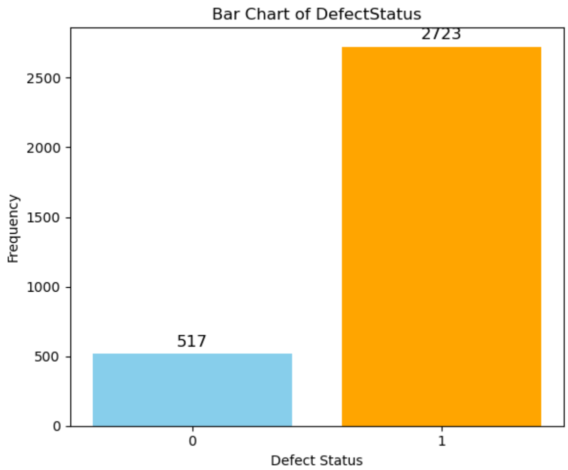

Figure 2. Imbalanced distribution of the target variable

Figure 3 presents the histograms and their density curves (KDE) of the distribution patterns for the 16 most important features of the dataset. These, in turn, exhibit a comparatively similar distribution pattern for evenly spread values, while those such as DefectRate and QualityScore demonstrate a more concentrated distribution, whence it can be inferred that data points lie more densely in some places than others. There are features such as DeliveryDelay and SafetyIncidents, which are discrete and have their values grouped into categories. In contrast, others, such as Energy Efficiency and Additive Material Cost, are continuous and cover their entire range. This gives an overall glimpse of the internal structure of the dataset and its behavior.

4.3. Data Preprocessing

The dataset used in this study was of high quality, with no missing, noisy, or incomplete data. However, this study identified the challenge of addressing imbalanced data distributions. Correlation analysis revealed linear relationships between variables in the dataset [41, 42]. By examining these relationships, correlation analysis helped identify features that strongly influenced the target variable, enabling the removal of features with weak or redundant correlations. A correlation matrix and a heatmap were used to visually represent the relationships between variables, providing a clear and comprehensive view of the dataset's structure.

Additionally, Figure 4 provides a summary of correlations, indicating that there are no significant correlations between the independent features. This indicates that no features are redundant and each can be used in the modeling process. The study was based on analyzing 16 original features, and the cumulative analysis, which also featured Information from the Random Forest algorithm, selected the top 7 features as they collectively represent 80% of the overall critical information. The importance of each feature in predicting the variable is considered and displayed in Figure 4 [43].

A cumulative feature importance analysis was conducted to determine the optimal number of features to select. Features were ranked by their importance, and their cumulative impact was assessed. Based on this analysis, the top 7 features, accounting for approximately 80% of the information in the dataset, were selected [44].

Figure 6 outlines the model's selected feature set: MaintenanceHours, DefectRate, QualityScore, ProductionVolume, AdditiveMaterialCost, StockoutRate, and EnergyEfficiency. Focusing on these seven features, rather than the initial sixteen, allowed the models to concentrate on more relevant and informative variables.

Figure 3. **Data distribution on histograms and density plots**

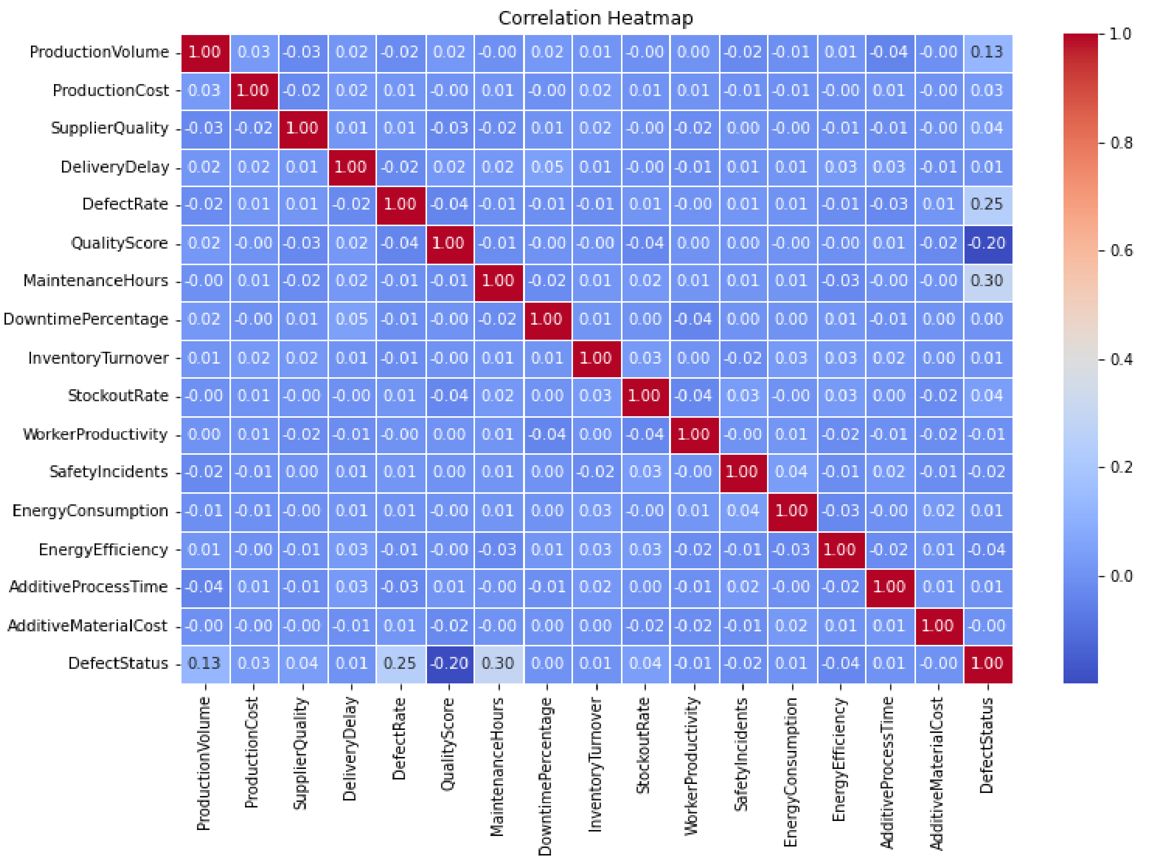

Figure 4. **Correlation Heatmap**

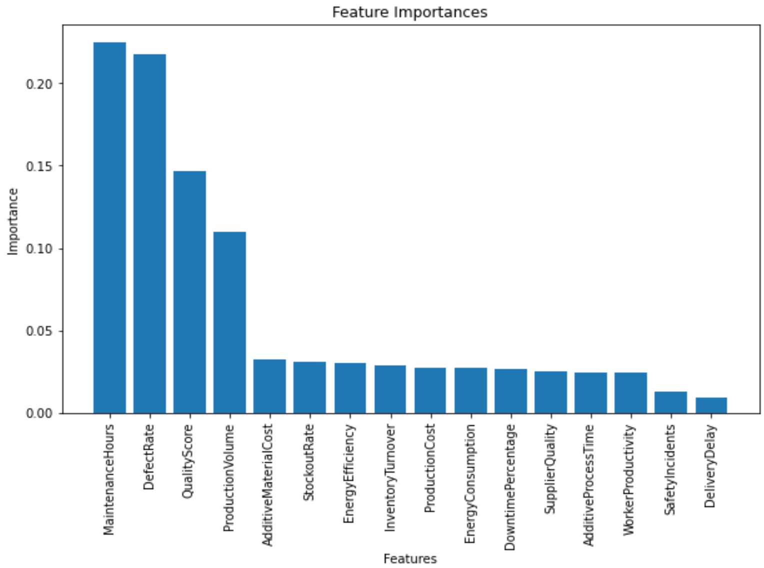

Figure 5. **Feature Importance**

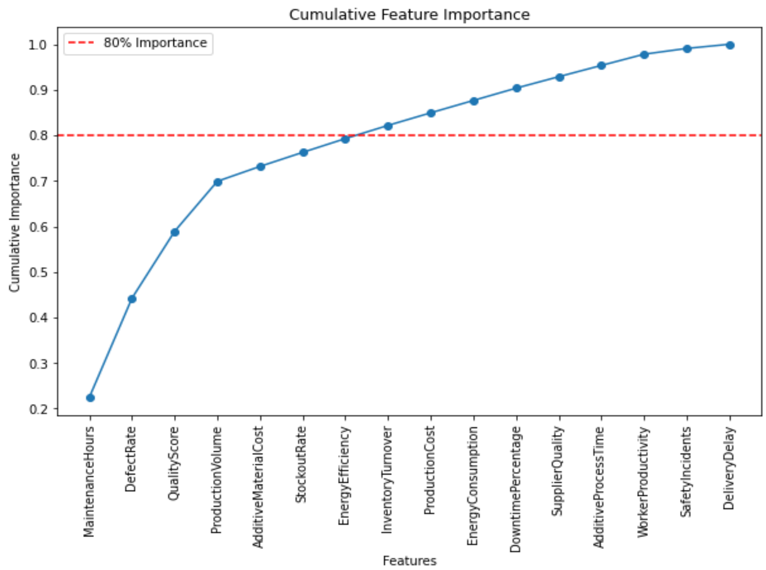

Figure 6. **Cumulative feature importance**

4.4. Data Balance

To address data imbalance, the SMOTE (Synthetic Minority Over-sampling Technique) method was applied to increase minority class samples. SMOTE generates synthetic samples to reduce imbalance and improve model performance in predicting the minority class [45]. The method selects a random minority class sample, called the reference sample, and identifies its nearest neighbors using the K-Nearest Neighbors (KNN) algorithm (commonly with k=5). A new synthetic sample is then generated at a point between the reference sample and a randomly selected neighbor in the feature space [46]. The following formula governs the process:

$$X_{new} = X_{sample} + gap \times (X_{neighbor} - X_{sample}) \qquad (1)$$

Here, Xsample represents the reference sample, Xneighbor is one of the nearest neighbors, and gap is a random number between 0 and 1. In this study, the dataset was divided into two parts: 80% of the data was used for training the models, while the remaining 20% was used to evaluate their performance.

4.5. Hybrid modeltpm32

This paper recommends a hybrid model based on the stacking technology as an ensemble learning method [47]. Ensemble learning is performed using different models to enhance the prediction ability and robustness of the model [48]. Stacking improves classification and regression by combining outputs from the base models and providing them to a meta-model, which gives the final predictions [49]. This hybrid model employed XGBoost, LightGBM, and CatBoost as base models and Random Forest as the meta-model. The hyper-parameter optimization of the model was done using the Optuna Optimizer for 50 trial runs, tuning the tree count, model depth, learning rate, and number of neurons in a neural network [50]. This process greatly enhanced the accuracy and performance level of the model. The architecture of the proposed stacking ensemble model is depicted in Figure 7, illustrating the interaction between the base models and the meta-learner.

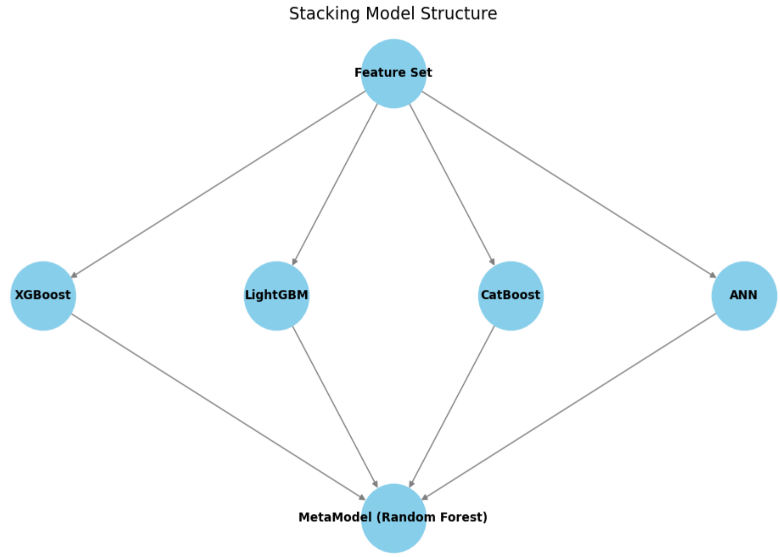

Figure 7. Stacking model structure

The stacking model used in this study consisted of two main layers, with the base models forming the first layer. In this layer, four powerful machine learning models—XGBoost, LightGBM, CatBoost—and an Artificial Neural Network (ANN) were employed for prediction. Each model brings unique features that contribute to improved prediction performance:

XGBoost: XGBoost uses gradient boosting to create decision trees, minimizing errors and enhancing efficiency in learning complex nonlinear patterns through features like tree pruning and model complexity control [51].

LightGBM uses Leaf-wise Splitting and histogram-based binning to optimize memory usage and computational efficiency, making it ideal for large, high-dimensional datasets and reducing training time [52].

CatBoost: CatBoost is a preprocessing technique that directly processes categorical variables, employing Ordered Boosting to reduce prediction error and resist overfitting [53].

The ideal hyperparameter values found for the three base models utilized in the stacking ensemble—XGBoost, LightGBM, and CatBoost—are compiled in Table 3. To improve each model's performance in terms of generalization and prediction accuracy, these parameters were adjusted using the Optuna optimization framework.

Table 3. Optimal hyperparameter values for XGBoost, LightGBM, CatBoost

model	value parameter	Optimal
XGBoost	max_depth	7
	learning_rate	0/239679
	n_estimators	189
LightGBM	num_leaves	41
	learning_rate	0/160612
	n_estimators	182
CatBoost	depth	8
	learning_rate	0/276133
	iterations	214

Artificial Neural Network (ANN): The most important part of an artificial neural network is that it has multiple layers connected to each other, which can propagate data through weighted connections using activation functions such as ReLU and Sigmoid [54]. ANNs are capable of learning complex nonlinear relationships and hidden patterns in data through feedback iteration [54]. In the study, the ANN general structure for both the input and output layers consisted of one input layer, two hidden layers, and one output layer, as depicted in Figure 8. In the case of each hidden layer of 12 neurons with ReLU as its activation function, it helps solve nonlinear relations [55]. A sigmoid activation function was used as the output layer, which produced values between 0 and 1 as they were suitable for binary classification. Adam optimizer [56] was used for the weight updates. The network was trained up to 110 epochs with a batch size of 10 and refined accuracy. The parameters of the ANN used in this study are presented in Table 4.

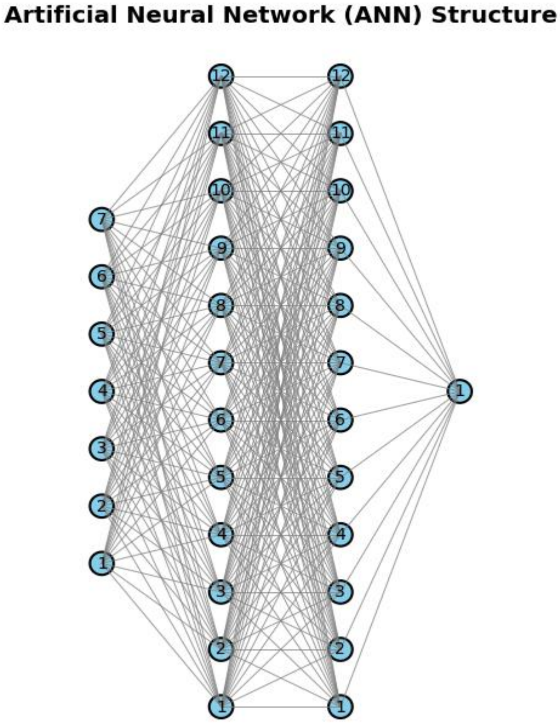

Figure 8. **Neural network structure used in stacking**

Table 4. **ANN parameters**

Layer	Number of neurons	Activation function
Input	7	-
First Secret	12	ReLU
Second Secret	12	ReLU
Output	1	Sigmoid

Random Forest, consisting of multiple decision trees, was employed in this study as the metamodel layer. These trees are built using a variety of features and characteristics of the data samples, and their outputs are aggregated—typically through averaging or voting—to produce the final prediction [57, 58]. Random Forest effectively mitigates overfitting by incorporating randomization techniques, enabling it to generate stable and accurate predictions. In the stacking structure, Random Forest serves as the metamodel, combining the outputs from the base models to produce the final prediction [59]. To optimize the performance of the Random Forest model, key hyperparameters were fine-tuned, with optimal values determined as n_estimators=93 and max_depth=6.

4.6. Comparison of the Hybrid Model with Other Machine Learning Methods

To evaluate the performance of the hybrid (stacking) model, its results were compared to those of seven other machine learning models. Each model was optimized using Grid Search to ensure their optimal performance. Brief descriptions of these methods are provided in Table 5.

Table 5. **Other machine learning methods used for comparison with the hybrid model**

Method	Explanation
SVM	An algorithm that separates data by finding an optimal hyperplane that maximizes the margin between classes. For complex problems, it uses nonlinear kernels like the Radial Basis Function (RBF) to create advanced class boundaries [45].
KNN	A simple algorithm that classifies new data based on its proximity to the K nearest neighbors. This algorithm does not require prior training and classifies data solely based on the distance to the training examples [46].
Naive Bayes	A statistical model based on Bayes' theorem, valued for its speed and efficiency in classification. Despite assuming conditional independence among features—a simplification often violated—it consistently delivers strong performance [60].

Decision Tree	A tree-based structure that uses data features to make decisions, with each node representing a decision point. Splits are based on the feature providing the most information, continuing recursively to the leaf nodes for final decisions([11].
Random Forest	A collection of decision trees trained on random data subsets, with final predictions made by majority voting (classification) or averaging (regression). This method enhances accuracy and reduces overfitting compared to individual trees [54].
Logistic Regression	A linear model predicts classes by estimating the probability of each class within the range [0,1]. It uses the logistic (sigmoid) function, making it ideal for binary classification problems [11].
MLP (Neural Network)	An artificial neural network (ANN) uses hidden layers to capture nonlinear relationships in data. A Multilayer Perceptron (MLP) comprises an input layer, one or more hidden layers, and an output layer, trained using the backpropagation algorithm. These networks are highly effective for addressing complex, nonlinear problems[61].

Accuracy, Precision, Recall, and F1 score were used to evaluate model performance. The metrics are derived from the concepts of TP, TN, FP, and FN. Correctly identified defect cases are denoted by TP, and cases that are accurately predicted as non-defective are denoted by TN [62]. FP refers to incorrect predictions of the defects while no defect exists, and FN indicates that the defect cases have been missed. This is what makes up the basis for evaluating the model's accuracy and adequacy of the model. 5 5-fold cross-validation was used to assess the generalizability and stability of the model. Four commonly used classification metrics—Accuracy, Precision, Recall, and F1 Score—were used to evaluate the machine learning models' performance. These metrics provide a comprehensive evaluation of the model's performance, particularly when working with unbalanced datasets. Table 6, which is based on Jafarnejad et al. [63], provides the definitions and mathematical formulas for each metric.

Table 6. Evaluation metrics for machine learning models

Index	Definition	Formula
Accuracy	The ratio of correct predictions (both positive and negative) to the total number of samples.	$\frac{TP + TN}{TP + FP + FN + TN}$
Precision	The ratio of correctly predicted instances of a class to the total instances predicted as that class.	$\frac{TP}{TP + FP}$
Recall	The ratio of correctly predicted instances of a class to the total actual instances of that class.	$\frac{TP}{TP + FN}$
F1 Score	The harmonic mean of Precision and Recall to balance the trade-off between them.	$\frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$

4.7. Findings

In this section, the performance of the hybrid model is examined and compared with that of other machine learning models. The Python programming language was utilized for this study, and all models were executed on a system equipped with an Intel Core i7-13700H processor, 16 GB of RAM, and Python version 12.3. The performance results of the models are presented in Table 7.

Table 7. Performance results of the models

Model	Accuracy	Precision	Recall	F1 Score
SVM	0/8982	0/9043	0/8962	0/9003
KNN	0/8688	0/9522	0/7835	0/8597
Naive Bayes	0/9028	0/9086	0/9835	0/9446
Decision Tree	0/9083	0/8603	0/9803	0/9164
Random Forest	0/9257	0/8794	0/9911	0/9319
Logistic Regression	0/7917	0/8051	0/7835	0/7942
MLP	0/8991	0/9212	0/8784	0/8993
Ensemble (Stacking)	0/9606	0/9510	0/9732	0/9620

The assessment performed on various machine learning models suggested that the ensemble stacking model had an edge over all the other models. The accuracy of 0.9606 is higher than that of its individual models, indicating significant predictive power in distinguishing between defective and non-defective samples. The ensemble achieved a precision of 0.9510, indicating a good proportion of correct predictions for positive samples. In comparison, Random Forest and Naive Bayes showed relatively low precision scores of 0.8794 and 0.9086, respectively, which again gives a glimpse into the strength of the ensemble model in reducing the false positive error. The ensemble model had the highest recall value of 0.9732 among all, confirming its superior ability to identify true positives. While Naive Bayes (0.9835) and Decision Tree (0.9803) gave good recall values, the ensemble was optimizing recall against other competing metrics. The hybrid model achieved the highest F1 score of 0.9620, indicating an optimal balance between precision and recall. This balance is characterized by a very high positive detection rate and high prediction accuracy. In comparison, F1 scores for Naive Bayes and Random Forest were at 0.9446 and 0.9319, respectively; even then, they could not surpass the hybrid model. Overall, the hybrid model aptly combined the features of each of the models while diminishing the weaknesses, either by merging the outputs of base models or employing a metamodel. When compared to the single model approaches such as Random Forest, SVM, and Naive Bayes, the hybrid model proved superior on all counts due to its multilayered architecture.

Figure 9 illustrates the performance of various machine learning models. The stacking hybrid model outperformed all other models across these metrics. This comparison highlights the advantages of the stacking technique, which leverages the strengths of base models while mitigating their weaknesses. The hybrid model's use of this technique resulted in substantial improvements in predictive performance and a balanced optimization of all evaluation metrics.

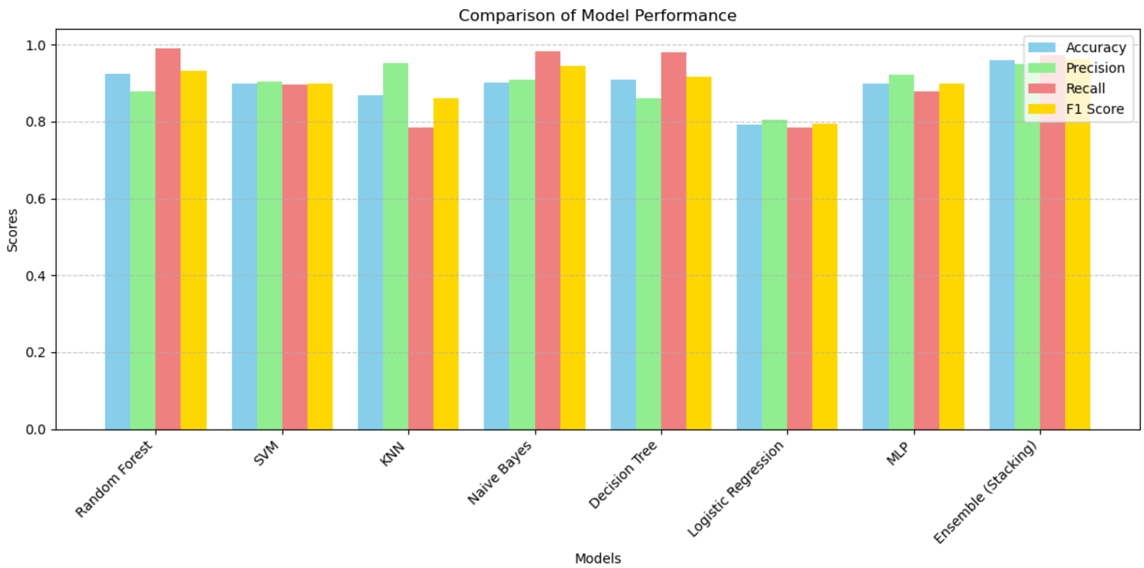

Figure 9. **Performance of various machine learning models**

4.8. Conclusion and Suggestions

This study develops a defect prediction using a stacking based ensemble learning model. Four base models were included: XGBoost, LightGBM, CatBoost, and ANN with Random Forest as the metamodel. In comparison with the single models, this technique provided ample improvement in performance. Finally, the performance of the models was evaluated using the main performance metrics, including accuracy, precision, recall, and F1 score. Since it utilizes the pros of the base models and avoids their deficiencies, the results have established a significant advantage of the stacking hybrid model over the individual models in all performance metrics. With an accuracy of 96.06%, the model can indeed predict defect and non-defect samples correctly. Additionally, false positive mistakes were significantly minimized, with a precision of 95.10% at a level exceeding the degree of measurement, and the positive prediction was measured at a higher accuracy than expected. Recall wise, the stacking hybrid model could almost capture all of the actual defect samples with a value of 97.32%. Furthermore, the F1 score of 96.2.0% showed good balance between precision and recall for this technique. Since these problems are complicated and involve dealing with imbalanced datasets, these analyses show that ensemble learning techniques, particularly stacking, achieve a significant uplift in terms of improvements in model performance. The reduction of model complexity and efficiency was achieved partly by employing data preprocessing methods, such as SMOTE, for balancing the classes and feature selection.

The present study aims to achieve a more accurate prediction of defects in industrial manufacturing processes by using a stacking hybrid model that efficiently detects and predicts defects, outperforming earlier techniques. The results point towards the better performance of the proposed methodology across numerous crucial parameters, being in line with earlier studies. One significant distinction of this study from prior works, such as Wang et al. [33] and Ma et al. [39] , is its use of a diverse industrial dataset. In contrast, many earlier studies relied on data confined to specific systems. This data variety enhanced the generalizability of the hybrid model compared to previous approaches. In terms of model design, the present study mitigated the weaknesses of individual models by stacking and combining four base models: XGBoost, LightGBM, CatBoost, and ANN. In contrast, earlier studies, such as Kosim et al. [38] and Lee et al. [6], often employed single models like CNN, which limited their ability to identify complex patterns. Furthermore, the present work introduced a more precise and real-time applicable model relative to studies like Yang et al. [1], which cited problems, such as the inability to conduct real-time predications and limited capabilities in handling complex data. This was accomplished through hyperparameter optimization and preprocessing methods such as SMOTE, which helped to lay down an excellent way of solving the problems of imbalanced datasets. Regarding data preprocessing, correlation analysis, and feature selection methods based on feature importance were utilized: seven important features were selected that contributed to nearly 80% of the relevant information. These techniques reduced the problem's dimensionality, improved model accuracy, and increased training speed. By contrast, studies such as Liu et al. [4] and Li et al. [35] provided limited details about feature selection and its impact on model performance. Overall, this study addressed existing research gaps by focusing on model combination, comprehensive optimization, and utilizing diverse industrial data. The proposed approach not only achieved higher prediction accuracy but also paved the way for broader applications of machine learning models in real-world industrial environments.

The applications of this research will prove to be useful in automotive, electronics, pharmaceuticals, and packaging industries. Due to its flexible nature, the proposed hybrid model will be applicable in diverse scenarios, thereby identifying defects at different stages of the production phase. This has great potential for enhancing quality, reducing costs, and improving productivity. The study presents a stacking-based ensemble learning model that, through the application of advanced machine learning techniques, significantly improves defect prediction in manufacturing processes. To advance the achievements, future work can contemplate implementing advanced deep-learning models. Such models can capture complicated hidden patterns, accordingly improving predictive performance under complicated data circumstances. Another direction for future work is using the hybrid model by industries on their production lines. This will open the door for an assessment of the performance of the model, considering factors that come up in practice, including data noise, processing capabilities, and operational variability. In real industrial settings, implementing this model could help industries identify and implement defect prevention practices, thereby achieving excellent operational goals. Although the results are encouraging, there are some limitations to this study. First, the model was trained and tested on an industry-specific dataset. Thus, if you wish to expand into other industries, you may need to consider that. Second, while the SMOTE algorithm allowed us to address imbalances in data, which allowed us to create a good model, it could introduce synthetic noise. Finally, the model has not been adapted to accommodate real-time dynamic updates to reflect changes in the production context. In future directions, we could have applied the model in dynamic live industrial environments, with a focus on adaptive learning, and created evaluations based on the performance of the model in a host of manufacturing domains.

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