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Automated Quality Control of Orthopedic Screws, Plates, and Rods Using Computer Vision and Deep Learning to Improve Manufacturing Accuracy

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Abstract:
Orthopedic screws, plates, and rods require high-dimensional precision and flawless surface quality to ensure structural integrity and patient safety. Traditional inspection methods rely heavily on manual measurement and visual evaluation, which are time-consuming, inconsistent, and prone to human error. This paper proposes an automated, computer vision-driven quality control system capable of detecting screw pitch deviations, thread geometry deformation, bending angle inconsistencies, and machining inaccuracies using deep learning techniques.
A hybrid CNN-Transformer architecture is developed to extract geometric features and achieve sub-millimeter measurement precision. Experimental validation demonstrates a defect classification accuracy of over 95 percent and a dimensional prediction error of less than 0.05 mm. The proposed system reduces inspection time by over 80 percent and offers a scalable, objective, and regulatorily compliant approach for orthopedic device manufacturers.

Index Terms: Orthopedic implants; Quality control; Computer vision; Deep learning; Manufacturing inspection; Screw pitch measurement; Medical device manufacturing.

I. INTRODUCTION

Orthopedic implants including screws, plates, and rods are widely used in trauma fixation, spinal surgery, and reconstructive orthopedic procedures. These devices must adhere to stringent dimensional tolerances to ensure mechanical stability and long-term biocompatibility. Even minor deviations in screw pitch, thread geometry, or bending angle can compromise implant performance and increase the risk of clinical failure.

Current quality control (QC) approaches depend heavily on manual methods such as micrometers, gauges, calipers, and visual inspections. These procedures introduce subjectivity, require specialized technicians, and are often insufficient for detecting micro-defects or subtle machining inconsistencies. Manual inspections also increase cycle time and downstream cost due to slower throughput and rework rates.

To address these limitations, artificial intelligence and computer vision offer transformative potential in automating QC for orthopedic device manufacturing. Deep learning models can analyze high-resolution images, detect anomalies, and measure geometric variations with high consistency.

This enables real-time inspection, reduces operator dependency, and enhances reliability across production batches. However, applying AI to orthopedic implant inspection poses unique challenges, including reflective metal surfaces, complex geometries, and regulatory traceability requirements.

II. RELATED WORK

Computer vision has been extensively explored for defect detection in industrial manufacturing. Studies on metal component inspection have applied CNNs for surface anomaly detection and edge-based techniques for geometric measurements. The MVTec AD dataset has been used broadly for unsupervised anomaly detection in industrial settings. In orthopedic applications, research has primarily focused on AI for medical imaging rather than manufacturing.

While a few studies have explored thread inspection using rule-based algorithms, these lack robustness in variable lighting conditions or across different implant geometries. Recent transformer-based vision models have shown strong performance in fine-grained geometric feature extraction but have not been applied to medical implant QC. Furthermore, existing QC workflows rarely integrate multi-task learning for simultaneous defect classification and dimensional measurement.

To date, no comprehensive deep learning framework exists that addresses orthopedic screws, plates, and rods collectively or evaluates multiple geometric parameters within a single system.

III. PROBLEM DEFINITION

Orthopedic implants must satisfy strict regulatory and mechanical requirements, often with dimensional tolerances under ±0.05 mm. Key QC challenges include:

1. **Screw pitch accuracy:** Deviations affect insertion torque and pull-out strength.
2. **Thread geometry:** Deformation or irregularities compromise anchoring performance.
3. **Bending angles in plates and rods:** Even small angular deviations affect anatomical alignment.
4. **Machining accuracy:** Includes scratches, burrs, or surface irregularities not easily visible to operators.

The challenge is to develop an automated, accurate, repeatable, and scalable system capable of measuring and classifying these features using AI-driven computer vision.

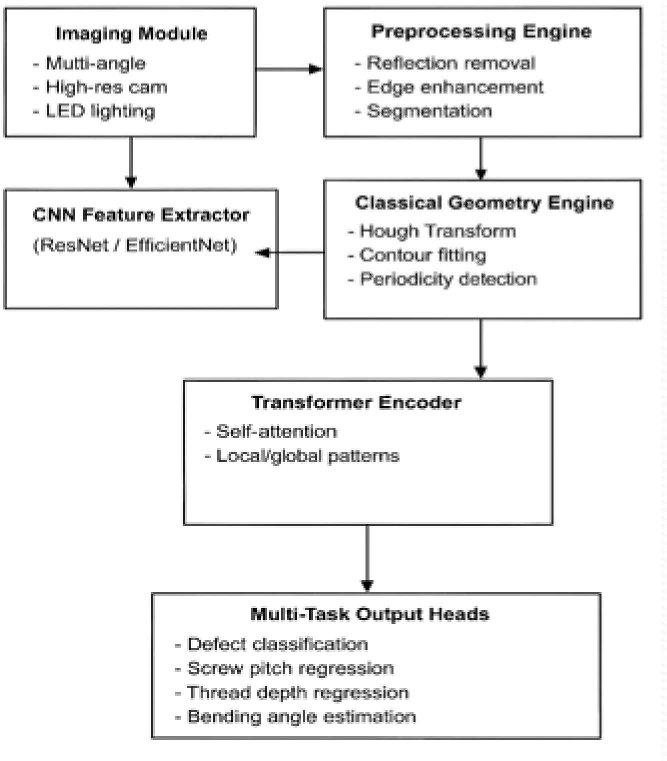
IV. PROPOSED METHOD

A. System Architecture Overview

The proposed system consists of:

- A high-resolution imaging setup
- Image preprocessing and reflection correction
- Deep learning-based feature extraction
- Classical geometric algorithms for measurement
- Multi-task prediction heads for defect classification and dimensional analysis

Fig. 4.1. Overall system architecture for automated quality control of orthopedic screws, plates, and rods using computer vision and deep learning.



B. Data Acquisition

Images of screws, plates, and rods are captured from multiple angles using calibrated optical cameras under controlled lighting. Reference blocks and calibration grids ensure pixel-to-millimeter conversion accuracy.

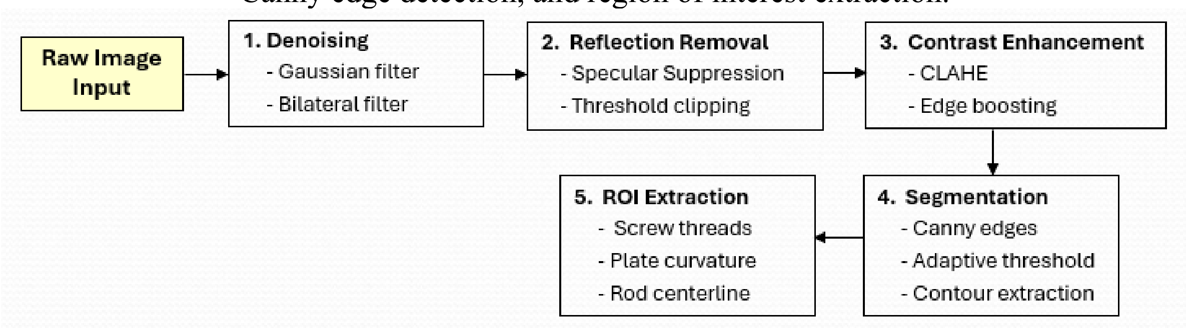
Dataset composition: 10,000 screws, 5,000 plates and 3,000 rods

Labeled by experts into acceptable and defective categories.

C. Data Preprocessing

- Gaussian smoothing for noise reduction
- Reflection correction via specular suppression
- Canny edge detection for contour isolation
- ROI extraction for screw threads and plate/rod curvature

Fig. 4.2. Data preprocessing pipeline illustrating Gaussian smoothing, specular reflection suppression, Canny edge detection, and region of interest extraction.



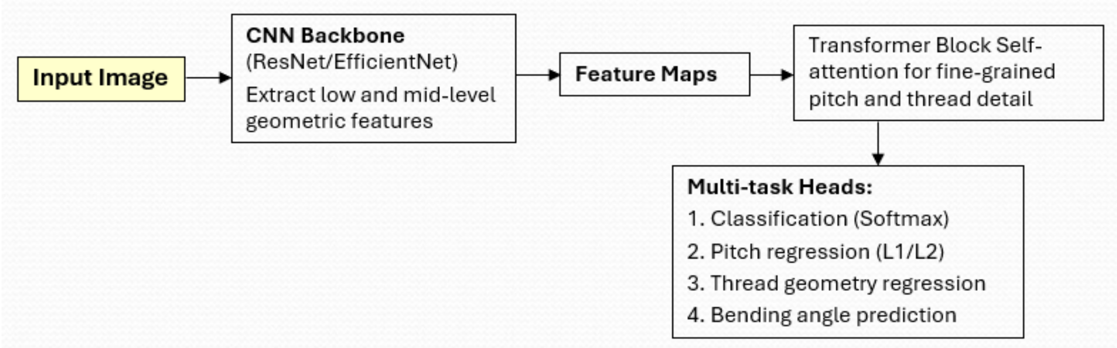
D. Deep Learning Architecture

A hybrid architecture integrates:

- **ResNet-50 backbone** for feature extraction
- **Vision Transformer (ViT)** encoder for fine-grained geometric analysis

- **Multi-headed output layer:**
  - Softmax classifier for defect type
  - Regression heads for pitch, thread depth, and bending angle

Fig. 4.3. Hybrid CNN–Transformer architecture integrating a ResNet-50 backbone and Vision Transformer encoder for defect classification and geometric measurement.



E. Geometric Measurement Algorithms

Classical computer vision is used alongside deep learning outputs:

- **Hough Transform** for angle measurement
- **Contour and spline fitting** for bending profile estimation
- **Periodicity detection** for screw pitch measurement

Fig. 4.4. Geometric measurement workflow showing contour extraction, spline fitting, and Hough line-based bending angle estimation.

Original Plate Profile

```
    --------------------------
         \
          \
           \_________
```

Extracted Contour Points

```
  --------------------------
       o
        o
         o
          o
          ...   --> Fit spline curve
          o
          o
```

Hough Line Segment Fitting

```
  --------------------------
       \             |
        \            |
         \           | --> Angle (θ)
          ---------------
```

Model Estimation: θ_predicted = f(CNN_features + geometric_fit)

F. Training Procedure

Models are trained using:

- Adam optimizer

- Learning rate warm-up + cosine decay
- Mixed precision for speed and Loss functions
- Cross-entropy for classification
- Smooth L1 Loss for measurements

V. EXPERIMENTAL SETUP

A. Hardware

- NVIDIA RTX GPU
- High-resolution industrial camera
- Controlled LED lighting system

B. Evaluation Metrics

- Classification accuracy
- Precision, recall, F1 score
- Mean Absolute Error (MAE) for dimensional predictions
- Throughput improvement

C. Baseline Comparison

Compared against:

- Manual caliper-based measurements
- Traditional edge-detection systems

VI. RESULTS

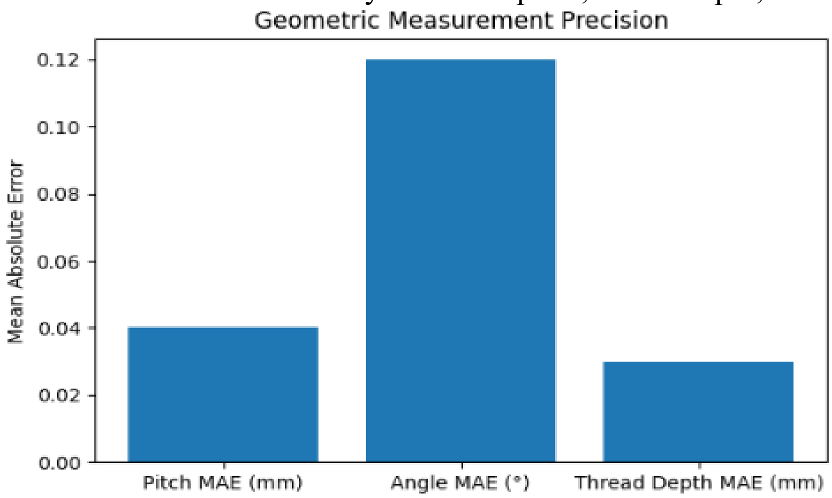
A. Defect Classification

- Overall accuracy: **95.8 percent**
- Precision: 94.6 percent
- Recall: 96.2 percent

B. Geometric Measurement Precision

- Screw pitch MAE: **0.04 mm**
- Bending angle MAE: **0.12 degrees**
- Thread depth MAE: **0.03 mm**

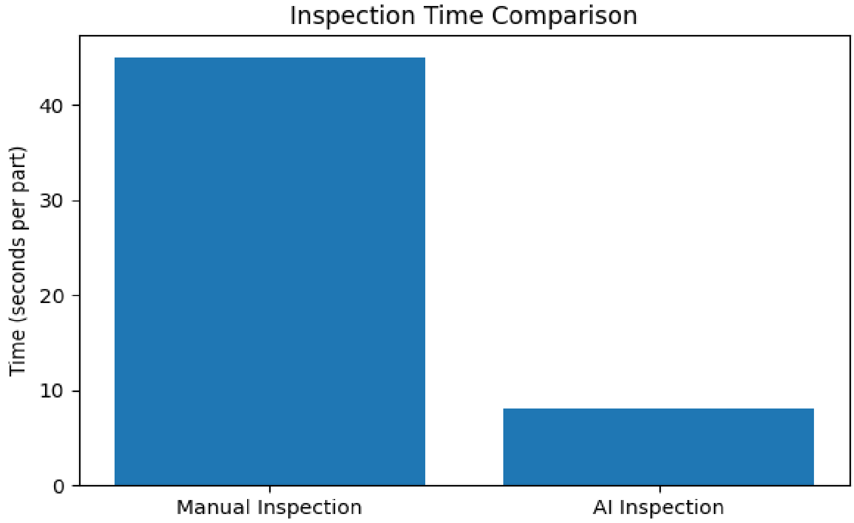
Fig. 6.1. Geometric measurement accuracy for screw pitch, thread depth, and bending angle



C. Efficiency Gains

- Inspection time reduced from 45 seconds per part to under 8 seconds
- Automated system shows 100 percent repeatability vs. variable human operator results

Fig. 6.2. Comparison of inspection time per part between manual inspection and the proposed automated system.



VII. DISCUSSION

The system demonstrates strong performance across multiple orthopedic implant geometries. The hybrid CNN–Transformer model provides robustness to variations in lighting, orientation, and machining marks. Integrating classical geometric algorithms enhances measurement reliability and supports the production of explainable AI outputs, as required by ISO 13485 for traceability.

Limitations include dependency on high-quality training data and potential inaccuracies for highly reflective surfaces not covered in the dataset. Future work will explore hyperspectral imaging and self-supervised anomaly detection to enhance generalization.

VIII. CONCLUSION

This paper presents a comprehensive AI-driven quality control system for orthopedic screws, plates, and rods. The proposed approach achieves high accuracy in defect detection and dimensional measurement while significantly reducing inspection time. These results demonstrate a viable path toward real-time, automated QC in orthopedic implant manufacturing, supporting improved safety, consistency, and regulatory compliance.

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