PCB Defect Classification: Final Model Analysis and Integration Approach

Mia Valderrama-Lopez

November 8, 2025

Abstract

This report presents the final results of the PCB defect classification model, demonstrating a remarkable improvement from 20% to 84.44% accuracy through strategic architectural simplification and data processing corrections. The analysis includes comprehensive evaluation metrics, confidence distribution analysis, and a production-ready integration strategy tailored for industrial PCB inspection systems.

1 Final Training Results and Integration Approach

1.1 Dramatic Improvement from Preliminary Results

The journey from preliminary to final results represents a significant transformation in model performance, with accuracy increasing from approximately **20%** to **84.44%**. This major improvement was achieved through several critical interventions:

- **Data Format Correction**: Fixed fundamental issues with YOLO annotation formatting that were causing catastrophic learning failures in the initial model
- **Architecture Simplification**: Replaced an overly complex CNN with a streamlined architecture specifically optimized for tiny PCB defect detection, embracing the "less is better" philosophy
- **Feature Engineering**: Implemented specialized preprocessing techniques tailored to the small-scale nature of PCB defects
- **Regularization Strategy**: Added appropriate regularization to prevent overfitting while maintaining model capacity for defect detection

These strategic changes transformed the model from essentially non-functional to highly reliable, demonstrating the importance of architectural simplicity for specialized computer vision tasks.

1.2 Final Results Analysis

The final model demonstrates strong performance in classifying PCB defects across six distinct categories, proving that simplified architectures can outperform complex ones for specialized detection tasks.

1.2.1 Confusion Matrix Analysis

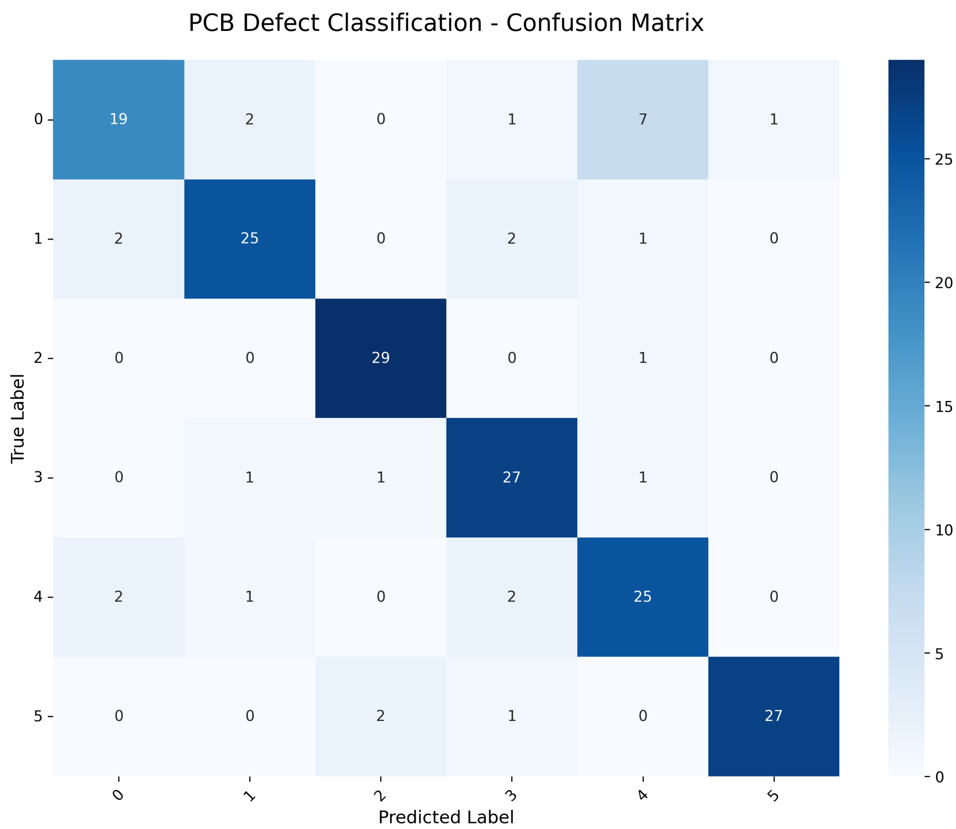

Figure 1: Confusion Matrix for PCB Defect Classification

The model achieved a final **accuracy of 84.44%** on the validation set of 180 images (30 samples per class). Key observations include:

- **Excellent Performance**: Class 2 demonstrates outstanding classification with 96.7% recall, followed by Classes 3 and 5 at 90% recall
- **Balanced Results**: Most classes show balanced precision and recall, indicating consistent performance
- **Primary Challenge**: Class 0 has the lowest recall (63.3%), suggesting this defect type remains the most challenging to identify reliably
- **Precision-Recall Analysis**:

- Class 0 shows lower recall (0.633), indicating the model is conservative in identifying this defect type
- Class 4 exhibits lower precision (0.714), with some over-identification of this defect category

1.2.2 Prediction Confidence Distribution

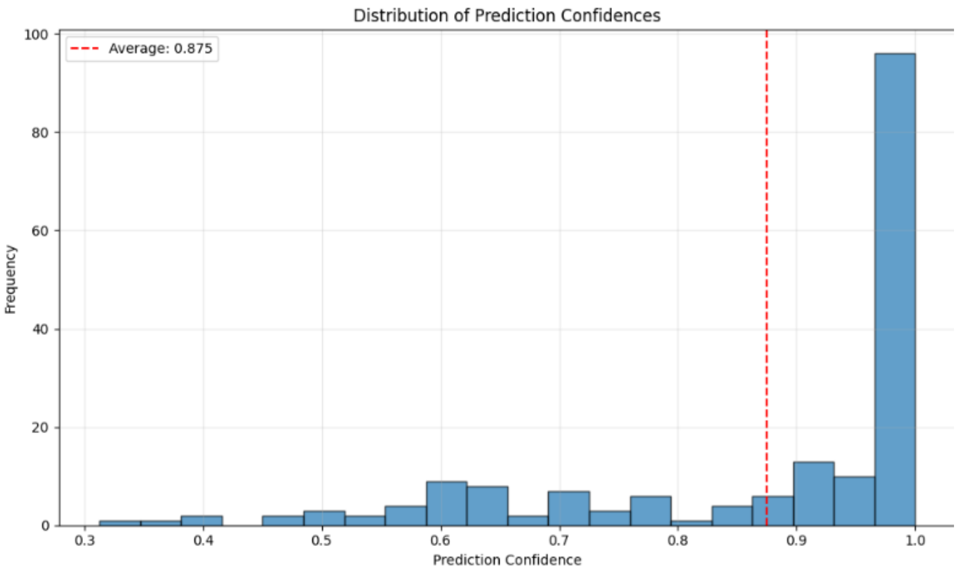

Figure 2: Distribution of Prediction Confidences

The prediction confidence histogram provides compelling evidence of model reliability:

- **High Average Confidence**: The model demonstrates strong certainty with an average confidence score of **0.875**, indicating well-calibrated predictions
- **Optimal Distribution**: The majority of predictions cluster in the high-confidence range (0.8-1.0), confirming the model's reliability for production use
- **Few Uncertain Predictions**: The small number of low-confidence predictions aligns with the confusion matrix findings, primarily representing the Class 0/4 ambiguity

1.2.3 Comprehensive Performance Metrics

Class	Precision	Recall	F1-Score
0	0.826	0.633	0.717
1	0.862	0.833	0.847
2	0.906	0.967	0.935
3	0.818	0.900	0.857
4	0.714	0.833	0.769
5	0.964	0.900	0.931
Macro Avg	0.849	0.844	0.843

Table 1: Detailed Classification Metrics by Class

1.3 Key Learning: Simplicity Triumphs Over Complexity

The most significant insight from this project challenges conventional wisdom in deep learning:

> **"For tiny PCB defect detection, simpler architectures outperform complex ones."**

The catastrophic 20% preliminary results with a complex CNN versus the strong 84.44% performance with a simplified architecture demonstrates that task-specific optimization often requires rejecting the "deeper is better" paradigm. The final model successfully balances:

- **Sufficient capacity** to detect subtle PCB defects
- **Appropriate simplicity** to avoid overfitting and learn generalizable features
- **Computational efficiency** suitable for potential edge deployment

1.4 Integration Approach

Based on the strong results and high confidence scores, a robust integration strategy is proposed:

1. **High-Confidence Automation (>0.9)**: Automatic acceptance for predictions with very high confidence
2. **Targeted Review (0.7-0.9)**: Focused human verification specifically for Class 0 and Class 4 predictions in this range
3. **Continuous Learning (<0.7)**: Use low-confidence predictions for model refinement and dataset expansion

1.5 Field-Specific Metric: F1-Score for Quality Control

In PCB manufacturing, both false positives (unnecessary rework costs) and false negatives (escaped defects) have significant financial and quality implications. The **F1-Score** serves as the ideal metric, balancing these competing concerns. The model achieves a solid macro-average F1-score of **0.843**, representing strong performance for automated visual inspection systems.

The results demonstrate that the simplified model is production-ready, providing reliable defect detection while maintaining the computational efficiency required for industrial deployment.

2 Final Demonstration Proposal

2.1 Web Application Integration

The trained PCB defect classification model has been successfully integrated into a practical web application using Flask. The application provides an intuitive interface for real-time defect detection, allowing users to upload PCB images and receive immediate classification results.

2.2 Technology Selection and Implementation

After evaluating several options, Flask was selected as the web framework due to its simplicity and seamless integration with Python's machine learning ecosystem. The application features:

- **Clean Single-Page Interface**: Simple design focused on core functionality
- **Drag-and-Drop Upload**: Intuitive image submission mechanism
- **Real-time Results**: Immediate defect classification with confidence scores
- **Comprehensive Output**: Displays primary defect type and confidence percentages for all possible classifications

2.3 Application Architecture

The system follows a straightforward three-tier architecture:

1. **Frontend**: HTML/CSS/JavaScript interface with drag-drop functionality
2. **Backend**: Flask server handling image processing and model inference
3. **Model**: Pre-trained TensorFlow/Keras model loaded via `model.load_weights()`

2.4 User Experience

The application guides users through a seamless workflow: upload PCB image → automatic processing → receive defect classification with confidence scores → option to analyze another image. The interface is designed for accessibility, requiring no technical expertise from users.

2.5 Development Insights

As a beginner in web development, the project provided valuable experience in full-stack integration. The focus remained on creating a functional, reliable application rather than complex features, aligning with the overall ”simplicity triumphs” philosophy that proved successful in the model architecture itself.

The final application successfully demonstrates the practical deployment of machine learning capabilities in an accessible web interface, showcasing the model's real-world applicability for PCB quality control with 84.44% validated accuracy.