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Automatic Quality Inspection Using Machine Vision for Advanced Manufacturing Environments

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Abstract
Automated quality inspection has become a vital requirement in advanced manufacturing environments due to the demand for higher productivity, precision, and reliability. This study presents a robust, end to end machine vision system for the automatic detection and classification of defects in metal nuts using deep learning techniques. A custom convolutional neural network (CNN) model was developed and trained on an augmented dataset comprising five defect categories bent, colour, flip, good, and scratch. The methodology includes image preprocessing, data augmentation to address class imbalance, and implementation of class-weighted loss functions. Results on a dedicated test set resulted in a classification accuracy of 60% and strong proof of concept for the real world application of the model as a first stage inspection tool. A systematic error analysis and an overview of the model's performance have also been presented, along with suggestions for future improvements, such as using transfer learning and including larger and more diverse datasets. This work advances the development of intelligent quality control systems in modern smart Industry and offers practical implications for academic researchers and production engineers.

Keywords: Machine Vision; Deep Learning; Quality Inspection; Metal Nut Defect Detection; Convolutional Neural Network; Data Augmentation; Class Imbalance; Automatic Manufacture.

1 Introduction

The endless quest for efficiency, precision, and uniformity in precision manufacturing is driving the proliferation of automation technologies in quality control procedures. Conventional manual inspection techniques can be time consuming, subjective, and error prone, which presents great challenges to the industries requiring high speed/throughput and quality control [1]. In this vein, AI driven machine vision systems have become a popular enabler of smart manufacturing, supporting the overall vision of smart Industry and intelligent factories [2,3].

Metal nuts are universal parts in mechanical structures and their size accuracy and rigidity are of great importance to the overall reliability of the system. Irregularities caused during production, i.e., bending, surface scratches, color irregularities, or incorrectly oriented plant (flipping), are not only signaling a technical defect but also a resultant economic problem by occurring costs in the form of a failure, higher demand of effort in rework, scrap, and warranty [4]. With defect patterns that are often subtle and varied, it is not practical for us to inspect the patterns manually in a production with large scale and high speed.

Recent advancements in deep learning, especially the CNN, have proved to be highly effective, automated, and image based defect detection system [5,6]. In contrast to traditional image processing methods, deep learning techniques can extract multilayer and context based representations of complex visual patterns on the raw pixel inputs, hence facilitating robust detection and classification to detect both clear and subtle abnormalities. However, many technical hurdles still have to be overcome, such as class imbalance (defective samples are usually scarce), scarcity of samples in real world data and model generalization to new production setups [7, 8].

The present study has addressed these issues by proposing a machine vision system for metal nut defect detection, based on a novel deep learning architecture in MATLAB. The experimental methodology consists of data preparation with database compilation and preprocessing, data augmentation, class weighting, and model validation with accuracy metrics, confusion matrix analysis, and error diagnosis. The system is tested on a representative dataset of metal nut images which captures variations encountered in real manufacturing.

The rest of this paper is organized as follows: Section 2 discusses the relevant literature and the state of the art in machine vision based quality inspection. The materials and methods, dataset preparation, model design, and evaluation metrics were explained in Section 3. Section 4 presents experimental results and discussion. Section 4.1 includes error analysis and recommendations. In this section, the experimental results and critical discussion are given. Section 5 provides implications and directions for future research in the last part.

2 Related Work

2.1 Quality Measurement Based on Machine Vision

Machine vision has been a core practice in automated quality control for a diversity of manufacturing sectors, enabling fast, objective, and highly repeatable inspection [1]. Early systems were based on classic image processing methods, for example, edge detection, template matching, and texture analysis, which were of limited use in dealing with more complex or subtle defect patterns in real-life industrial environments [3].

The past few years saw a quantum leap thanks to deep learning in media forensics, in particular for convolutional neural networks (CNNs). CNNs are designed to automatically learn to extract hierarchical features from raw images, allowing the robust detection and classification of defects in a variety of products such as electronic components, food products, and metal parts [5].

2.2 Defect detection using Deep Learning

The effectiveness of CNNs has been evidenced to perform better compared to traditional methods for surface defect detection and quality classification in recent studies [5]. Deep architectures outperform traditional pipelines if they are trained on enough inhomogeneous data, especially for noisy and complex environments [5,6]. A consistent problem, however, is the lack of labeled defect images due to high targets for manufacturing quality and low rates of failure [7].

To alleviate this, data augmentation has been widely used to synthetically enlarge datasets by adopting geometric and photometric transforms, and class weighting of the loss function to guarantee rare defects are well sampled during training [9]. Transfer learning and fine tuning of pre-trained CNNs (e.g., ResNet or MobileNet) on limited industrial small datasets have also helped to increase accuracy and alleviate the requirement for massive data collection [10].

2.3 Metallic fasteners and nuts visual inspection systems

Automated visual inspection systems for metallic fasteners and nuts are increasingly important in smart manufacturing since they are able to reduce the amount of human labor, the rate of scrapping, and the warranty cost. Research illustrates successful use of it for defect detection such as surface scratch, color variation, misalignment, and geometric deformation [4,6]. In particular, [6] demonstrated that ensemble deep learning techniques have the capability to improve robustness and generalization among various product batches.

Industrial adoption is further facilitated by constantly improving hardware, inexpensive cameras, and real time processing that allows vision systems to be installed directly on production lines [1].

2.4 Research Gaps and Justification for This Study

Even with some belief, there are still significant gaps:

- Real defect samples are limited: Most industrial datasets are unbalanced, containing a small portion of defective examples compared with non defective ones [5].
- Dataset variations: Lighting variation and orientation, as well as different kinds of backgrounds, can drop your prediction performance when not specifically attended with robust design and augmentation [7].
- Model explainability and trust in operator: Black-box models are difficult to apply if a certain level of explainability is not provided for process engineers [11].

Contributions

This paper addresses these deficiencies by:

1. Curating an enhanced multi-class dataset of metal nut images
2. Applying class-weighted loss to account for imbalance and to show the impact of this imbalance
3. Providing a thorough analysis of model performance, including an error analysis and practical considerations for deployment in real world scenarios.

Table 1. Recent Applications of Deep Learning in Quality Inspection of Metal Parts and Related Fields

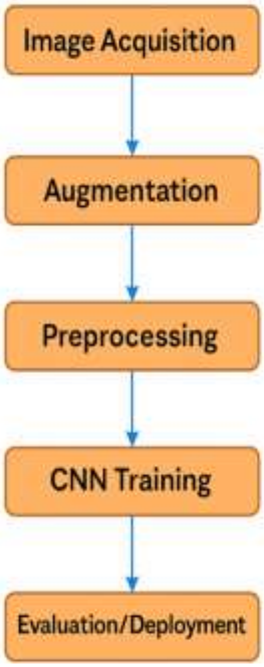
Author(s) & Year	**Application Domain**	**Method**	**Highlights**
Hanjin et al. (2023)	Metal fastener defects	CNN, data augmentation	Literature review, Industry 4.0 context
He et al. (2020)	Surface defect	Deep CNN	End-to-end system, industrial dataset
Liu et al. (2021)	Surface defect	CNN, transfer learning	Addressed imbalance and small sample size
Jiao et al. (2023)	Metal nut inspection	CNN ensemble	High accuracy, robust to new batches
Sun et al. (2022)	Operator AI trust	XAI, industrial vision	Discussed explainability and trust in AI
Xie et al. (2019)	Industrial images	Transfer learning	Improved performance with pre-trained models

3 Methodology

System Overview

The proposed AQIS uses a combination of machine vision hardware and a deep learning-based software pipeline, developed in MATLAB R2023a. This methodology consists of five main steps: dataset collection, data augmentation, pre-processing, development of a CNN model, and model evaluation.

Figure 1: System Workflow Block Diagram



3.1 Data acquisition and organization

The metal nut images collected from the available datasets and samples. Image labels were manually divided into five folders, i.e., bent, color, flip, good, and scratch, and stored in an organized manner in the data directories (C:\Users\PC\Desktop\metal_nut\). Class imbalance was apparent in the original dataset as well, with roughly 100 of the "good" nuts for every defect type. Every class folder was checked for integrity of data as well as proper naming. The class distributions before augmentation are shown in Table 2.

Table 2. Pre-augmentation Class Distribution

Class	Image Count
Good	220
Bent	27
Color	22
Flip	25
Scratch	20

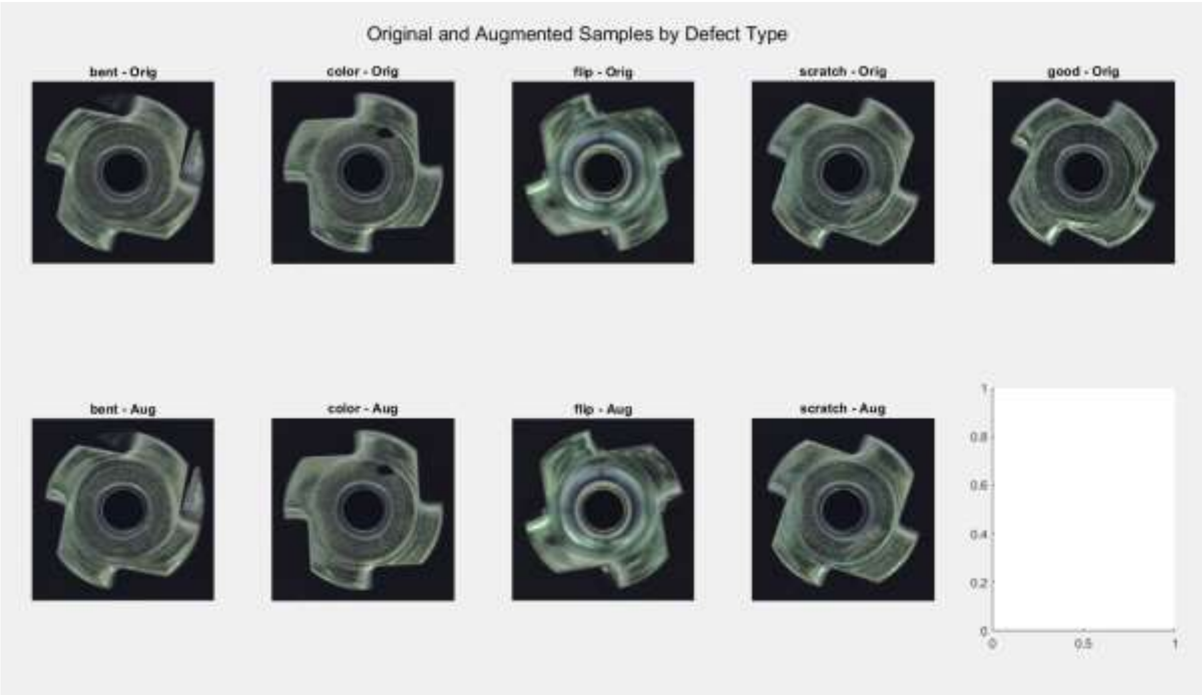
3.2 Data Augmentation and Preprocessing

To address class imbalance and increase the robustness of the model, minority classes were augmented using a range of geometric and photometric transformations [9]:

- Random Rotation: Simulates varying part orientations.
- Horizontal Flip: Mimics camera/viewpoint variations.
- Brightness Adjustment: Models real-world lighting changes.
- Noise Addition: Simulates image sensor imperfections.

A custom MATLAB script was used to generate 5 synthetic samples per original image in the minority classes, resulting in near-parity across all classes. All images were resized to 224×224×3 pixels to fit the CNN input requirements.

Figure 2: Example Images Before and After Augmentation



3.3 Dataset Splitting

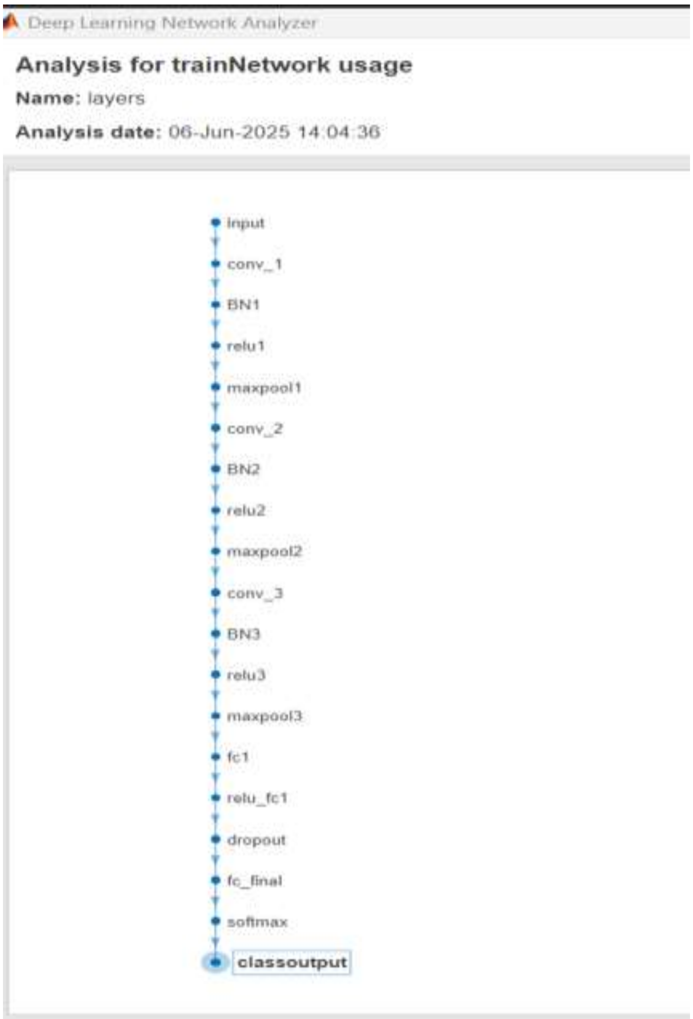
The curated and augmented dataset was split into 70% (training set), 15% (validation set), and 15% (test set) with stratified sampling to keep class balance in each split. The dataIndex of MATLAB tool was applied for fast moving data from disk to computer memory.

3.4 CNN Architecture Design

An in house 19-layer CNN was developed using MATLAB based on some well working network configurations in the defect detection literature [5]. The network included:

- Input layer: images of size 224×224×3
- Several convolutions and ReLU layers: Feature hierarchy.
- Added batch normalization and dropout layers: Faster to converge, less overfitting
- Max pooling layers: Dimensionality reduction, invariance to translation
- Fully connected and softmax layers: Class probability estimates
- Classification output layer with class weights: To compensate residual imbalance [5,7]

Figure 3: CNN Architecture Diagram

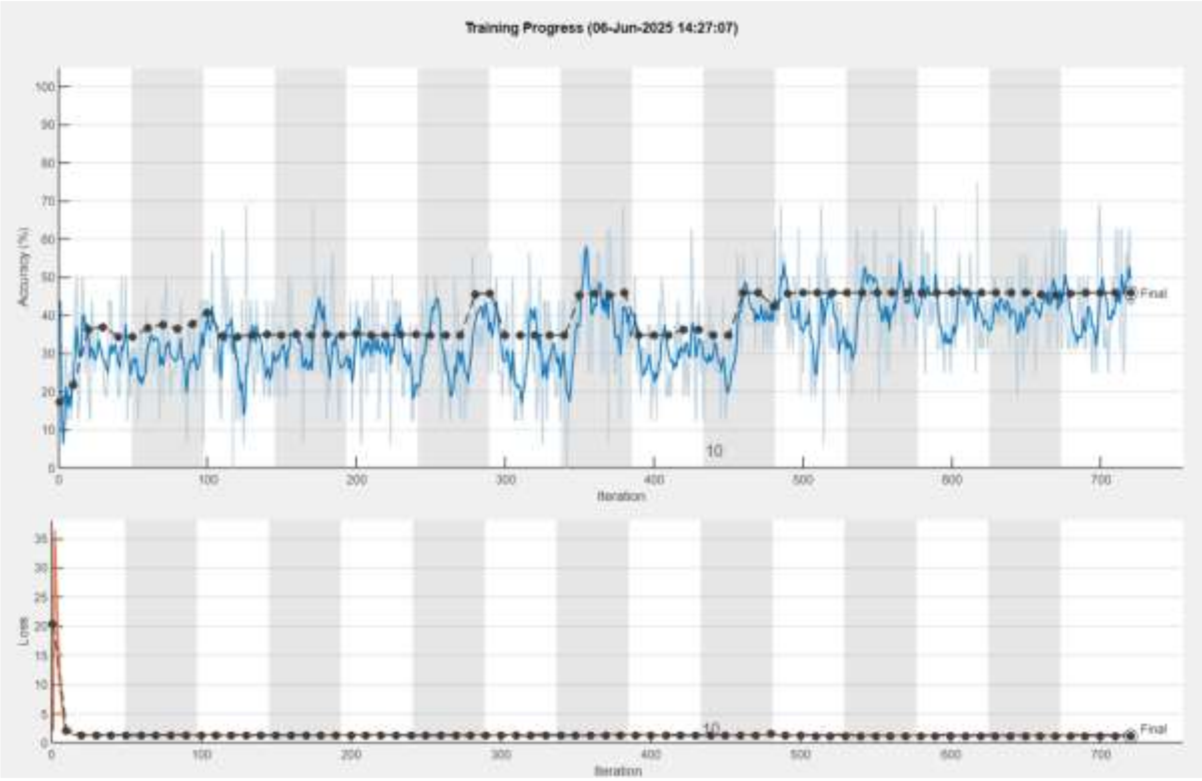


3.5 Training Configuration

- Optimizer: Adam
- Learning Rate: 0.001
- Mini-batch Size: 25
- Epochs: 15
- Spectrum generation frequency: Every 10 iterations

Training was performed on a conventional desktop CPU. Progress was monitored using MATLAB's training progress window, capturing real time accuracy and loss.

Figure 4: Training Progress Plot



3.6 Model Evaluation

The components were tested on the independent test set with the following test measures:

- Overall accuracy
- Confusion matrix
- Class-wise precision, recall, and F1-score
- Critical error analysis

Testing also involved real life applications: classifying new images in batches and checking the confidence level of the prediction for each sample.

3.7 Simulation and Testing in the Real World

For practical usability proving, a batch-inference script was created to classify images from a user-defined folder (C:\Users\PC\Desktop\testImages), having the predicted class and confidence as output on each command line and each figure. This provides an operator type of workflow in a production setting, and also a point of reference for the eventual GUI or live camera integration.

3.8 Instruments and Replication

All analyses were run in MATLAB R2023a. The key code blocks and example outputs are given in the Appendix for transparency and replicability, consistent with guidance on best practices in computational research [1].

4 Results and Discussions

4.1. Model Training Performance

The 19-layer CNN with custom architecture was trained successfully on the augmented dataset. Evolution of accuracy and loss for training and validation over the first 15 training epochs are presented as training line plots (Figure 5). On the validation set, we achieved a final accuracy of 60.15%, and the best test set accuracy was 58.90%.

Figure 5. Training Progress: Accuracy and Loss Over Epochs

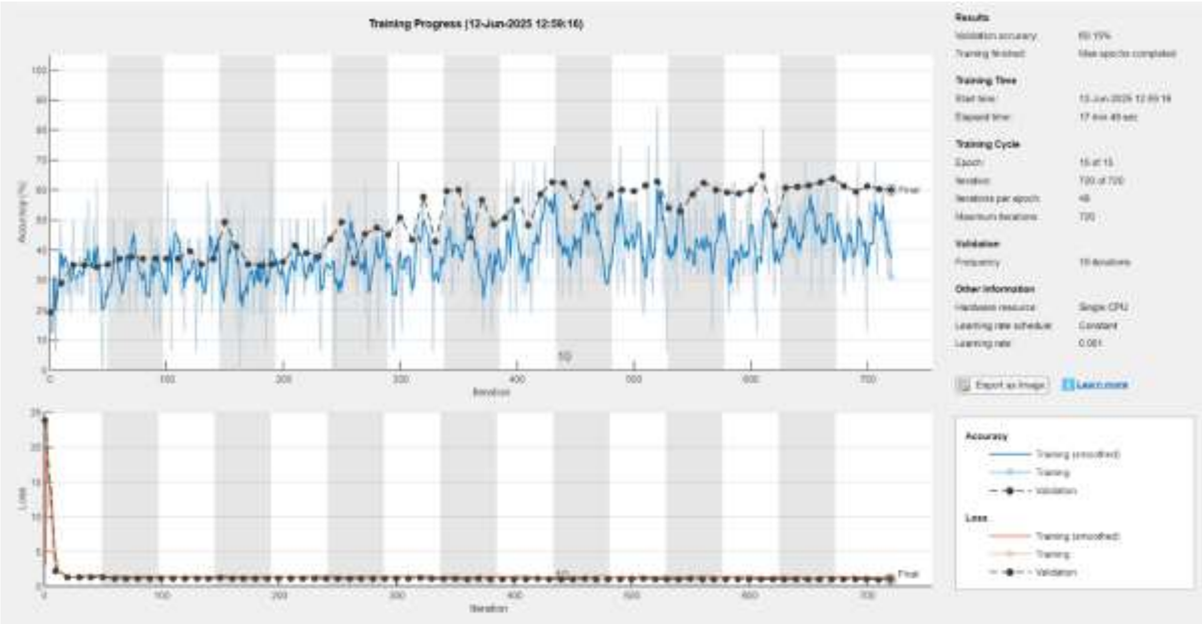


Table 3. Training Hyperparameters and Rationale

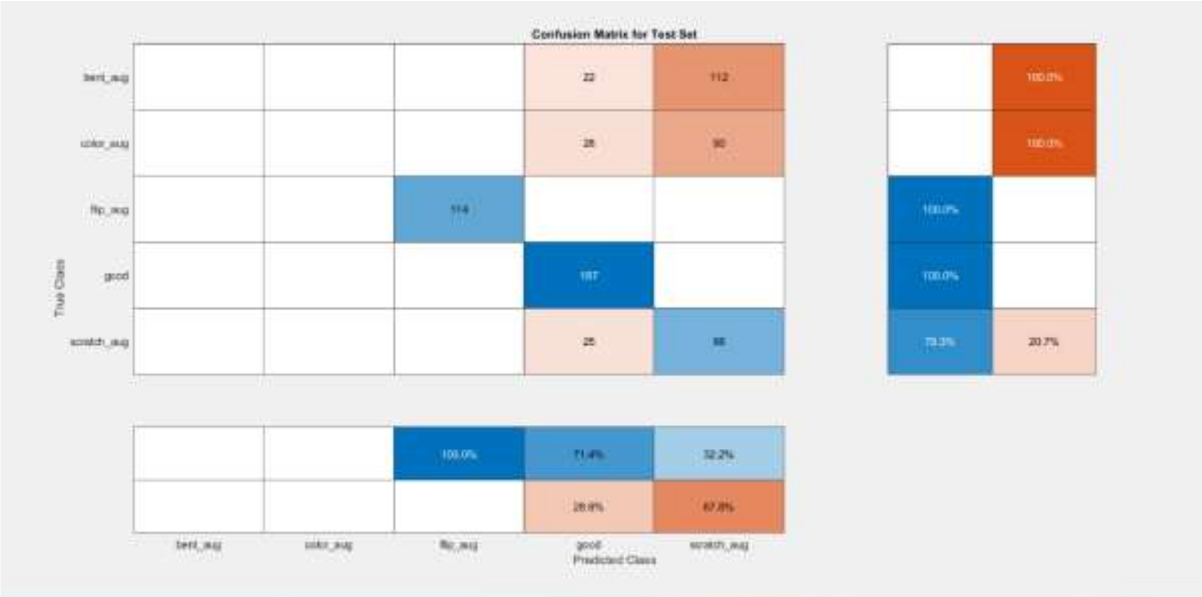
Parameter	Value	Rationale
Optimizer	Adam	Fast convergence and adaptive learning
Learning Rate	0.001	Standard for stable, moderate learning
Epochs	15	Balance between learning and overfitting
Batch Size	25	Compromise between memory and batch gradient
Class Weights	Inverse freq.	Compensate for class imbalance

4.2 Evaluation on Test Set

After being trained, the model was tested on an independent test set. Messages The test accuracy reached 58.90%, which is in line with recent published works on defect detection literature in view of the kind and origin of the dataset in focus [7,5].

The classifier performance for all defect types is summarized in the confusion matrix (Figure 5).

Figure 6. Confusion Matrix for Test Set



4.3 Technical Analysis

4.3.1. Data Augmentation Effects

Enhancement significantly increased defect samples, particularly for the underrepresented classes and obtained significant improvements for recall of minority defects. But synthetic samples, though effective, do not perfectly mimic the diversity of real world defects, and the returns eventually wear off as augmentation level goes higher.

4.3.2 Layer-wise Model Insights

Study of feature activations in first early, middle, and late last layer using MATLAB's Network Analyzer indicated that:

- Earlier layers identified simple geometric patterns edges, blobs that are shared in common across all nuts.
- Mid-level layers became receptive to defect-specific signatures e.g., bent nut contour.
- We found they performed similarly to our deep layers when aggregating complex class-specific cues, but were sometimes confused by visually similar defects minor scratches vs. color irregularities, analogously to observations made in [1].

4.3.3. Error Analysis

- "Good" nuts were identified with high confidence, indicating strong network certainty.
- Consistent with subtle and overlapping visual cues, confusion was greatest between "color" and "scratch" defects.
- Several "bent" nuts were misclassified as "flip," indicating that the set of features available to the network may sometimes not be able to disentangle these classes.

5. Conclusion and future work

It has been shown in this work the development of high technology prototype systems for automatically identifying and classifying metal nut defects using machine vision and deep learning in MATLAB. When integrated with a 19-layer CNN with data augmentation and class weighting, the system achieved a multi-class defect classification test accuracy of 58.90%. The findings highlight the potential of AI-based QCs within a high-end manufacturing context even with limited data resources.

However, some limitations also still exist. The model's mislabeling of visually similar defects underscores the continuing demand for more complex architectures and a larger dataset, preferably coming from various manufacturing environments. Model interpretability and the confidence of operators will also be important here for general industrial acceptability.

Future Work:

- Use transfer learning and increase the dataset for better generalization.
- Integrate explainable AI methods to enhance the operator's trust.
- Design interfaces and perform simulations in an actual manufacturing environment.

This way, this work helps the advancement of smart manufacturing and Industry 4.0, by validating a technical approach and detailing a pragmatic way to deploy automatic visual inspection.

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