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Gear Profile Error Detector with Help of Deep Learning

Ghode Priyanka[1], Wategaonkar Dhanashree[2], Lakhe Shubham[3], Devkar Nikhil[4], Rakate Kishor[5], Gaikwad Saurabh[6]

[1,2,3,4,5,6]*Annasaheb Dange Collage of Engineering & Technology, Ashta, Dist. Sangli, Maharashtra, 416301, India*

ABSTRACT

a technique that uses sampling to draw representative data from a group. If only 2 or 3 of a batch of 100 gears are checked, for instance, the entire batch may be rejected if even one gear contains an error. As a result, we must inspect each and every gear in the batch, but doing so physically takes a long time. As part of our project, we are creating a system that will inspect each and every gear.. We use a conveyer belt for movement of gear, a camera for capturing and checking the gear parameter stored at the back end. If the parameters are matched with the stored parameters then it goes to the accepted lot otherwise with the help of shooting gun it goes to the rejected lot. In this work we use a software called “MATLAB” to determine gear parameters. MATLAB is broadly used for scientific & research purposes. The program is easy to understand & when executed it ask the inputs and performs the necessary design calculations and gives necessary output values. As computers are used to perform this task, gear design becomes simple & error free.

Keywords: Gear surface; Object detection; Deep learning; Convolutional neural networks (CNN); Computer vision; Image processing; Machine learning; Artificial intelligence; Training dataset; Testing dataset; Precision engineering; Industrial automation; Manufacturing; Quality control;

1. Introduction

1.1 Background

Gear inspection is the process of evaluating and analyzing the quality and accuracy of gears to ensure their proper function in machines and other mechanical devices. Gears are crucial components in many types of machinery, such as automobiles, airplanes, and industrial equipment, and even small defects or inaccuracies in gears can cause significant problems or failures. Gear inspection typically involves a combination of visual inspections, dimensional measurements, and functional testing. Visual inspections involve looking for signs of wear, damage, or other defects on the gear teeth and other components. Dimensional measurements involve using precision instruments such as micrometers, calipers, and coordinate measuring machines (CMMs) to measure various dimensions of the gear, including the pitch diameter, tooth thickness, and run out. Functional testing involves running the gear under load to test its performance and ensure that it operates smoothly and without excessive noise or vibration. The gear inspection process is critical in ensuring that gears are of high quality and meet the required specifications for their intended application. It is typically performed by trained technicians and can be conducted at various stages of the manufacturing process, including during production and before installation. In addition to ensuring the proper function of machinery, gear inspection can also help to identify potential problems early on and prevent costly downtime and repairs.

1.2 Problem Statement

At most of an automotive gear manufacturer, the current quality control inspection process requires human operators to manually inspect all gear for the presence of defects. However, the accuracy of such a system depends on the ability of the inspector to recognize defects in the gears. As the defects are infrequent and have diverse profiles, and as the gears themselves have different shapes and material characteristics (e.g., reflective surfaces), inspection can be a challenging and time consuming process.

A sampling method of gathering representative data from a group. For example, a manufacturing might check only 10 or 15 gears from a batch of 100 gears due to which the whole lot gets rejected if maximum gears in between has error in it. Thus, we need to check each and every gear in the batch but physically this process is time uncontrollable.

1.3. Objectives

- Accuracy: The system should be able to detect gear profile errors accurately and reliably, with a low rate of false positives and false negatives.
- Speed: The system should be able to analyze gear profiles quickly and efficiently, providing results in real-time or near-real-time.

- Automation: The system should be fully automated, requiring minimal human intervention or interpretation.
- Flexibility: The system should be adaptable to different types of gears and gear configurations, with the ability to handle a variety of gear profile errors.
- Cost-effectiveness: The system should be cost-effective, with low implementation and maintenance costs compared to traditional gear inspection methods.
- Scalability: The system should be scalable, able to handle large datasets of gear profiles and potentially integrate with other machinery monitoring systems.
- Reliability: The system should be reliable, providing consistent and accurate results over time.

2. Process

Data Collection: Gather images of gear surfaces with and without defects. The images should be taken from different angles, under different lighting conditions, and with varying levels of noise.

Data Preprocessing: Preprocess the images to ensure that they are standardized in size, orientation, and color. This step might include techniques such as resizing, cropping, and normalizing pixel values.

Training Data Preparation: Label the images as either defective or non-defective. Use a portion of the labeled images to train the deep learning model and the rest for validation and testing.

Model Selection: Choose a deep learning model for classification, such as a convolutional neural network (CNN), that can detect patterns and features in images.

Model Training: Train the selected deep learning model on the labeled training data using a stochastic gradient descent algorithm or other similar optimization techniques. This step will involve setting the hyper parameters, such as the learning rate and number of layers, and evaluating the model's performance on the validation data.

Model Evaluation: Evaluate the trained model on the test data to measure its accuracy, precision, recall, and F1 score. Deployment: Integrate the model into an application or system that can detect gear surface defects in real-time.

3. Methodology

For this project, the methodology will involve a deep learning-based approach that leverages a convolutional neural network (CNN) to detect gear surface defects. The CNN will be trained on a labeled dataset of images of gear surfaces with and without defects, and the output will be a binary classification of whether or not a given image contains a defect.

The methodology will involve the following steps:

1. Data Collection and Preprocessing: Collect and preprocess a dataset of images of gear surfaces with and without defects.
2. Model Selection: Choose a suitable deep learning model, such as a CNN, that is capable of detecting patterns and features in images.
3. Training Data Preparation: Label the dataset images as defective or non-defective and split the dataset into training, validation, and testing sets.
4. Model Training: Train the CNN model on the labeled training data, using techniques such as data augmentation, to increase the model's ability to generalize to new images.
5. Model Evaluation: Evaluate the trained model on the testing data to measure its accuracy, precision, recall, and F1 score.
6. Deployment: Integrate the model into an application or system that can detect gear surface defects in real-time.

4. Actual setup

5. Test Results

Fig.: - Accepted Gears

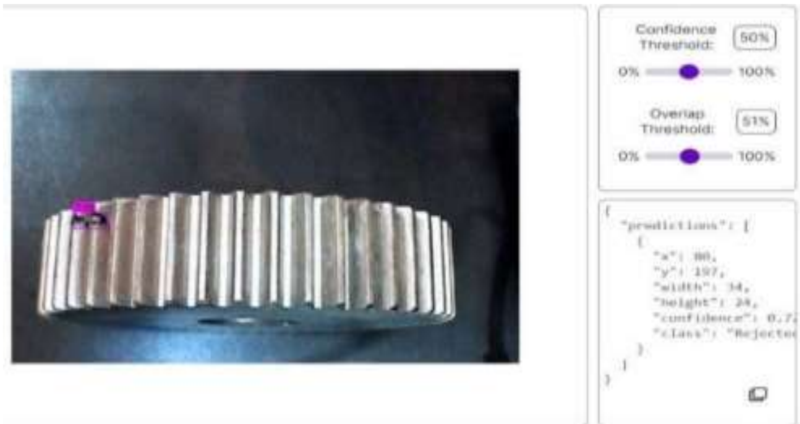

Fig.: - Rejected Gear

The expected results of this project are to develop a deep learning-based model that can accurately detect gear surface defects in real-time. The performance of the model will be evaluated using metrics such as accuracy, precision, recall, and F1 score.

If the model performs well, it could be deployed in a variety of industrial settings where gear surface defects can cause equipment failure and downtime. This could help to reduce maintenance costs and improve operational efficiency.

6. Conclusion

Deep learning models are open to improvement after deployment. A deep learning approach can increase the accuracy of the neural network through the iterative gathering of new data and model re-training. The result is a “smarter” visual inspection model that learns through increasing the amount of data during operation. In this work, we focused on training a single model to detect a single defect. When applied in a real world industrial setting, there are several benefits to this kind of approach: from the obvious ability allowing a model to specialize to detect a single type of defect (damaged teeth defect), to the lesser obvious, but still important aspects of model maintenance. Adding a new type of defect to the detection pipeline would require a new model to be trained—rather than performing the time-consuming and laborious process of re updating the current model, again, for every defect. In addition, credit assignment and blame becomes more straightforward for management personnel in these situations. In this work, we focused on training a single model to detect a single defect. When applied in a real-world industrial setting, there are several benefits to this kind of approach: from the obvious ability allowing a model to specialize to detect a single type of defect (damaged teeth defect), to the lesser obvious, but still important aspects of model maintenance. Adding a new type of defect to the detection pipeline would require a new model to be trained—rather than performing the time-consuming and laborious process of re-updating the current model, again, for every defect. In addition, credit assignment and blame becomes more straightforward for management personnel in these situations.

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