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Hybrid CNN with transfer learning and MobileNetV2 for advanced multi-class PCB defect detection

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Abstract: Printed Circuit Board (PCB) plays an important role in the world of electronics. Regarding PCBs, manufacturing defects not only worsen the product qualification rate but can also lead to catastrophic failure of the electronic devices themselves. This study introduces a new model to accurately and efficiently detect different types of PCB defects, including spur, open circuit, short, mouse bite, missing hole, and spurious copper. The proposed model presents and then overcomes challenges in detecting PCB defects using a dense layer in a Convolutional Neural Network and advanced digital image processing and augmentation techniques such as contrast, scaling, and rotation. This study is based on the MobileNetV2 framework in proposing a hybrid Convolutional Neural Network scheme that combines the strength of convolutional feature extraction with the beneficial reorganization of features by fully connected layers to enable accurate and efficient detection of common Printed Circuit Board defects. The hybrid Convolutional Neural Network is responsible for classification, while feature extraction is performed through MobileNetV2. The results certify that the proposed model achieves an accuracy of 96%. Moreover, ROC curves provide an AUC measure higher than 0.99 for all types of defects. Comparative results show a substantial improvement in performance over traditional models.
Keywords: *Defect detection, Hybrid convolutional neural network, MobileNetV2, Printed circuit board, Transfer learning.*

1. Introduction

Nowadays, Printed Circuit Boards (PCBs) play an important role in the world of electronics. PCBs are the platforms used to interconnect electronic components and conduct signals among them [1-3]. Electronic hardware and equipment are advancing in the fields of increasing complexity, miniaturization, and density. Therefore, the manufacturing of PCBs is becoming more strict and rigorous. In the PCB production industry, there are issues such as problems with equipment stability or limitations in production processes that result in defects in PCBs. These defects include missing holes, mouse bites, open circuits, short circuits, spurs, and spurious copper [4]. The following is a description of several defects. Missing hole: This occurs when one or more drilled holes (such as vias or component mounting holes) are absent or not properly drilled. This can prevent electrical connections or component insertion and is often due to errors in the drilling process or missing drill data. Figure 1 (a) shows this type of defect. Mouse bite: Mouse bites are small, jagged edges left on a PCB after it has been separated from a panel using perforated breakaway tabs. These rough edges can affect board fitting and may require additional cleaning or filing. Figure 1 (b) shows this type of defect. Open circuit: An open circuit is a break in the intended electrical path, which interrupts current flow. This can result from incomplete copper traces, broken connections, or poor solder joints. Figure 1 (c) shows this type of defect. Short circuit: A short circuit occurs when two or more conductive paths unintentionally connect, often due to solder bridging, excess copper, or design errors. Shorts can cause malfunction or permanent damage to components. Figure 1 (d) shows this type of defect. Spur: Spurs are small, narrow protrusions

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of copper that extend from a trace or pad. They are often caused by over-etching or design errors and can lead to unintended connections or signal noise. Figure 1 (e) shows this type of defect.

Spurious copper: Spurious copper refers to unwanted pieces or fragments of copper left on the board after etching. These slivers can become loose, causing short circuits or interference with signal integrity. Figure 1 (f) shows this type of defect.

These manufacturing defects not only worsen the product qualification rate but can also lead to catastrophic failure of the electronic devices themselves [5]. The implications are more than financial since defective PCBs can lead to system failure, with severe safety implications in critical applications. For instance, in aerospace or medical equipment, even minimal PCB defects can escalate into serious operational failures. Due to this, detection, diagnosis, and mitigation of PCB defects have been active research issues that have led to the development of advanced inspection technologies and manufacturing process optimization methods. Most traditional PCB defect detection methods are carried out through manual visual inspection or rule-based image processing algorithms [6].

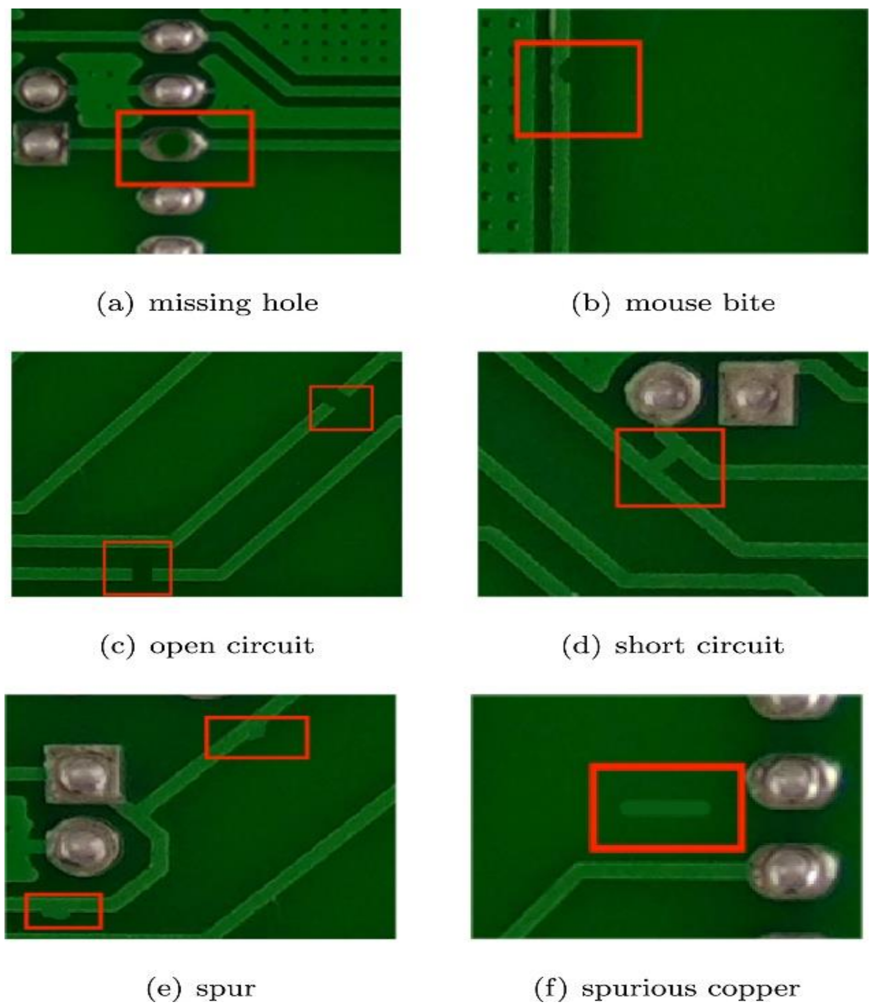

Figure 1.
Common defects in PCBs.

Manual inspection is a simple approach but is only correct and reliable if the inspector has adequate experience and expertise. Furthermore, as PCB designs become more complex, manual inspection becomes much less efficient and is not suitable for modern high-density designs [7]. Like rule-based detection algorithms, which are systematic, they are not good at capturing the diverse patterns of defects such as faint or irregular anomalies, and they are prone to errors in the presence of background interference that is complicated and noisy. These limitations indicate the necessity for more advanced methods to overcome such challenges [8]. As a result, there has been a strong interest from both academic and industrial communities in the development of smart detection methods that are robust, effective, and adaptable to various defect characteristics [9]. Recently, the progress of artificial intelligence technology has been swift and has brought many innovations in various domains, and image processing based on deep learning has become a hot research topic in printed circuit board (PCB) defect detection. Convolutional Neural Networks (CNNs) have been proven to have excellent feature extraction abilities, that is, to extract multi-level semantic information from raw images, making it possible to precisely classify and localize defect patterns that are complicated and abundant in PCB defects. However, when these advanced technologies are integrated into PCB defect detection workflows, detection accuracy and speed are further improved, and new innovative methods and solutions are generated to address longstanding challenges in the field [10]. The adoption of deep learning techniques indicates how they can be used to automate quality control processes and increase the reliability of PCB manufacturing systems. Due to its excellent performance, deep learning technology has been widely used in computer vision tasks, including target detection, image segmentation, and classification. As one of the core models of deep learning, a convolutional neural network (CNN) can gradually extract information from low-level textures to high-level semantics through its hierarchical structure, which is suitable for processing high-resolution PCB defect images [11].

In the field of PCB defect detection, CNN has three advantages: automatic feature extraction, high robustness, and end-to-end training.

1.1. Automatic Feature Extraction

Inspired by this success, Convolutional Neural Networks (CNNs) have proven to auto-learn and discover valuable features directly from raw data in a learning process without an automated feature extraction rule. Typical methods may require a lot of domain knowledge and heavily depend on handcrafted features, which may not be able to completely acquire the (full) complexity of data. On the other hand, CNNs learn adaptive representations that are suitable for the particular task at hand, ranging from low-level features, such as edges and textures, to high-level, such as abstract patterns [12]. It does not rely on knowledge of the domains and significantly improves the systems' efficiency, accuracy, and scalability in working with real industrial world challenges.

1.2. High Robustness

The fact that CNNs can learn from large and diverse datasets makes them extremely robust to defects and environmental condition variations [13]. By training on sample cases, these networks can generalize independently across a broad spectrum of defect samples. CNNs can effectively handle noise, cluttered or complex backgrounds, and subtle defect variations, resulting in reliable performance even in unfavorable and unpredictable environments. Specifically, this robustness is critical for the industrial application of PCB defect detection, where defects vary by form and under various conditions, creating a need for robust yet accurate defect detection.

1.3. End-To-End Training

One of the key advantages of CNNs is that they allow for end-to-end trainable architectures [14]. The networks map input images directly to classification or detection outcomes without requiring explicit lengthy preprocessing steps and human involvement. Such a simplified workflow streamlines the data pipeline, reduces model development complexity, and accelerates the process. Moreover, the end-to-end nature of CNN-based systems enhances scalability, making it effortless for the model to

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generalize to new tasks and datasets. This flexibility is valuable in dynamic industrial environments where defect features may evolve, requiring adaptable and effective solutions [15, 16].

However, the successful functioning of CNN generally relies on the support of large-scale annotated datasets. In PCB defect detection, defect datasets are small and imbalanced, which discourages the application of CNN, and ample calculations are excessively resource-consuming. To solve this problem, transfer learning technology emerged. Transfer learning exploits models pre-trained on large-scale general datasets (e.g., ImageNet) and applies them to targeted tasks by fine-tuning parameters. Lightweight networks, represented by MobileNetV2, are highly suitable for transfer learning scenarios [17, 18]. Low computational cost and high feature extraction capabilities enable them to remain effective even in small dataset scenarios [19].

This approach minimizes training time and effort and democratizes access to cutting-edge machine learning techniques, enabling researchers and practitioners with limited computational resources to train high-performing models [20, 21]. The conservation of resources is particularly valuable in industrial and academic environments, where efficiency and affordability take top priority. The reduced training time facilitates increased iterative experimentation in research settings, with the potential to experiment with various model architectures and hyperparameter tuning with far less time investment. Combining transfer learning and deep learning architectures results in substantial improvements in accuracy and computational efficiency.

Deep neural network models, particularly convolutional neural networks (CNNs), excel at extracting hierarchical, high-dimensional features directly from raw image data, capturing intricate details such as edges, textures, and abstract patterns [22, 23]. Transfer learning enhances this capability by providing a pretrained foundation of extracted features, reducing the time and computational cost of training from scratch. This accelerates model convergence and allows practitioners to construct high-performing models with relatively limited computational resources.

2. Materials and Methods

2.1. Dataset Preparation

2.1.1. Data Source and Description

The quality and diversity of the dataset are the basis for training deep learning models. The dataset for this study focuses on six typical defects in PCB manufacturing: missing holes, mouse bites, open circuits, short circuits, spurs, and spurious copper. The following link provides datasets related to these six types of PCB defects: https://www.kaggle.com/datasets/dajianwan/pcbdatasets. These defects exhibit different physical manifestations in actual industrial scenarios. For example, missing holes usually appear as the absence of regular geometric patterns, while rat bites and burrs present irregular edge features. To better simulate real-world application scenarios, data samples were collected from multiple PCB manufacturers, including samples produced under different processes and conditions. This diversity enhances the model's adaptability in real environments. During the data annotation process, standard image annotation tools were used, and experts familiar with PCB defect detection performed the annotations. The defect type and the precise bounding box position of each defect are provided as annotation content. This information is stored in a structured manner within XML format annotation files, which can be used later for data pre-processing and cropping. Additionally, to ensure the representativeness of the test set, the data was split using a stratified sampling strategy to maintain the same distribution ratio of each defect category in both the training and test sets.

2.1.2. Data Trimming and Normalization

The process of preprocessing input images is important in deep learning-based PCB defect detection models to improve their training performance and efficiency. As original images usually contain a lot of background information that is not useful to the model learning, cropping the image only to contain defective regions is a good way to boost the learning efficiency of the model. Bounding box annotations in the dataset are used to carry out the image cropping. Python's OpenCV library is used to automatically crop the operation to ensure accuracy and consistency in the dataset.

After cropping, all images are resized to a uniform resolution of 128×128 to ensure that input sizes are consistent. The resolution represents a balance between computational load and feature retention. High resolution incurs more computational load, which may strain hardware, especially in the current era of supercomputers, while lower resolution loses critically important defect features needed for classification. The chosen resolution also ensures that computational demands are manageable and detail is retained.

Another important stage in deep learning workflows is normalizing images. Normalization decreases the impact of varying numerical ranges on training gradient updates by scaling pixel values to a consistent range [0, 1]. Normalization stabilizes and improves the optimization process and enables faster convergence. Normalization also avoids amplifying numerical differences between samples and thus minimizes variance, and the model becomes less sensitive to outliers. This results in a more stable gradient descent algorithm, improving generalization and test-time performance.

2.1.3. Data Augmentation

In industrial scenarios, uneven distribution of data categories is a common problem. This study designed a series of data enhancement strategies to improve the model's learning ability for small sample categories. Unlike conventional geometric transformations, experiments were conducted with targeted extended designs based on the characteristics of PCB defects.

2.1.3.1. Random Rotation

The rotation transformation is intended to replicate angular errors that are ubiquitous in PCB boards due to assembly errors in real-world production processes. The model is exposed to a wider range of orientations by applying random rotations in the range [−20°, 20°], which helps generalize unseen data. Experimental results show that this range of random rotation enhances model performance to a point robust to defects at all angles.

2.1.3.2. Panning and Scaling

Defect samples are generated at random locations in the image and presented at random scales by panning and scaling. The effect augments the spatial and scale-related features available to the model during training, increasing variation in defect distributions whilst improving the model's robustness to variations in defect distribution.

2.1.3.3. PCB Defects Inheritance

Vertical and horizontal flipping are impactful and meaningful, since numerous PCB defects are geometrically symmetric by inheritance. In this regard, we apply mirroring transformations to augment the dataset.

2.1.3.4. Uneven Condition

There are some uneven conditions that commonly occur during PCB imaging, such as uneven shooting or uneven lighting. These conditions obscure defect patterns. To address this issue, brightness and contrast are adjusted to simulate images captured under different lighting environments. This augmentation method enables the model to learn from a broader set of lighting variations, improving its ability to detect defects under various real-world lighting conditions.

During data enhancement, the Image Data Generator module of the Keras library was used. The built-in functions of the method support several enhancement methods and can be used seamlessly with the training process.

2.2. Model Design

2.2.1. Selection of Transfer Learning Model

Transfer learning is highly suitable for PCB defect detection when dealing with small sample size problems. Traditional training methods are less effective with PCB defect datasets than with general-purpose datasets because the datasets tend to be less diverse and smaller. Transfer learning fills this gap by providing robust feature representations that can be fine-tuned for PCB defect-specific characteristics, such as fine textures or geometric patterns.

Transfer learning demonstrates advantages in industrial applications by utilizing MobileNetV2 as a representative of lightweight convolutional neural networks. Its modular design, which includes depthwise separable convolutions and inverted residual blocks, achieves high computational efficiency without compromising feature extraction capabilities. This efficiency makes MobileNetV2 highly suitable for real-time and resource-constrained environments, such as automated PCB inspection systems. The study presents an effective approach to obtaining accurate and efficient PCB defect detection by combining the powerful yet lightweight structure of MobileNetV2 with the benefits of transfer learning.

2.2.2. Hybrid Convolutional Network Architecture

This study was based on the MobileNetV2 framework in proposing a hybrid CNN scheme that combines the strength of convolutional feature extraction with the beneficial reorganization of features by fully connected layers. The architecture is detailed as follows.

2.2.2.1. Convolution Part

This part uses the pre-trained weights of MobileNetV2 to extract the basic features of the input images, such as textures, edges, etc. Although these features are low-level, they are considered strong for detecting small defects in PCB images.

2.2.2.2. Architecture of a Global Pooling Layer

This layer reduces the high-dimensional convolutional feature maps to a small vector. In fact, this layer summarizes the most salient features across its spatial dimensions to offer a condensed but complete representation of the input image without losing essential information in the transformation. It also lowers computational complexity, enabling downstream processing to be done efficiently.

2.2.2.3. Fully Connected Custom Layer

This is a fully connected 3-layer network designed to adapt the extracted features to the specific task of PCB defect classification. Such high-dimensional feature transformation is enabled by these layers, which have 128, 256, and 512 neurons, respectively. Each layer is designed to enhance high discriminative capabilities. The fully connected layers reorganize and refine the feature representations, allowing the model to focus on defect-specific characteristics and improve discrimination among different defect categories. Furthermore, the fully connected layers strengthen the depth of feature learning through their hierarchical structure, enabling the model to handle complex classification tasks.

2.2.2.4. Advanced Regularization Techniques

A mechanism for regularization is incorporated to stabilize training and prevent model overfitting. Fully connected layers are interspersed with Batch Normalization layers to normalize feature distributions (reducing the internal covariate shift) and speed up convergence. Moreover, dropout layers are incorporated to deactivate neurons randomly during training with stochasticity in learning. This simplifies the model and improves the generalization performance while having robust behavior on unseen data.

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2.2.2.5. Softmax Activation Function

A final classification is made using the Softmax activation function, which provides a probability distribution over the six predefined defect categories. It guarantees that the classification result for any input sample is clear and interpretable. The use of Softmax offers a probabilistic understanding of the model predictions, which is useful in real-life applications. This enables these architectural components to work together to create a highly efficient and accurate PCB defect detection model capable of overcoming the unique challenges of this domain.

2.2.3. Model Optimization Strategy

Achieving good performance and generalizability from deep learning models is a critical step, which is best accomplished by optimizing the model. The cross-entropy loss function, used by the Categorical Cross-Entropy, guides the model optimization process. This function calculates the Kullback-Leibler (KL) divergence between the predicted probability distribution and the true label distribution. The approach aims to align the model's output with the ground truth, focusing on correct classification while also being effective with imbalanced and multi-class datasets. An adaptive learning rate schedule is employed to enhance training efficiency. The initial learning rate is set at 0.001, facilitating rapid convergence from a good starting point. A combination of L2 regularization and Dropout is used to mitigate overfitting and improve the model's generalization ability. L2 regularization constrains the weights of the model, keeping their magnitude small and producing a solution less likely to overfit the data. Dropout randomly drops neurons during training, adding noise to the network and encouraging the model to learn robust feature representations. Together, these regularization techniques produce a well-regularized model that performs effectively on unseen data.

The experiment then divided the training into two stages: in the first stage, the low-level convolution weights of MobileNetV2 are frozen, and only the fully connected layers are trained; in the second stage, the high-level convolution layers are unfrozen for fine-tuning to utilize the connections of the pre-trained features and the target task features.

2.3. Experimental Setup

2.3.1. Dataset Division

The dataset is divided into a training set and a test set in an 80:20 ratio, ensuring a balanced allocation for model development and performance evaluation. To further enhance the reliability of the training process, a 5-fold cross-validation technique is applied within the training set.

2.3.2. Comparative Experimental Design

To comprehensively evaluate the model performance, this study conducted comparative experiments with the BP neural network. The input of the BP neural network is a manually extracted feature vector, the network structure is a single hidden layer multi-layer perceptron (MLP), and the activation function is ReLU. The experimental results demonstrate that the classification accuracy of the BP neural network is significantly lower than that of the transfer learning model, especially in high-dimensional feature learning and complex pattern recognition.

3. Results and Discussion

Based on the rules of transfer learning, the developed Hybrid CNN model outperformed other models in the PCB defective classification task. The model's high overall test set accuracy was 96%, which is much higher than a BP neural network (comparison model), with 55%. This remarkable improvement is attributable to the fact that the Hybrid CNN can extract and utilize features from complex datasets more efficiently than the CNN.

The stability of the Hybrid CNN is also confirmed by a thorough analysis of the classification report and the confusion matrix. In most categories of defects, the model exhibited high precision and recall, indicating its strong generalization ability. This demonstrates that the Hybrid CNN not only accurately classifies common defect types but also performs consistently across various and challenging categories.

More specifically, the difference in performance between the Hybrid CNN and the BP neural network is quite significant, especially in classifying the complex defect categories. For simple defect categories like missing holes, the BP neural network was sufficient, but performance was very poor for more complex categories, such as burrs and spurious_copper. These results indicate the inherent constraint of the BP neural network's ability to extract features that cannot be distinguished by the network and cannot sufficiently describe the complicated and high-dimensional features necessary for discriminating intricately complex defects.

Whereas the Hybrid CNN leverages the fact that deep feature extraction of convolutional layers and task-specific flexibility brought about by transfer learning can be fully concurrent. It is able to effectively detect simple as well as complex defects, and thus offers a more comprehensive and better solution to the problem of PCB defect detection. The practical significance and industrial relevance of the Hybrid CNN in enhancing the accuracy and efficiency of automatic quality control systems are reflected in these results.

3.1. Classification Performance of Hybrid CNN Model

As per the classification report, the Hybrid CNN demonstrates a very consistent performance in terms of precision and recall across the six defect categories in the test set. Its F1 score reflects the overall effectiveness of the model in the classification task, as analyzed below:

1. The F1 value of the Missing_hole category defect is spot-on at 1.00, indicating the model achieves errorless detection for every sample from this category. Such high accuracy results from crisp and well-defined features belonging to Missing_hole defects, such as defined boundaries and very distinguishable appearances. Additionally, the training set has a good amount of sample support for this type of defect, and the model has enough data to learn and generalize well. These factors contribute to the model classifying missing_hole defects perfectly with high precision and recall.

2. For the Mouse_bite category, the model has a precision of 0.91 and a recall of 0.98, indicating that it can strongly identify these defects with few false negatives. Nevertheless, a few of these false positives appear to be based on similarities in local edge characteristics between Mouse_bite defects and other categories, like burrs. When these similarities exist, the model can misclassify some samples. Overall, the performance is quite high. However, should the false positives be addressed through enhanced feature differentiation or improved edge-based learning, the accuracy can be improved for this category.

The model is able to achieve F1 scores of 0.98 for both Open_circuit and Short defect categories, which indicates the model's stability and precision in defect detection. The deep learning model is likely to perform well due to its ability to accurately capture localized features, such as breakpoints in open-circuit defects or short-circuit connections in Short defects. These specific characteristics enable the model to maintain consistent and steady performance in both categories, even in complex cases.

4. The Spur F1 score is 0.91, which is slightly lower than other categories. We further analyzed the Spur defect samples and found that some of them had a recall rate of 0.85 with fuzzy morphology of features or partial overlap with Mouse_bite. The model can be further improved in the future in terms of recognition ability for this category by increasing the diversity of the samples or by optimizing the feature extraction module.

5. The classification ability of the model is demonstrated by the fact that it achieves an F1 score of 0.97 for the Spurious_copper category. Nevertheless, there are still a few misclassifications that might occur, possibly because of overlaps with other defect categories or noise in the dataset. These minor errors do not impact the performance of the model in identifying Spurious_copper defects. The corresponding classification capabilities of the model can be further refined, for example, through more sophisticated regularization techniques or by augmenting the training data to eliminate these remaining misclassifications. From a macro-indicator perspective, the weighted Hybrid CNN model has an average F1 score of 0.96, which indicates that it can still perform excellent classification on a class-imbalanced

dataset. The strong robustness of the model stems from the pre-training characteristics of transfer learning prediction, which enables it to achieve efficient feature expression on limited data.

Figure 2 shows partial prediction results of the Hybrid CNN model.

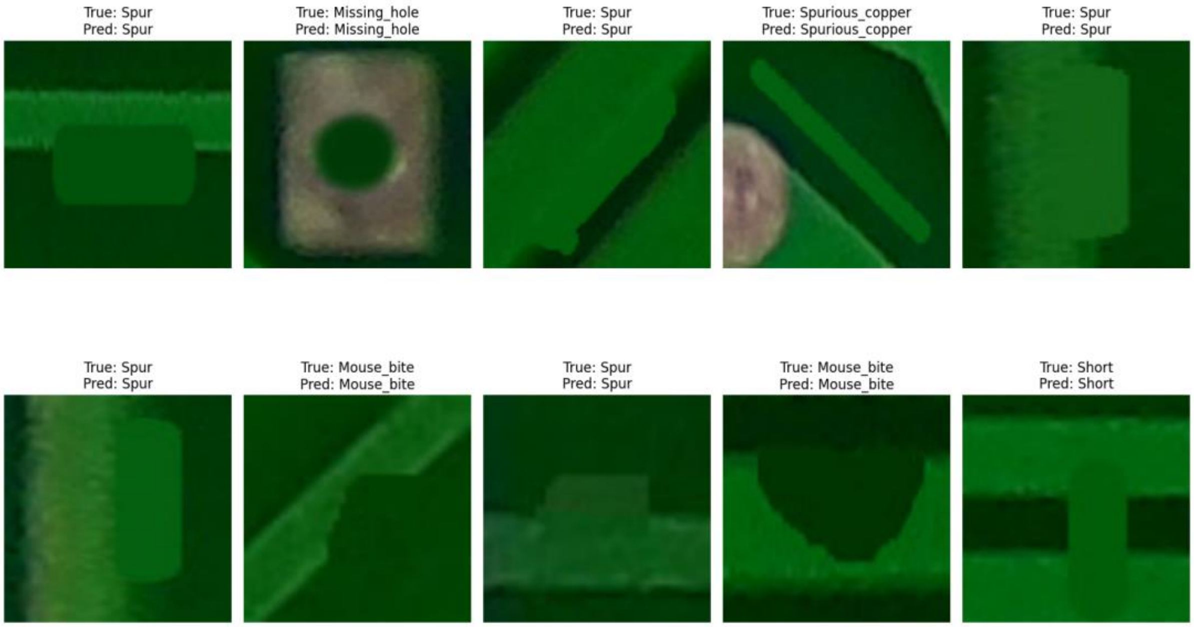

Figure 2.
Partial prediction results of the Hybrid CNN model.

3.2. Classification Performance of BP Neural Network

In contrast, the performance of the BP neural network on complex defect categories is significantly insufficient. Although it performs well on the Missing_hole category (F1 score of 0.99), the F1 scores of other categories are below 0.70, and even Open_circuit and Spur are close to 0, reflecting the limited ability of the BP neural network to capture high-dimensional features.

3.2.1. Judging from Specific Performance

1. The recall rate for the Mouse_bite defect category reaches 0.91, suggesting that the BP neural network successfully identifies most instances of this defect type. Nevertheless, the precision rate is only 0.46, which indicates a high false positive rate. The imbalance here implies that the network overpredicts this category by misclassifying samples of other defect types as Mouse_bite. Such overprediction may be a result of the model being unable to perform well in differentiating the subtle features that distinguish Mouse_bite defects from categories similar to it, e.g., Spur or burrs. Both the high false detection rate and the poor feature extraction ability of the BP neural network reduce the model's reliability, and therefore, the model should not be used if the high false detection rate cannot be reduced.

2. As can be seen, the BP neural network almost completely fails to classify the open-circuit and spur defects, which indicates that it is not suitable for these categories. Often, these defects present with complex and variable morphological characteristics, requiring the extraction of high-dimensional features, which tend to be unmanageable by the BP neural network. These defect types demonstrate intricate patterns that the single-layer perceptron architecture and manually extracted features used in the BP neural network cannot capture well, which is why the poor performance is evident.

3. The Spurious_copper category has an F1 score of 0.46, which is very close to random classification. The low score indicates that the BP neural network is not very effective in discriminating

Spurious_copper defects from other categories. While the network may have learned some basic features of this defect type, it does not possess the robustness to consistently and accurately classify these defects, especially in the presence of noise or overlapping features with other categories, thus providing only a slight improvement over random performance.

One limitation of BP neural networks in learning features and another proof of the superiority of transfer learning models in complex tasks is reflected in these results.

The Hybrid CNN model performed exceptionally well in all defect categories, with an average F1 value of 0.96. It achieved perfect classification, especially on simple defects such as a Missing hole (F1=1.00), and also performed well on complex defects such as a Spur (F1=0.91). The BP neural network has limited effectiveness on simple defects like a Missing hole (F1=0.61) and is almost unable to classify complex defects such as an Open circuit and a Spur (F1≈0). The table illustrates that the hybrid CNN is significantly superior to the BP neural network in classification performance, especially with obvious advantages when dealing with complex defects.
Figure 3 shows some prediction results of the BP neural network model.

Table 1 shows the comparison of classification performance between the hybrid CNN model and the BP neural network.

Table 1.
Classification Performance Comparison between Hybrid CNN and BP Neural Network.

Classification Performance Analysis (F1 Value)	**Missing hole**	**Mouse bite**	**Open circuit**	**Short circuit**	**Spur**	**Spurious copper**
Hybrid CNN Model	1.00	0.94	0.98	-	0.91	0.97
BP Neural Network	0.61	-	Not suitable	-	Not suitable	0.46

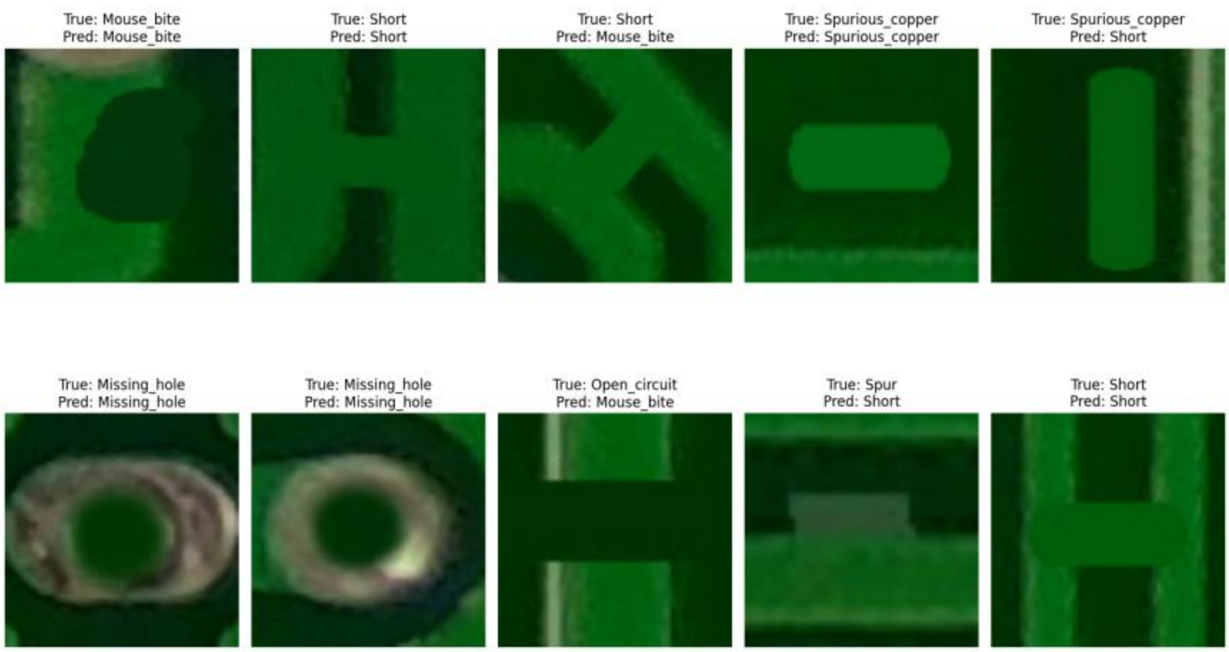

Figure 3.
Sample of prediction results of the BP Neural Network.

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3.3. Confusion Matrix of Hybrid CNN Model

The confusion matrix provides a detailed insight into the classification performance of the Hybrid CNN model across specific defect categories, highlighting both its strengths and areas for improvement:

1. The primary diagonal of the confusion matrix displays consistently high values, signifying the model's exceptional accuracy in correctly classifying the majority of samples within their respective categories. For instance, the diagonal values for the Missing_hole and Spurious_copper categories are 112 and 96, respectively, each accounting for 100% of the total samples within these categories. These results confirm the model's ability to reliably detect certain defect types with absolute accuracy, particularly for categories with distinct and easily recognizable features.

2. The off-diagonal elements, representing misclassified samples, are sparse, indicating that the model demonstrates robust discrimination across most categories. However, the misclassifications observed are primarily concentrated between the Mouse_bite and Spur defect types. A closer examination of these samples reveals that the edge features of these two defect types exhibit substantial visual similarities, especially along their feature boundaries. This overlap in feature representation may lead to confusion in the model when distinguishing between these categories. Figure 4 presents a chaotic matrix regarding the hybrid CNN model.

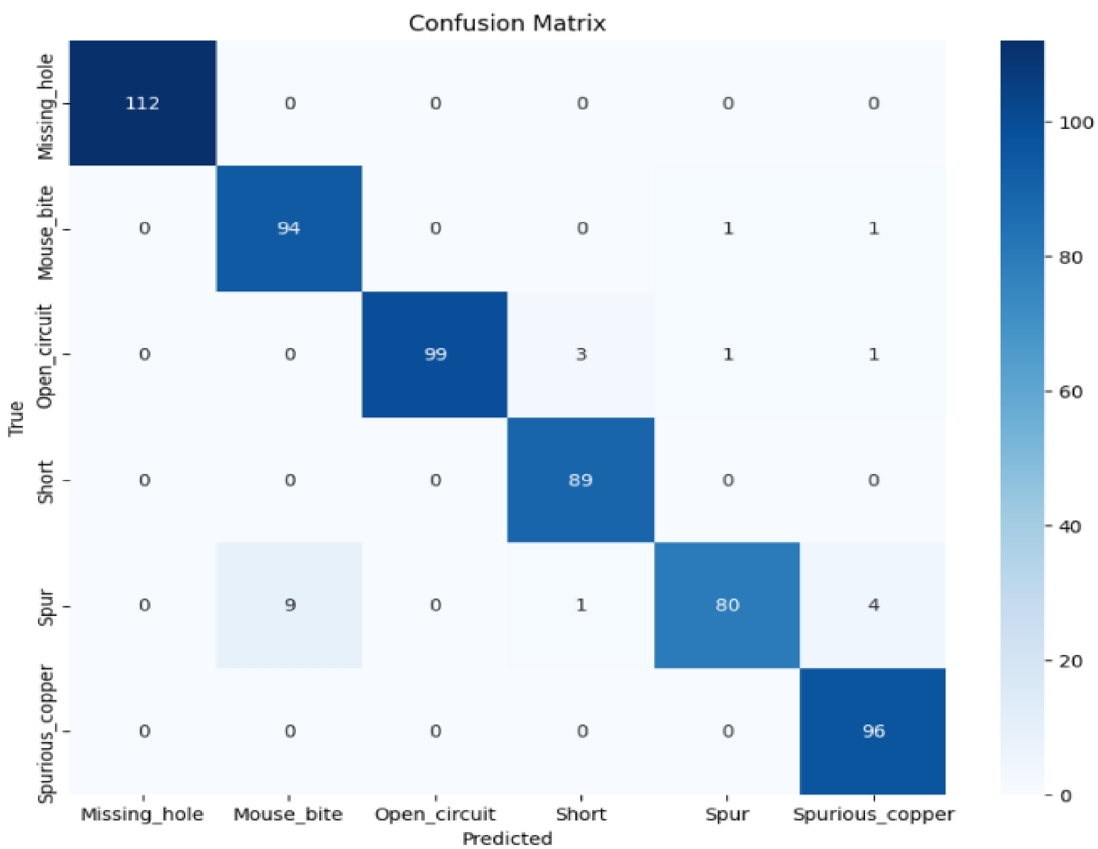

Figure 4.
Chaotic matrix display of the Hybrid CNN model.

3.4. Confusion Matrix of BP Neural Network

However, as shown in Figure 4, the confusion matrix of the BP neural network exhibits significant deficiencies in classification performance, particularly in complex PCB defect detection tasks. It is important to note that:

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1. Most defect categories are significantly lower for the main diagonal elements, which represent correctly classified samples. For example, the main diagonal value for Open circuit is 0, meaning that there is no correct classification of any samples in this category. This result shows the inability of the BP neural network to learn and represent some features distinguishing certain defect types. Unfortunately, the network is unable to achieve successful classifications for Open circuit defects, which are known to be high-dimensional and intricate representations.

2. There are high values for the off-diagonal elements, which indicate that there is significant misclassification between categories. One such example is the Spur defect category, in which most samples are misclassified as Short or Spurious_copper. This result suggests that the BP neural network has difficulty classifying between defect types that have overlapping or similar features, such as edge patterns or texture variations. Since the model relies on manually engineered features and has a shallow architecture, it cannot capture the nuances and complexities between defect categories that are closely related.

The phenomenon in Figure 5 indicates that it is difficult for the BP neural network to effectively learn the complex distribution of PCB defect features, and the classification results are very different.

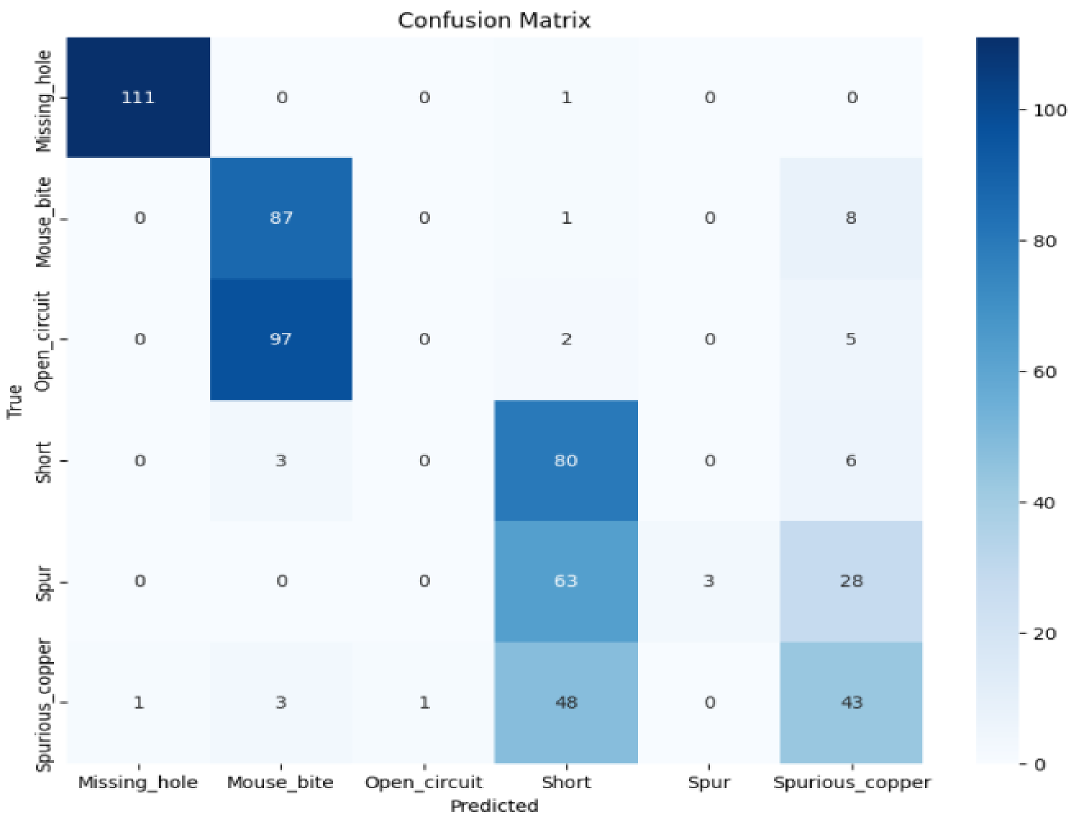

Figure 5.
Chaotic matrix display of BP Neural Network.

The diagonal value of the confusion matrix of the Hybrid CNN model is high, indicating accurate classification. Only a few samples were misclassified between the Mouse bite and Spur categories due to feature similarity. The diagonal values of the confusion matrix of the BP neural network are generally low. Especially, the classification of Open circuit defects completely fails (the diagonal value is 0), and misclassification is widespread (for example, a Spur is misjudged as Short or Spurious copper). The table

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illustrates that the classification stability of the Hybrid CNN is significantly higher than that of the BP neural network, and the latter has difficulty distinguishing defect categories with similar features.
Table 2 presents the comparison of the confusion matrix between the hybrid CNN and the BP Neural Network.

Table 2.
Comparison of the Confusion Matrix between Hybrid CNN and BP Neural Network.

Analysis of the Confusion Matrix		**Missing hole**	**Mouse bite**	**Open circuit**	**Short circuit**	**Spur**	**Spurious copper**
Hybrid CNN Model	Diagonal	High values	High values	High values	High values	High values	High values
	Off-diagonal	Low confusion	Robust	Robust	Low confusion	Robust	Robust
BP Neural Network	Diagonal	Low values	0	Low values	Low values	Low values	Low values
	Off-diagonal	high values	high values	high values	high values	high values	high values

3.5. Training Characteristics of Hybrid CNN

The loss and accuracy curves clearly show that the training process of the Hybrid CNN model is effective, and the model exhibits robust convergence behavior.

3.5.1. Loss Curve

The training loss shows a very quick decrease in the first 10 epochs, as this indicates that the model is able to quickly pick up on the major information from the dataset. The model's architecture is able to extract meaningful patterns from the input data, thus leading to the swift learning phase. Then, after this brief descent, the loss stabilizes around 20 epochs, indicating that the model has reached a plateau in learning and that training has been sufficiently completed without overfitting.

3.5.2. Accuracy Curve

The accuracy curve reveals that the validation set accuracy steadily improves throughout training, ultimately converging to approximately 96% in the later epochs. This high validation accuracy aligns closely with the test set performance, confirming that the model generalizes well to unseen data.

Figures 6 and 7 present the loss curve and accuracy curve of the chaotic matrix of the Hybrid CNN model, respectively.

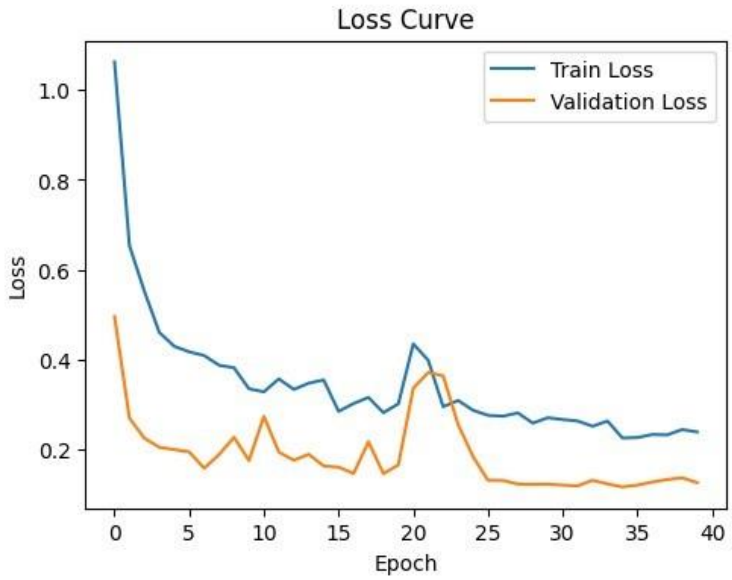

Figure 6.
Loss curve of the chaotic matrix of the Hybrid CNN.

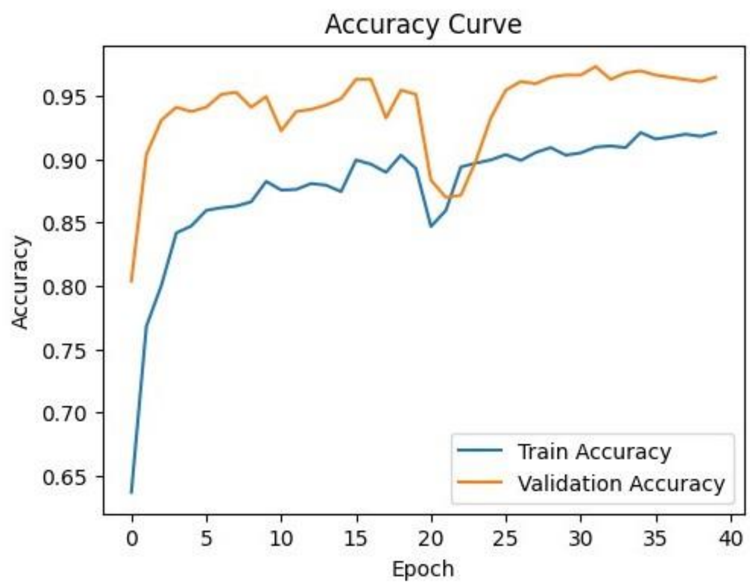

Figure 7.
Accuracy curve of the chaotic matrix of the Hybrid CNN.

The convergence property also benefits from the efficiency of pre-trained weights transfer learning, which shortens the time to reach a convergence state. On the other hand, the introduction of Dropout and regularization technology also significantly decreases the risk of overfitting of the model.

3.6. Training Characteristics of BP Neural Network

The training curve of the BP neural network is highly unstable and exhibits poor learning dynamics compared to the model's ability to learn the complexities of PCB defect detection tasks.

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3.6.1. Loss Curve

The loss curve shows a very distinct difference between the training and validation performance. The first stage of the training loss declines steadily, indicating that the model is learning from the training data. However, the last stage of validation loss begins to rise, which is a sign of overfitting, such that the model becomes too specialized to the training data and performs poorly on unseen data in general. The poor generalization ability in the validation set hints at the BP neural network's inability to learn features that are indicative of the overall defect patterns in the dataset.

3.6.2. Accuracy Curve

The accuracy curve for the validation set presents the model's inability to learn further. The validation accuracy increases for the first time until approximately 55% after which it plateaus and remains stagnant until the end of the training process, with no noticeable improvement in later epochs. The model fails to extract higher-level or hierarchical features, which are required to distinguish between the complex defect categories, thus resulting in this stagnation. This also implies that, while the shallow architecture of the BP neural network and manual extraction of features are not enough to handle the high-dimensional and intricate defective data.

This phenomenon reflects the inadaptability of BP neural networks to high-dimensional input data, and its structure is too simple to learn the complex characteristics of PCB defects, as shown in Figures 8 and 9.

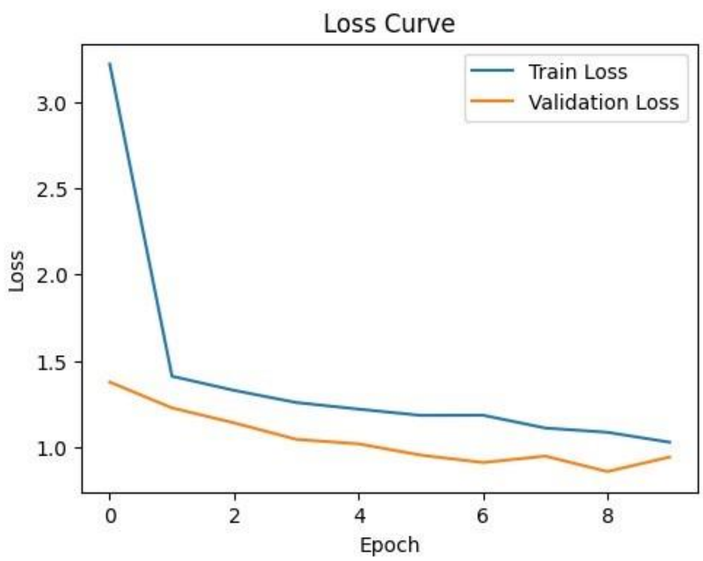

Figure 8.
Loss curve of the chaotic matrix of the BP Neural Network.

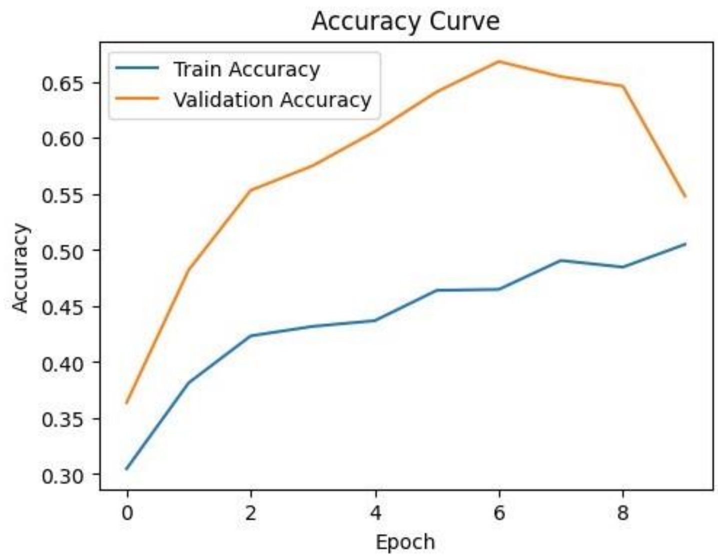

Figure 9.
Accuracy curve of the chaotic matrix of the BP Neural Network.

The loss curve of the Hybrid CNN model converges rapidly and stably. The accuracy rate of the validation set reaches 96%, and there is no overfitting phenomenon, thanks to the pre-training weights and regularization techniques. The loss curve of the BP neural network shows that the training loss decreases but the verification loss increases, and the verification accuracy rate stagnates at 55%, indicating that the model is overfitted and unable to learn high-dimensional features. The table illustrates that the training process of the Hybrid CNN is efficient and has strong generalization ability, while the BP neural network is limited due to its simple structure and manual feature extraction.

Table 3 presents a comparison of loss analysis and accuracy between the hybrid CNN and the BP neural network.

Table 3.
Comparison of Loss and Accuracy curves between Hybrid CNN and BP Neural Network.

Analysis of loss and accuracy iteration curves (Training Characteristics)		
Hybrid CNN Model	Loss curve	The model has reached a plateau in learning, and training has been sufficiently completed without overfitting.
	Accuracy curve	The model generalizes well to unseen data
BP Neural Network	Loss curve	Inability to learn features that are indicative of the overall defect patterns in the dataset.
	Accuracy curve	The shallow architecture of the BP neural network and manual extraction of features are not sufficient to handle high-dimensional and intricate defective data.

3.7. ROC Curve Analysis

3.7.1. ROC curve of hybrid CNN

Figure 10 illustrates the ROC (Receiver Operating Characteristic) curve of the Hybrid CNN, demonstrating its exceptional ability to distinguish between six defect categories in PCB images. The AUC (Area Under the Curve) values for all categories exceed 0.99, highlighting the model's outstanding classification performance across diverse defect types. This high level of accuracy indicates that the model maintains excellent sensitivity and specificity, effectively balancing the trade-off between true positive and false positive rates across all categories. Notably, the AUC values for Missing_hole and Spurious_copper are close to 1.00, suggesting that the model's classification performance for these two defect types is nearly perfect.

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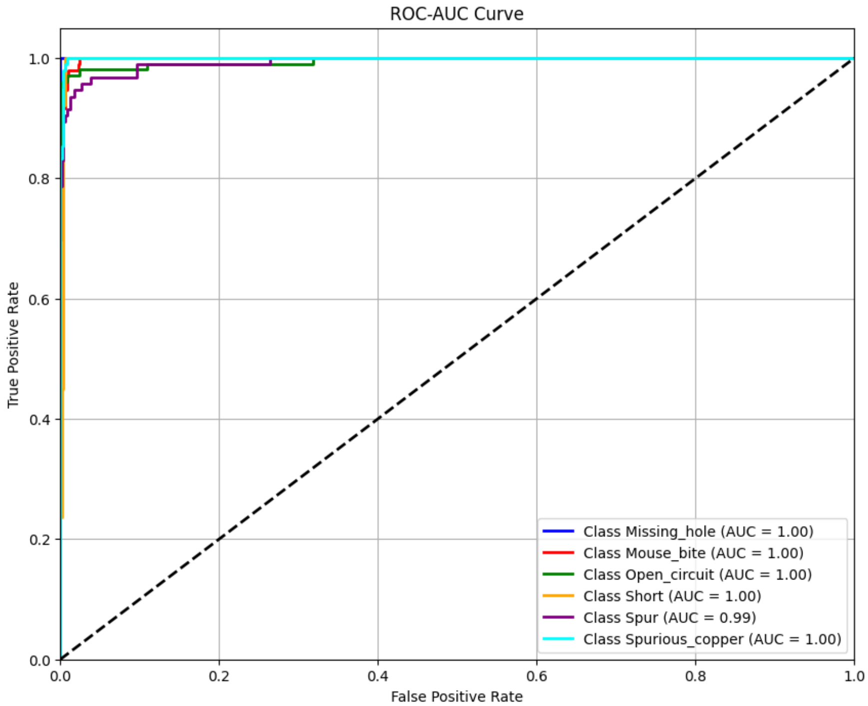

Figure 10.
Chaotic matrix of the Hybrid CNN model.

3.7.2. ROC Curve of BP Neural Network

The ROC curve of the BP neural network reflects significant shortcomings. For instance, the AUC values of Mouse_bite and Spurious_copper are not ideal, as they are near 0.85. This implies that the BP neural network is not able to effectively learn the characteristic distribution of these two types of defects, as shown in Figure 11.

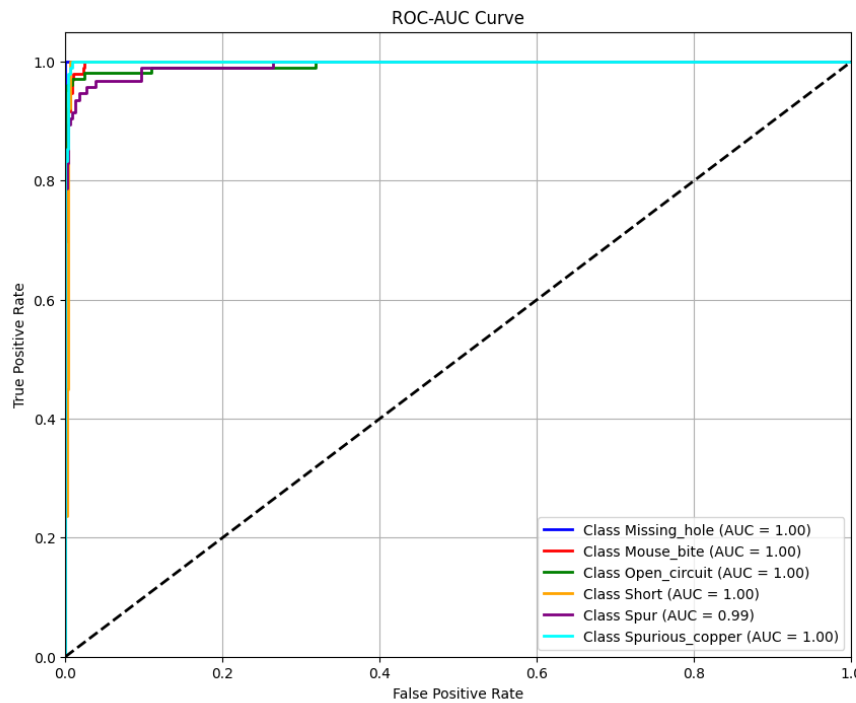

Figure 11.
Chaotic matrix of BP Neural Network.

Table 4 presents a comparison of ROC curve analysis between the hybrid CNN model and the BP neural network.

Table 4.
Analysis comparison of ROC curves between Hybrid CNN and BP Neural Network.

Analysis of ROC curves	
Hybrid CNN Model	Exceptional capability to distinguish defect categories. The better AUC values, excellent sensitivity, and specificity.
BP Neural Network	The ROC curve has shortcomings: the AUC values are not ideal; it is not able to well learn the characteristic distribution of these two types of defects.

The loss curve of the Hybrid CNN model converges rapidly and stably. The accuracy rate of the validation set reaches 96%, and there is no overfitting phenomenon, thanks to the pre-training weights and regularization techniques. The loss curve of the BP neural network shows that the training loss decreases but the verification loss increases, and the verification accuracy rate stagnates at 55%, indicating that the model is overfitted and unable to learn high-dimensional features. The table illustrates that the training process of Hybrid CNN is efficient and has strong generalization ability, while BP neural network is limited due to its simple structure and manual feature extraction.

To further demonstrate the effectiveness of the proposed method, Table 5 presents a comparison of the classification performance (F1-score) between the proposed Hybrid CNN model and the traditional BP Neural Network across six typical PCB defects. It is evident that the Hybrid CNN has achieved significant improvements across all defect types, with an average F1-score reaching 0.96, substantially higher than the 0.51 obtained by the BP neural network. This result underscores the outstanding accuracy, robustness, and generalization ability of the Hybrid CNN model in PCB defect classification tasks.

Table 5.
Performance (F1 Score) comparison of the hybrid CNN and the BP Neural Network.

Defect Category	Hybrid CNN (F1-score)	BP Neural Network (F1-score)
Missing hole	1.00	0.61
Mouse bite	0.94	0.61
Open circuit	0.98	--
Short circuit	0.98	--
Spur	0.91	--
Spurious copper	0.97	0.46
Average	0.96	0.51

4. Conclusion

This study adopts a new type of hybrid convolutional neural network (Hybrid CNN) method based on the principle of transfer learning, aiming to solve common problems in the defect detection of printed circuit board (PCB) manufacturing. By combining the pre-trained MobileNetV2 architecture with a custom fully connected layer, the proposed model achieves a strong balance between efficiency and accuracy, and is particularly suitable for the classification of six types of PCB defects. This enables the model to fully leverage the advantages of transfer learning by integrating pre-trained features and architectures designed for task requirements, and effectively address the unique demands of PCB defect detection.

Through a large number of experiments and verifications, this method is superior to the traditional BP neural network in terms of classification accuracy, robustness against diverse defects, and generalization ability on different datasets. The above-mentioned advantages further highlight the practical application value and promotion potential of this method.

The results of this study also emphasize the adaptability and scalability of deep learning methods in industrial applications. These advancements will accelerate the intelligent transformation of the electronics manufacturing industry and provide innovative solutions for quality control in various industrial fields. Through the coordinated development of data, models, and hardware, future research in this field is expected to completely transform the industrial quality assurance system, drive operational efficiency and product reliability to new heights, thereby enhancing PCB inspection efficiency, reducing production costs, and strengthening enterprise competitiveness.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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