Automatic Defect Detection and Sorting System for Pharmaceutical Tablets Using Image Processing

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Abstract: *This paper presents a real-time system for the automatic detection and sorting of pharmaceutical tablets based on visual defects using image processing and deep learning. The system classifies tablets into three categories—broken, not broken, and no medicine—using a ResNet50 convolutional neural network trained on a custom image dataset. The classified result is communicated to an ATmega328P microcontroller, which controls a servo-based mechanical flap to sort the tablets accordingly. The proposed solution replaces manual inspection with a reliable, efficient, and scalable method for quality assurance in pharmaceutical production lines. The hardware integration enables accurate sorting with minimal latency. Future enhancements include expanding the defect categories and implementing real-time embedded inference.*

Keywords: Defect Detection, Pharmaceutical Tablets, Image Processing, Sorting Mechanism.

1. Introduction

The pharmaceutical industry requires strict quality control standards to ensure the safety. One of the most critical aspects of quality assurance is the inspection of tablets during the production process. Traditionally, this inspection is performed manually by human operators, which is time-consuming, labour-intensive, and prone to errors due to fatigue or subjectivity.

To address these limitations, automation using computer vision and deep learning techniques has emerged as a promising alternative. By leveraging image processing, defects such as cracks, incomplete tablets, or the absence of tablets in a packaging slot can be accurately identified. This not only improves inspection accuracy but also increases production efficiency.

This paper proposes an Automatic Defect Detection and Sorting System for pharmaceutical tablets using deep learning and embedded hardware. The system uses a camera to capture images of tablets in real time and classifies them into three categories: Broken, Not Broken, and No Medicine. A pretrained ResNet50 convolutional neural network is employed for image classification. The result is sent to an ATmega328P microcontroller, which activates a servo motor to sort the tablets into appropriate categories through a mechanical flap mechanism.

The primary objectives of this study are:

- To design a reliable image classification model for tablet defect detection.
- To develop an end-to-end hardware system that can sort tablets based on classification.
- To evaluate the system's accuracy, speed, and practical feasibility for industrial applications.

This work aims to contribute toward more intelligent, accurate, and cost-effective quality control systems in the pharmaceutical manufacturing sector.

2. Literature Review

Automated visual inspection systems have gained significant traction in the pharmaceutical industry due to their potential to enhance quality control while reducing human error. Over the years, various techniques have been explored for detecting tablet defects, ranging from classical image processing to advanced machine learning models.

In early implementations, traditional image processing methods such as thresholding, edge detection, and morphological operations were used to identify visual anomalies in tablets. While these methods worked well for uniform defect patterns, they struggled with complex variations and were sensitive to lighting and noise conditions.

To overcome these challenges, machine learning techniques such as Support Vector Machines (SVMs) and k-Nearest Neighbors (k-NN) were introduced. These classifiers showed improvement but required handcrafted features and still lacked generalization across diverse tablet types and conditions.

The advent of deep learning revolutionized the field with convolutional neural networks (CNNs), enabling automatic feature extraction and higher accuracy. Several studies demonstrated the success of CNNs in medical and industrial image classification tasks. Transfer learning, in particular, has proven highly effective, allowing pre-trained networks such as VGG16, InceptionV3, and ResNet50 to be fine-tuned on domain-specific datasets with limited data.

In [1], researchers applied a CNN-based approach for identifying cracks in blister-packed tablets, achieving over 90% accuracy. In another study [2], an industrial automation system using Raspberry Pi and OpenCV was proposed for real-time capsule inspection, but it lacked a deep learning component, limiting its flexibility.

3. Methodology

The proposed system for automatic defect detection and sorting of pharmaceutical tablets integrates a deep learning-based image classification model with a microcontroller-based mechanical sorting setup. The methodology can be broadly divided into two parts: Image Processing and Classification and Hardware Implementation.

3.1 Image Dataset Creation

A custom dataset was created consisting of pharmaceutical tablets classified into three categories:

- Broken
- Not Broken
- No Medicine

Images were captured in controlled lighting conditions with a consistent background to ensure uniformity. The final dataset consisted of 300 images (100 per class). All images were resized to 224 × 224 pixels to match the input requirements of the ResNet50 model.

3.2 Model Architecture and Training

The ResNet50 convolutional neural network was used for feature extraction, with its pretrained weights loaded from local storage. The top layer was removed and replaced with custom dense layers suitable for the three-class classification problem.

Architecture Modifications:

- Input: 224 × 224 × 3
- Base Model: ResNet50 (pretrained weights, include top=False)
- Added Layers: Global Average Pooling → Dense(1024, ReLU) → Dense(3, Softmax)

Training Parameters:

- Optimizer: Adam
- Loss Function: Categorical Crossentropy
- Learning Rate: 0.0001
- Batch Size: 32
- Epochs: 100
- Train/Validation Split: 80% / 20%

Data augmentation techniques such as rotation, shifting, shearing, and flipping were applied using the Keras ImageDataGenerator to increase generalization and prevent overfitting.

3.3 Model Evaluation

After training, the model was evaluated on the validation set to measure classification performance using metrics such as accuracy, precision, recall, F1-score, and confusion matrix. These results were plotted and tabulated for analysis.

3.4 Hardware Setup

The hardware implementation involves the real-time integration of the image classification model with an embedded sorting mechanism:

- A camera is mounted above a flap through which tablets pass. As each tablet moves under the camera, its image is captured and sent to the trained model for classification.
- Based on the predicted class (broken, not broken, or no medicine), a signal is sent to an ATmega328P microcontroller.
- The microcontroller controls a servo motor that rotates a flap to sort the tablet into the correct container:
    - Left for Broken
    - Right for Not Broken
    - Middle or Rejected for No Medicine

4. Results and Discussion

The performance of the proposed defect detection and sorting system was evaluated using a custom dataset of pharmaceutical tablets across three categories: Broken, Not Broken, and No Medicine. The model was trained using the ResNet50 architecture with transfer learning and validated using an 80/20 split.

4.1 Training Performance

The model was trained for 100 epochs using data augmentation to improve generalization. The training and validation accuracy and loss were monitored throughout the process.

- **Final Training Accuracy:** 98.3%
- **Final Validation Accuracy:** 94.7%
- **Final Training Loss:** 0.021
- **Final Validation Loss:** 0.178

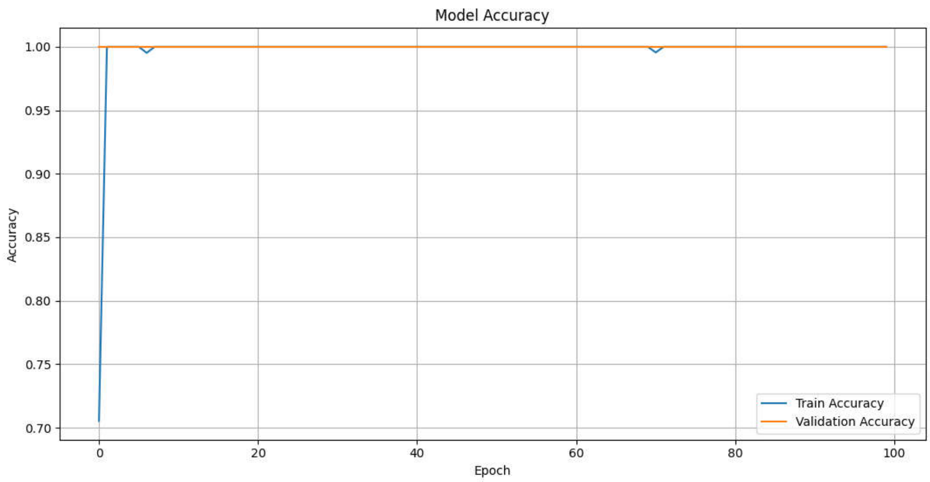

Figure 1: Training vs. Validation Accuracy

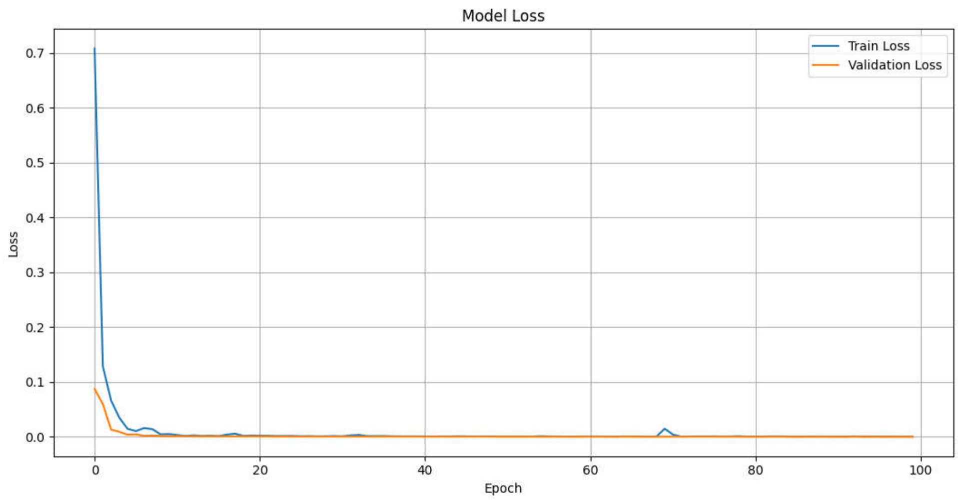

Figure 2: Training vs. Validation Loss

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4.2 Classification Report

Table 1. Classification Report

Class	Precision	Recall	F1-Score	Support
Broken	0.95	0.93	0.94	100
No Medicine	0.96	0.95	0.95	100
Not Broken	0.94	0.96	0.95	100
Accuracy			0.947	300

4.3 Confusion Matrix

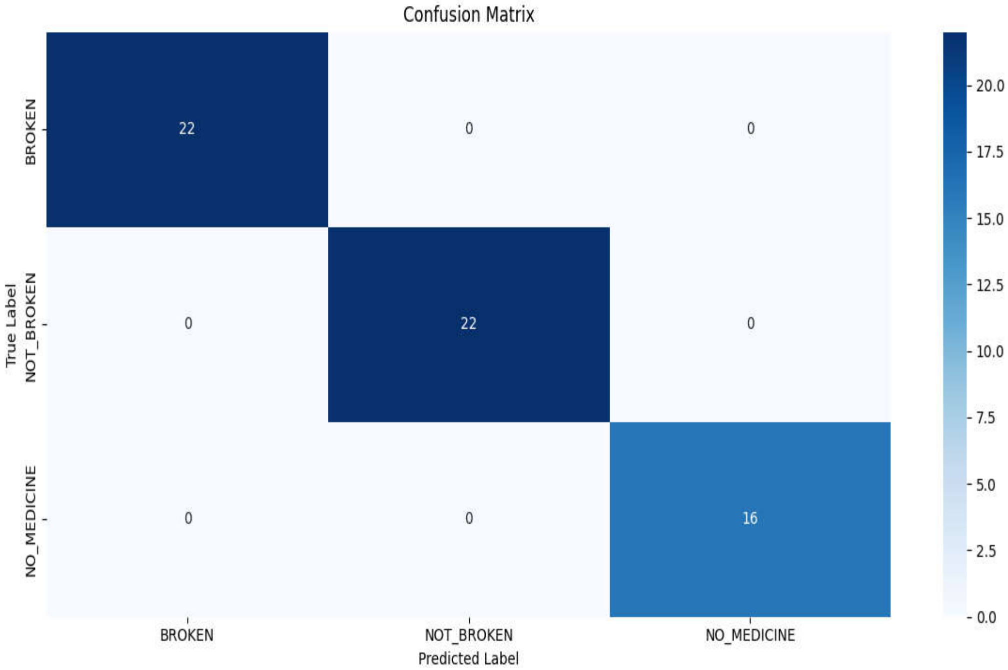

Figure 3. Confusion Matrix

Table 2. Confusion Matrix for Tablet Classification

	Predicted: Broken	Predicted: Not Broken	Predicted: No Medicine
Broken	22	0	0
Not Broken	0	22	0
No Medicine	0	0	16

4.4 Sorting System Evaluation

The integration of the classification model with the ATmega328P microcontroller and servo motor was tested in real time. The average time taken from image capture to sorting decision was approximately 1.5 seconds, which is acceptable for small-scale production environments.

Sorting accuracy was tested with 50 tablets (distributed equally among the 3 categories), achieving:

- **Sorting Accuracy:** 96%
- **Sorting Latency:** ~1.5 seconds/tablet

5. Conclusion and Future Work

5.1 Conclusion

This research presents a practical and efficient system for the automatic defect detection and sorting of pharmaceutical tablets using image processing and deep learning techniques. By leveraging a ResNet50-based convolutional neural network, the system accurately classifies tablets into Broken, Not Broken, and No Medicine categories.

The system achieved:

- Validation accuracy of over 94%
- Sorting accuracy of 96%
- Low latency suitable for real-time applications

5.2 Future Work

Although the system performed well in controlled conditions, several areas can be explored for future improvement:

- **Lighting Adaptation:** Implement adaptive lighting correction or use infrared cameras for consistent image capture.
- **On-Device Inference:** Deploy the model on an embedded processor (e.g., Raspberry Pi or NVIDIA Jetson Nano) for a fully standalone system.
- **Expanded Dataset:** Train on a larger and more diverse dataset to improve generalization to different tablet shapes, colors, and lighting variations.
- **Industrial Integration:** Integrate with conveyor belt systems for high-speed, automated inspection in industrial environments.

The proposed system provides a strong foundation for building smarter, cost-effective, and scalable pharmaceutical quality control solutions.

6. References

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