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Hybrid machine learning approaches to piston defect detection in industrial applications

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ABSTRACT

This study proposes a hybrid artificial intelligence approach for detecting surface defects in industrial piston components by combining deep learning based feature extraction with traditional machine learning classifiers. The experimental analysis was performed using the piston dataset, which includes both defected and perfect samples of industrial pistons. Four classification algorithms, namely Support Vector Machine, Artificial Neural Network, k Nearest Neighbors, and Random Forest, were implemented and compared based on their classification accuracy. The Support Vector Machine achieved the highest performance with an accuracy of 99.84%, demonstrating superior capability in distinguishing between defected and non-defected piston surfaces. The Artificial Neural Network followed closely with an accuracy of 99.69%, showing highly stable and consistent behavior. The k Nearest Neighbors model reached an accuracy of 98.75%, while the Random Forest achieved an accuracy of 94.84%, indicating a comparatively lower generalization performance. The results confirm that the hybrid combination of deep feature extraction and conventional classification methods significantly improves accuracy and robustness in defect detection. The proposed framework contributes to the industry 4.0 vision by providing a reliable, efficient, and intelligent quality control solution suitable for real-time manufacturing systems, supporting digital transformation in modern industrial environments.

Keywords: Piston; InceptionV3; Artificial Neural Network; Support Vector Machine; k-Nearest Neighbors; Random Forest

1. Introduction

Ensuring the reliability of mechanical components is a crucial requirement in modern industry. Pistons, as one of the most critical parts of internal combustion engines, must be free of defects to guarantee optimal performance and safety. Traditional inspection methods often rely on manual expertise, which is time-consuming, costly, and prone to human error. With the increasing complexity of manufacturing processes and the demand for higher precision, manual inspection alone has become insufficient. This situation has accelerated the integration of intelligent systems into industrial quality control, aiming to minimize errors while improving efficiency. Recent advancements in computer vision and deep learning have enabled automated defect detection systems that are both faster and more reliable than conventional approaches. Convolutional Neural Networks (CNNs) have shown outstanding performance in image-based classification tasks due to their ability to extract rich hierarchical features [1]. However, CNNs typically require large-scale datasets to achieve strong generalization capability, which may not always be available in industrial contexts where defect images are scarce. To address this limitation, researchers have increasingly adopted transfer learning and hybrid frameworks, in which pretrained CNN models are employed as feature extractors and the extracted representations are classified using machine learning algorithms.

Such hybrid strategies combine the representational strength of deep networks with the efficiency of classical classifiers, thus reducing overfitting risks in small-sample problems. For instance, [2] demonstrated that ResNet features combined with Support Vector Machines (SVM) provided superior accuracy in steel surface defect detection compared to end-to-end CNN training. Beyond ResNet and Inception, lightweight architectures such as MobileNet have been successfully applied in embedded and real-time systems, particularly in resource-constrained industrial environments [3].

Recent studies have demonstrated the applicability of hybrid methods in quality control. For example, ResNet-based convolutional neural networks have achieved high performance for weld defect classification across multiple radiographic datasets [4]. Similarly, transfer-learning CNN features combined with conventional classifiers have provided scalable and effective solutions for weld defect detection [5].

In the context of Industry 4.0, intelligent inspection systems are increasingly expected to handle multimodal data and operate in dynamic environments. Hybrid pipelines that pair CNN feature extraction with classifiers such as SVM or Random Forest have shown promise not only in visual inspection but also in vibration-based fault diagnosis for rotating machinery [6].

Advances in segmentation and detection techniques also contribute to improving defect recognition. The introduction of attention mechanisms [7] and transformer-based vision models [8] highlights a trend toward lighter yet robust architectures, with recent studies proposing CNN–Transformer hybrids for surface defect detection [4].

Specific to piston and engine components, [9] developed a hybrid system in which classical computer vision was employed for region-of-interest isolation followed by CNN-based classification. This method demonstrated robustness and practical applicability in detecting machining defects inside piston chambers.

Overall, integrating pretrained CNNs such as InceptionV3 [1] as universal feature extractors and combining them with established classifiers including SVM, kNN, Random Forest, or Gradient Boosting offers a balanced pathway between accuracy, robustness, and computational efficiency. This paradigm not only enhances the reliability of critical components such as pistons but also aligns with the broader industrial shift toward smart manufacturing and predictive maintenance [5]

Overall, the integration of deep learning architectures with classical machine learning classifiers provides a balanced pathway between accuracy, robustness, and computational efficiency. By leveraging pretrained models like InceptionV3 as universal feature extractors and applying established classifiers such as Support Vector Machine, k-Nearest Neighbors, Random Forest, or Gradient Boosting for decision-making, industries can achieve reliable defect detection even under data-constrained conditions. This paradigm not only enhances the reliability of critical components such as pistons but also aligns with the broader industrial shift toward smart manufacturing and predictive maintenance, ultimately contributing to safer, more efficient, and cost-effective production systems.

In this study, a novel hybrid framework is proposed for piston defect detection, where deep features extracted from the InceptionV3 architecture are classified using multiple machine learning algorithms. Unlike previous works focusing primarily on single-model approaches, this research provides a comprehensive comparison across multiple classifiers to identify the most effective combination for real-time industrial applications. The results contribute to the existing literature by demonstrating a robust, data-efficient, and generalizable solution for defect detection in mechanical components, supporting the evolution of intelligent inspection systems within the industry 4.0 ecosystem.

2. Materials and Method

In this study, a 5-fold cross-validation strategy was adopted to evaluate the classification performance on the piston defect dataset. Deep feature representations were first extracted using the InceptionV3 network, and these embeddings were subsequently classified with machine learning algorithms including support vector machine, random forest, k-Nearest Neighbors, and artificial neural network. This hybrid approach was chosen to leverage the representational power of deep learning while ensuring reliable decision-making through classical classifiers. The overall workflow and methodological framework of the study are summarized in Figure 1.

2.1. Dataset

In this study, we employed the piston image dataset, which was obtained from Kaggle [10]. The dataset consists of a total of 64 images of automobile engine pistons, categorized into two classes: 32 perfect pistons and 32 defective pistons. The defective images contained various visual anomalies and imperfections that may occur during the manufacturing process, while the perfect class represented defect-free piston samples. To enhance the diversity and size of the dataset, image augmentation techniques such as rotation, flipping, scaling, and brightness adjustment were applied, resulting in an expanded dataset comprising 640 images in total. Furthermore, a representative sample illustrating both perfect and defective piston images is presented in Figure 2, providing a visual overview of the two classes included in this study.

2.2. Inception V3

InceptionV3 is a deep convolutional neural network architecture that represents a significant evolution within the Inception model family, primarily designed for large-scale image classification tasks. It introduces factorized convolutions, replacing larger convolutional filters with smaller ones to optimize computational efficiency while maintaining strong feature representation capacity [11].

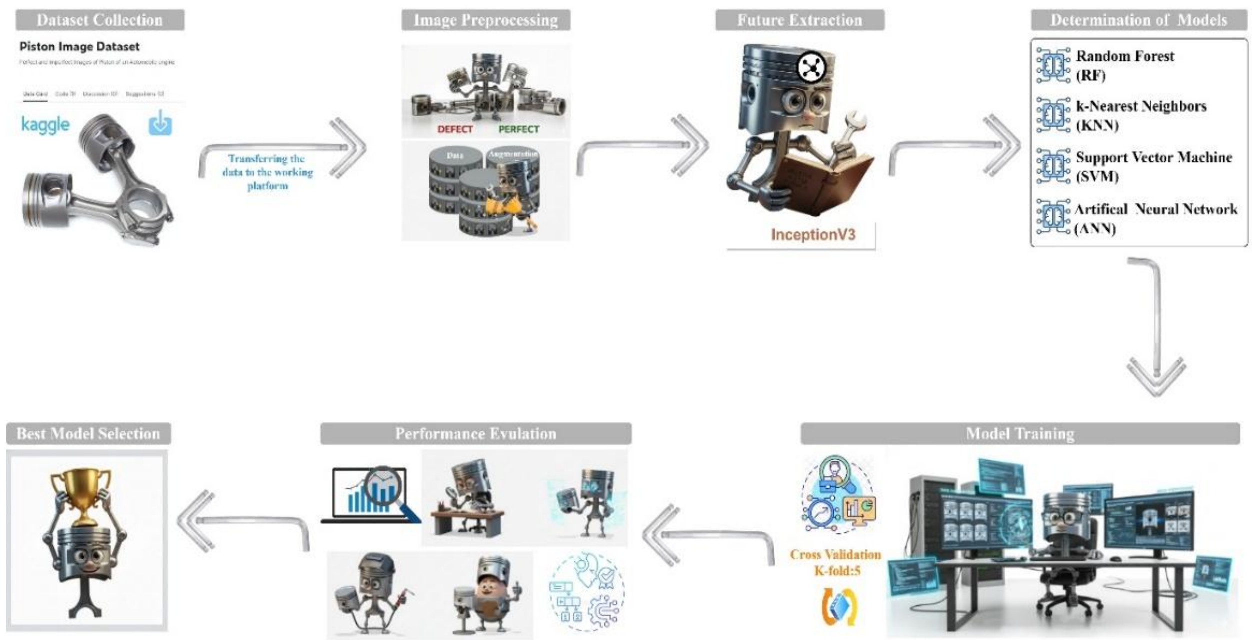

Figure 1. Workflow of the proposed hybrid model

Figure 2. Dataset

Additionally, the architecture integrates *auxiliary classifiers* to prevent vanishing gradients and to support better regularization during training. Through these innovations—combined with batch normalization and aggressive dimensionality reduction—InceptionV3 achieves high accuracy with reduced computational cost [12].

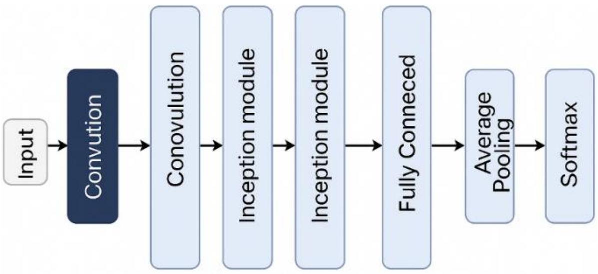

Figure 3. Inception V3 architecture

Figure 3 below illustrates the core structure of the InceptionV3 architecture, consisting of sequential convolutional and pooling layers that first extract low-level features such as edges and textures. These are followed by multiple Inception modules that operate in parallel using filters of different sizes (1×1, 3×3, 5×5), allowing the model to capture both fine and coarse visual patterns simultaneously [13]. Auxiliary classifiers embedded within intermediate layers enhance gradient flow and stabilize learning. The final stages include global average pooling to condense feature maps and fully connected with Softmax layers to generate class probabilities.

This hierarchical and modular design enables multi-scale feature extraction, enhancing the model's ability to generalize across diverse image datasets. In essence, InceptionV3 mimics a human-like perception process progressively identifying simple features, combining them into complex structures, and ultimately recognizing complete objects with remarkable accuracy and robustness [14].

2.3. Machine learning algorithms

2.3.1. Support Vector Machine

Support Vector Machine (SVM) is a supervised learning algorithm widely regarded for its robustness in both classification and regression tasks. It functions by identifying the optimal hyperplane that maximizes the margin the distance between the hyperplane and the closest data points of each class, known as support vectors. This maximization strategy enhances the model's generalization capacity. In scenarios where data are not linearly separable, kernel functions such as the Radial Basis Function (RBF) or polynomial kernels are deployed to project inputs into higher-dimensional spaces where linear separation becomes feasible [15].

In more intuitive terms, the SVM can be imagined as drawing an invisible line or in higher dimensions, a hyperplane that best separates data belonging to different categories [16]. Rather than simply finding any boundary, it searches for the one that creates the widest possible margin between the two classes, ensuring that new, unseen data points can be classified more reliably. The data points that lie closest to this boundary are known as support vectors, and they play a critical role in defining the decision surface. When the data cannot be separated by a straight line, SVM applies the kernel trick, a mathematical technique that transforms the data into a higher-dimensional space where linear separation becomes possible. This transformation allows SVM to handle complex, non-linear problems without explicitly computing the coordinates in that space, thus maintaining computational efficiency [17].

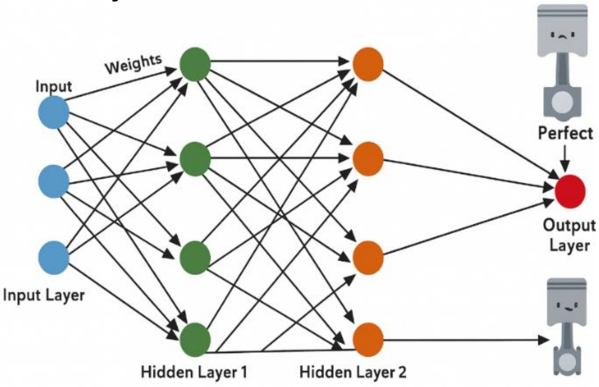

Figure 4. SVM architecture

Overall, SVM operates with a strong balance between simplicity and performance, providing robust results even when the dataset is small, noisy, or contains many features [17]. The accompanying schematic Figure 4 visually represents the general concept of a supervised learning model: data features are input through several layers of computation, and the model learns to distinguish categories such as "defect" versus "perfect" objects by adjusting internal parameters (weights) until the optimal decision boundary is achieved.

2.3.2. Random Forest

Random Forest (RF) is a robust ensemble learning technique that amalgamates predictions from multiple decision trees to enhance classification or regression performance [18]. Each tree in the forest is trained on a bootstrap sample of the original dataset, and randomness is further introduced by selecting a subset of features at each split this mitigates overfitting and reduces variance. RF is particularly valued for its capacity to handle large feature spaces, unbalanced data, and missing values, and it offers useful internal measures such as feature importance and out-of-bag error estimation, enhancing its interpretability and reliability in practical applications [19].

RF combines the decisions of multiple individual trees each trained with different subsets of data and features to produce a more stable and accurate final prediction [20]. This ensemble approach ensures that the model is less sensitive to noise and anomalies in the data, which often cause overfitting in individual decision trees [21].

Figure 5 illustrates the operational principle of the Random Forest model. Multiple independent decision trees are trained on different subsets of the training data, and each tree produces its own classification outcome. The final decision is obtained through a majority voting mechanism, where the most frequently predicted class across all trees determines the model output. In this example, the ensemble aggregates the outputs of individual trees to classify objects as either defect or perfect, demonstrating the robustness of the RF approach in minimizing overfitting and improving overall prediction accuracy [21].

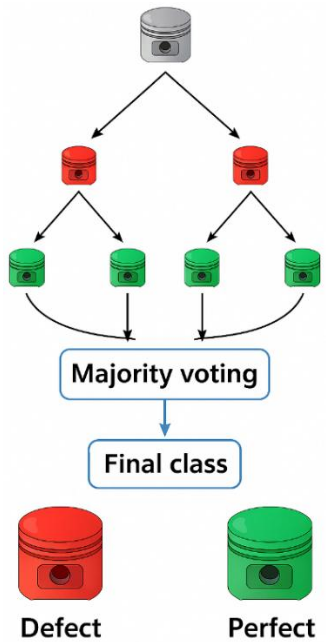

Figure 5. RF architecture

2.3.3 k-Nearest Neighbors

k-Nearest Neighbors (kNN) is a non-parametric, instance-based learning algorithm widely used for classification and regression tasks. Its core principle is to assign a label to a query sample based on the majority class or average value of its *k* closest neighbors in the feature space, measured typically by distance metrics such as Euclidean, Manhattan, or cosine similarity. The performance of kNN strongly depends on the choice of *k*, the distance function, and data normalization [22]. Unlike parametric models, kNN does not construct an explicit decision function or learn a model during the training phase. Instead, it stores all training instances and performs computations only at prediction time, which classifies it as a lazy learning algorithm. This structure allows kNN to model highly non-linear class boundaries while maintaining conceptual simplicity. However, its computational complexity increases with the dataset size, as distance calculations must be repeated for each new query instance.

The effectiveness of kNN improves significantly when combined with dimensionality reduction techniques (e.g., PCA, t-SNE) or deep feature extraction methods derived from convolutional neural networks or autoencoders. Such hybrid approaches enhance the discriminative capability of the neighborhood structure in the feature space [23]. Due to its flexibility and robustness with well-structured feature representations, kNN has been successfully implemented in biomedical image analysis, text categorization, and industrial defect detection tasks [24].

Figure 6 illustrates the operational mechanism of the kNN algorithm. For a given query instance (gray piston), the algorithm identifies its k closest data points within the query neighborhood, based on a chosen distance metric such as Euclidean or Manhattan distance. Each neighboring point contributes one vote toward determining the class of the query sample. Through a majority voting process, the sample is assigned to the class most frequently represented among its nearest neighbors [23]. In this illustration, the query piston is classified as defect since the majority of its neighboring instances belong to the defect class.

2.3.4 Artificial Neural Network

Artificial Neural Networks (ANN) are computational models inspired by the biological structure and functioning of the human brain. They consist of interconnected layers of artificial neurons organized as input, hidden, and output layers. Each neuron processes incoming signals by applying a mathematical activation function and adjusts its connection weights during training to minimize prediction error. Through this iterative optimization commonly achieved using the backpropagation algorithm the network progressively learns complex, non-linear relationships within the data [25].

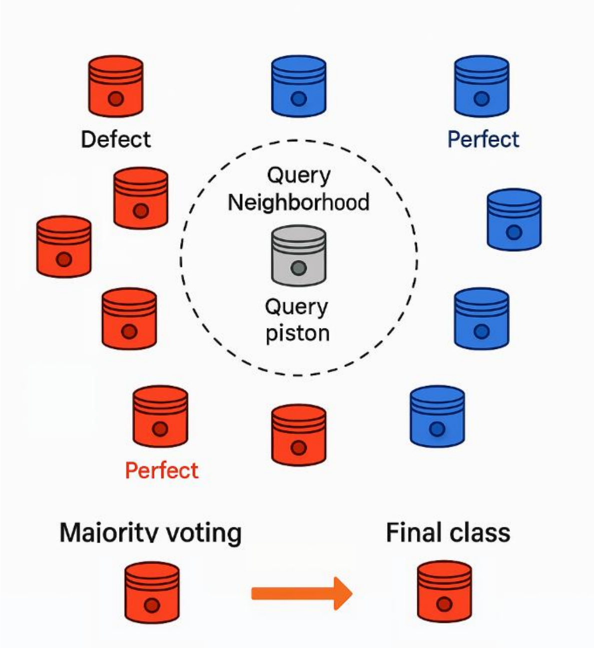

Figure 6. kNN architecture

ANNs are widely used in pattern recognition, classification, and prediction tasks due to their capability to model non-linear dependencies between multiple input variables [26]. Once trained, the network generalizes learned patterns to unseen data, enabling accurate and adaptive decision-making. As a foundational component of modern machine learning and deep learning, ANNs provide a flexible framework for high-dimensional data modelling and feature abstraction across domains such as image processing, speech recognition, and industrial quality control.

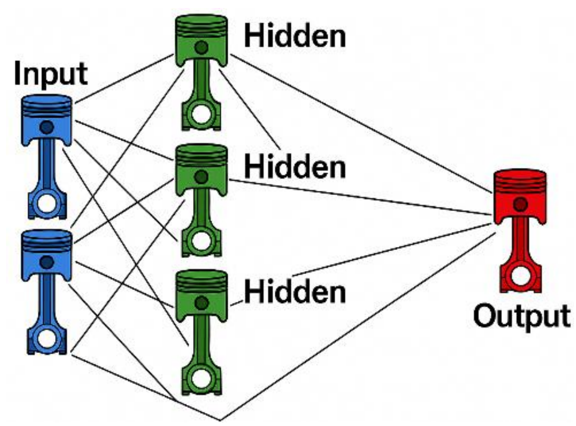

Figure 7. ANN architecture

Figure 7 represents a simplified feedforward artificial neural network consisting of an input layer, multiple hidden layers, and an output layer. Each input node transmits weighted signals to all neurons in the subsequent hidden layer, where non-linear transformations are applied [27]. The hidden layers aggregate and propagate these activations toward the output layer, which produces the final prediction. In this illustration, input pistons represent data features, hidden pistons correspond to intermediate processing neurons, and the output piston denotes the final predicted class. This structure demonstrates the flow of information and the hierarchical learning process within an ANN [27].

2.4. Performance evaluations

2.4.1. Cross validation

Cross-validation is a statistical technique used to evaluate the generalization performance of machine learning models [28]. The dataset is partitioned into *k* folds, where one-fold is used for validation and the remaining folds are used for training [29]. This process is repeated *k* times, and the results are averaged to provide a more reliable performance estimate [30].

In this study, 5-fold cross-validation was applied, which is among the most preferred approaches because it provides a strong balance between bias and variance. This means that the model is trained and evaluated multiple times using different data partitions, reducing the chance that the reported accuracy is the result of random data configuration.

Conceptually, cross-validation can be thought of as testing a model in several "mini experiments," each using a different portion of the data for evaluation [31]. This approach allows for a more realistic measurement of predictive capability compared to a single train-test split. It is especially effective when the dataset is of limited size, as it ensures that every sample contributes to both training and validation at least once, maximizing data utilization and improving the reliability of performance metrics [31].

2.4.2 Confusion Matrix and Performance Evaluation

To assess the effectiveness of the classification models, a confusion matrix was constructed, which provides detailed insights into the model's predictions by comparing actual labels with predicted labels [32]. The matrix consists of four key outcomes, True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). Table 1 shows that confusion Matrix for binary classes. From these values, several performance metrics were derived [33].

Table 1. Structure of the confusion matrix used for performance evaluation

	Predict	
Actual	**TP**	**FN**
	FP	**TN**

The performance of the classification models was evaluated using several widely adopted metrics derived from the confusion matrix. Accuracy represents the proportion of correctly classified instances among all samples, providing a general measure of predictive performance [34]. Precision indicates the proportion of correctly identified positive cases among all predictions labelled as positive, thereby reflecting the reliability of the model in making positive classifications. Recall, also known as sensitivity, measures the proportion of actual positive cases that were correctly identified, thus demonstrating the model's ability to capture relevant instances. Finally, the F1-score, calculated as the harmonic means of precision and recall, offers a balanced measure that is particularly valuable when dealing with imbalanced datasets, where accuracy alone may not provide sufficient insight into model effectiveness [35]. Table 2 shows that performance metrics formulas.

Table 2. Performance metrics formulas

Metrics	Formula
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
F1-Score	$\frac{2TP}{2TP+FP+FN}$

3. Results and Discussions

In this study, the classification results obtained from the four models namely Support Vector Machine, Artificial Neural Network, k Nearest Neighbors, and Random Forest were analyzed in detail to evaluate their capability in distinguishing between defected and perfect samples. The evaluation process was carried out through both confusion matrix analysis and quantitative performance metrics, which together provide a comprehensive understanding of each algorithm's classification behaviour, robustness, and sensitivity. The first stage of the evaluation focused on the confusion matrices, which reveal the distribution of true positives, true negatives, false positives, and false negatives for each model.

As shown in Figure 8, the Support Vector Machine classifier demonstrated a near perfect distinction between the two classes. Specifically, it correctly identified 319 defected and 320 perfect samples, with only one misclassification observed in total. This outstanding result reflects the model's ability to capture the optimal separating hyperplane within the feature space, maximizing the margin between classes and minimizing generalization error.

The Artificial Neural Network model also yielded highly competitive results, correctly classifying 319 defected and 319 perfect samples, with a single error in each class. This performance demonstrates the network's strong learning capacity and its effective mapping of nonlinear relationships between input features and output classes. However, the slight deviation from Support Vector Machine in precision values suggests a minor influence of weight initialization or possible overfitting to specific patterns during training. The k Nearest Neighbors algorithm produced relatively satisfactory results, correctly predicting 314 defected and 318 perfect samples, corresponding to a total of eight misclassifications six and two respectively. This outcome indicates that k Nearest Neighbors can achieve reliable predictions when class distributions are well separated but may struggle in regions with overlapping feature boundaries. Its sensitivity to the choice of the k parameter and the scale of the feature space makes it less robust than optimization-based approaches such as Support Vector Machine. The Random Forest classifier although capable of capturing nonlinear interactions displayed the weakest performance among the evaluated models. It correctly labeled 308 defected and 299 perfect samples while misclassifying 12 and 21 instances respectively. These results imply that the Random Forest model had difficulty in identifying subtle inter class variations possibly due to an insufficient number of decision trees or inadequate tree depth. Additionally, ensemble based models like Random Forest can be more prone to overfitting in small datasets where the number of samples per class is limited.

The confusion matrix comparisons collectively highlight that Support Vector Machine and Artificial Neural Network provided the most stable and reliable classifications, while k Nearest Neighbors and Random Forest exhibited performance degradation due to their dependence on local data characteristics and random feature sampling strategies respectively. The overall pattern of misclassifications suggests that both Support Vector Machine and Artificial Neural Network successfully generalized the distinguishing features of the dataset leading to minimal classification errors. Following the confusion matrix analysis quantitative performance metrics were computed using five fold cross validation to ensure statistical reliability. The obtained results are summarized in Table 3.

As presented in Table 3, the Support Vector Machine model achieved the best overall performance with the highest accuracy and F1 score values of 0.9984 as well as perfect precision of 1.0000. This result confirms that Support Vector Machine is particularly effective in handling high dimensional feature spaces and linearly separable structures even with limited training data. The model's ability to maximize the margin between classes contributes to its superior generalization capability which is further supported by the minimal number of false classifications observed in the confusion matrix. The Artificial Neural Network model followed closely with an overall accuracy of 0.9969 maintaining perfectly balanced precision recall and F1 score values. This indicates a robust and consistent learning process with minimal

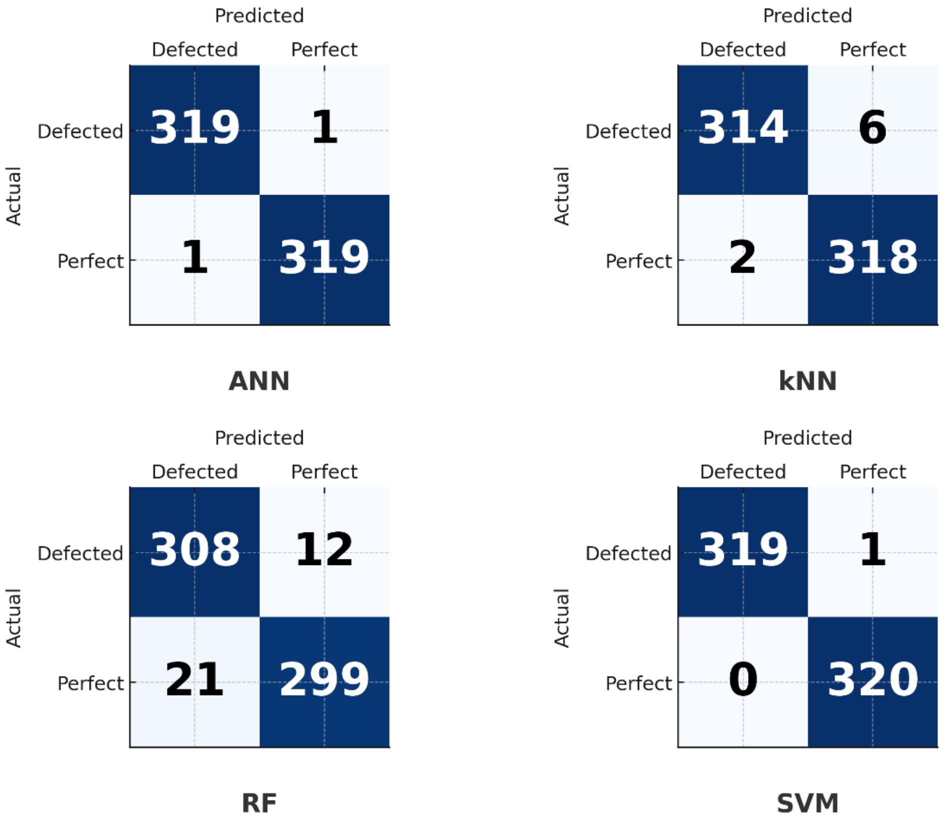

Figure 8. Confusion matrices results

Table 3. Performance metrics

Model	Accuracy	Precision	Recall	F1-Score
SVM	0.9984	1.0000	0.9969	0.9984
ANN	0.9969	0.9969	0.9969	0.9969
kNN	0.9875	0.9937	0.9812	0.9874
RF	0.9484	0.9362	0.9625	0.9492

bias toward either class. The slightly lower performance compared to Support Vector Machine may be attributed to the network's sensitivity to hyperparameter tuning including learning rate number of hidden neurons and regularization parameters. Nevertheless its performance demonstrates that deep multilayer architectures are well suited for complex nonlinear feature interactions typical of defect detection problems. The k Nearest Neighbors model achieved an accuracy of 0.9875 precision of 0.9937 and recall of 0.9812 reflecting a moderate trade off between sensitivity and specificity. While its simplicity and instance based learning mechanism make it computationally efficient for small datasets its reliance on distance metrics can lead to decreased performance when feature scales vary or when noise is present. Despite this limitation k Nearest Neighbors still produced satisfactory results confirming its validity as a baseline model in defect classification tasks. The Random Forest model obtained the lowest accuracy and precision among all classifiers although its recall indicated a relatively strong ability to detect positive cases. However, the combination of a higher false positive rate and overall weaker generalization points to model instability. This can occur when the feature set is not diverse enough to exploit ensemble averaging effectively or when the number of estimators and tree depth are insufficient for capturing fine grained data patterns.

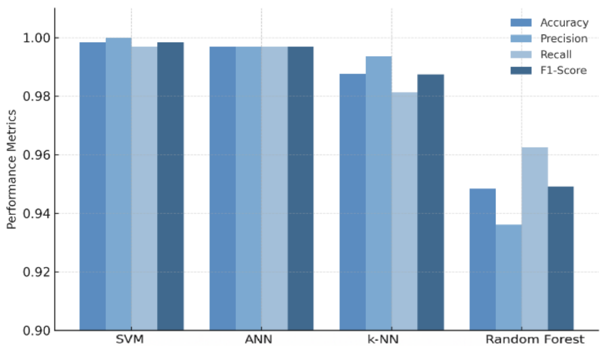

Figure 9. Comparison of classification model performances

Figure 9 visually compares the overall performance of the models, demonstrating that the Support Vector Machine and Artificial Neural Network surpass the other techniques across all evaluation criteria. The Support Vector Machine's consistent and steady outcomes illustrate its durability, whereas the Random Forest's comparatively inferior metrics underscore its restricted adaptation to intricate feature distributions. The aggregated results from confusion matrices and statistical metrics indicate that models optimized for features, particularly Support Vector Machines, are superior at differentiating between defective and flawless samples compared to distance or ensemble-based methods. This result is consistent with previous research in industrial defect detection, where Support Vector Machine exhibited consistently higher accuracy and generalization than other conventional classifiers. Furthermore, its computational efficiency and scalability render it a formidable contender for real-time quality control systems where high precision and minimal latency are essential. In conclusion, although all four models yielded satisfactory classification results, the Support Vector Machine proved to be the most reliable and precise method, closely followed by the Artificial Neural Network, while k Nearest Neighbors and Random Forest functioned as complementary but less robust alternatives. The comparison research verifies that the use of optimal feature extraction and margin-based classification can substantially improve detection accuracy.

4. Conclusion and Future Work

This study presented a hybrid machine learning based approach for industrial defect detection by integrating deep learning driven feature extraction with conventional classification algorithms, namely Support Vector Machine, Artificial Neural Network, k Nearest Neighbors, and Random Forest. The hybrid framework demonstrated remarkable robustness and adaptability, effectively combining the representational power of deep architectures with the interpretability and efficiency of traditional classifiers. Among all evaluated models, the Support Vector Machine achieved the highest overall performance, with an accuracy of 99.84%, precision of 1.0000, and F1-score of 0.9984, followed closely by the Artificial Neural Network, which exhibited balanced and stable metric values.

The confusion matrix analyses confirmed that the hybrid model structure not only enhanced classification accuracy but also minimized misclassification rates, particularly under limited data conditions. The superior performance of Support Vector Machine and Artificial Neural Network underscores the potential of optimization-based and connectionist approaches for reliable defect recognition in complex manufacturing environments. The proposed methodology aligns seamlessly with the Industry 4.0 vision, which emphasizes intelligent automation, cyber-physical systems, and data-driven decision-making. Owing to its high accuracy, low latency, and scalability, the developed hybrid model can be readily integrated into real-time quality control systems, enabling smarter, more autonomous, and more efficient production lines.

Looking ahead, several research directions can further extend the proposed framework. Expanding the dataset with diverse and complex defect categories will allow a more rigorous evaluation of scalability and generalization performance. The incorporation of advanced architectures such as Convolutional Neural Networks, Vision Transformers, and hybrid ensemble mechanisms may further enhance defect detection accuracy and robustness. Moreover, adopting explainable artificial intelligence techniques will provide valuable insight into model decision mechanisms, improving transparency and trust in industrial applications. Future efforts will also focus on deploying the hybrid models in real industrial environments to evaluate their real-time performance in terms of latency, adaptability, and resilience under operational variability. Additionally, exploring multi-modal data fusion, combining visual, thermal, and acoustic inputs, could significantly improve classification reliability. These developments are expected to strengthen the bridge between intelligent machine learning systems and Industry 5.0, fostering human-centric, adaptive, and sustainable manufacturing ecosystems.

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Conflict of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper. All findings, analyses, and conclusions were prepared objectively and independently by the authors.

CRediT Authorship Contribution Statement

Oya Kilci: Conceptualization, Literature Review, Methodology, Software, Data Curation, Formal Analysis, Visualization, Writing – Original Draft.
Murat Koklu: Validation, Supervision, Writing – Review & Editing, and Final Approval.
Both authors contributed to the interpretation of results, revised the manuscript critically for intellectual content, and approved the final version for publication.

Nomenclature

Abbreviation / Symbol	Description
TP	True Positive – correctly classified defected samples
TN	True Negative – correctly classified perfect samples
FP	False Positive – perfect samples incorrectly classified as defected
FN	False Negative – defected samples incorrectly classified as perfect
Accuracy	Ratio of correctly classified samples to the total number of samples
InceptionV3	Deep convolutional neural network used for feature extraction
SVM	Support Vector Machine, Margin-based supervised learning algorithm for optimal class separation
ANN	Artificial Neural Network , Multilayer computational model inspired by biological neural systems
kNN	k Nearest Neighbors Instance-based classifier that assigns labels based on the majority of nearest data points
RF	Random Forest, Ensemble method that aggregates multiple decision trees to improve prediction stability
Hybrid Model	Integration of deep feature extraction with classical machine learning classification
Industry 4.0	A technological paradigm emphasizing automation, digitalization, and intelligent manufacturing systems

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