Automated anomaly detection in magnetic crack testing: From simulation to practice
By Dennis Irmschler

Ensuring the quality of forged components is an essential step in the metal industry to confirm that critical parts are free of defects, such as cracks. Automated anomaly detection using AI offers significant potential to make the inspection process more efficient and precise. In an experiment, I explored and tested the basics of such a system using a simple Python program.

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1. The idea: Simulating and testing crack detection

Since I did not have real images of forged components with cracks, I developed a program to generate images with simulated "cracks." To increase the complexity, I intentionally added disturbances (e.g., random pixels) to the crack images, making anomaly detection more challenging.

The algorithm: An **Isolation Forest**, a technique from unsupervised learning, was used to identify deviations from "normal" images. With approximately 60 lines of code and the open-source library scikit-learn, I achieved remarkably precise results.

Why Isolation Forest?

- It works without labeled data, making it ideal for anomaly detection when examples of "defective" components are hard to obtain.
- The algorithm effectively isolates unusual data points, even in high-dimensional spaces.

2. What methods are available for anomaly detection?

In addition to Isolation Forest, several approaches are available:

- **Supervised Learning**: Requires labeled data of "good" and "defective" parts. Models such as Support Vector Machines (SVMs) or Convolutional Neural Networks (CNNs) deliver highly accurate results but require extensive datasets.
- **Unsupervised Learning**: Methods like Isolation Forest, autoencoders, or k-means clustering detect anomalies without labeled data.
- **Hybrid Approaches**: Combine supervised and unsupervised learning for more flexible models.

Which method is best suited?
For industrial integration, where defects are rare and data is limited, unsupervised learning is a practical starting point. As more real-world data becomes available, supervised learning or hybrid approaches can offer greater accuracy and robustness.

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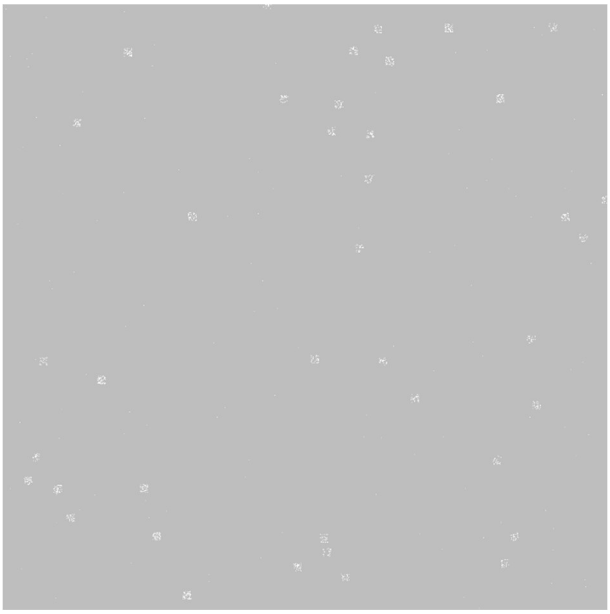
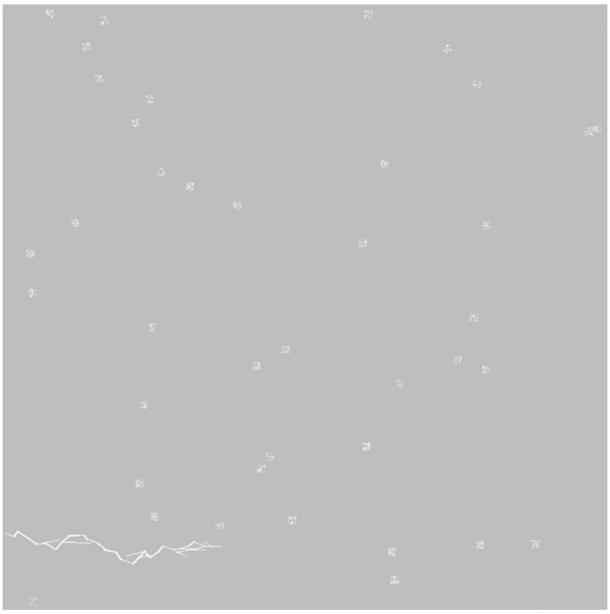
3. How does my system work?

1. **Data Preparation**: Images of "good" components were processed, and features such as the number of bright pixels were extracted.
   Example: An image of a generated "good" component.



2. **Model Training**: The Isolation Forest was trained on these features to learn the characteristics of normal images. Only 100 images were used for this training process.
3. **Anomaly Detection**: Artificially generated crack images were presented to the system. Despite the disturbances, the model was able to identify genuine anomalies with high accuracy. Example: An image of a generated "crack."



Results: Impressive precision with minimal code
Using a simple Python environment and just a few lines of code, I achieved surprisingly accurate results. This demonstrates that even straightforward approaches can be powerful when data is well-prepared. With a dataset of 100 images, the detection rate was 100%.

4. Black-and-White vs. Color Images: Which is Better?

Black-and-white images:

- Reduced data size, leading to faster processing.
- Particularly useful when focusing on contrasts, such as cracks made visible by magnetic particles.
- Less distraction from color variations, simplifying anomaly detection.

Color images:

- Provide more information, which can be useful for analyzing complex surface structures.
- Color information might be important when using different inspection media (e.g., fluorescent particles).

Conclusion: For magnetic crack testing, black-and-white images are often sufficient and efficient. However, color images could be beneficial in special cases, such as when fluorescent media are used. This would require additional testing.

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5. From experiment to industrial practice

What's next?

- **Using real data**: Instead of simulated images, real inspection images of forged components should be used. This requires installing camera systems capable of capturing high-resolution images.
- **Image preprocessing**: Methods such as noise reduction, edge enhancement, or contrast adjustment could help make relevant features more distinguishable for AI.
- **Leveraging big data**: In a production line generating thousands of images daily, big data offers opportunities to continuously improve algorithms. Analyzing patterns could also help identify production errors at an early stage.
- **Industrial integration**: An automated system could be structured as follows:
  - **Camera and lighting**: Capture images of magnetically marked surfaces.
  - **Real-time processing**: Analyze images in seconds and automatically sort defective parts.
  - **Feedback system**: Inspection data can be fed back to optimize production processes.

6. How can the experiment be implemented in practice?

Option 1: Automating an existing manual system with a robot
The existing manual inspection station is automated using a robot.

- A robotic arm takes over the task of precisely dipping chain links into the magnetic bath and transporting them to the inspection area.
- A high-resolution camera captures images of the magnetized parts, which are then analyzed for anomalies by an AI-based system.
- After inspection, the robot automatically sorts the parts into "good" and "defective."

This retrofit enhances repeatability, reduces human error, and improves the system's efficiency.

Option 2: Fully automated system with feeding unit, conveyor belt, and sorting mechanism
A fully automated system is developed, transporting chain links from a feeding unit via a conveyor belt to a magnetic bath.

- After magnetization, the parts are transferred to the inspection area, where a camera with optimized lighting captures high-resolution images.
- An AI system analyzes the images in real time, identifying defects.
- At the end of the line, an automated sorting system separates the inspected parts into bins for "good" and "defective."

This solution enables continuous, fully automated inspection with high speed and accuracy, ideal for large production volumes.

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7. Why this is important: The future of crack testing
The experiments demonstrate the potential of simple AI approaches. With increasing data availability and computational power, such systems could improve inspection quality, reduce costs, and virtually eliminate errors.

Open questions:

- How robust are these systems for different forged part geometries?
- How can AI models be scaled to detect both small and large defects?

8. Can this AI technique be applied to other use cases?

Anomaly detection using audio in industrial machine monitoring
Audio-based anomaly detection is an innovative method for monitoring machine conditions.

- Microphones record the sounds generated during operation.
- An AI system analyzes the audio data by extracting characteristics such as frequency spectra or vibrations and comparing them with "normal" operating sounds.

Using models like Isolation Forest or neural networks, unusual sounds indicating defects such as bearing damage, imbalances, or friction issues can be detected early.

Benefits:

- **Contactless Monitoring**: No physical interaction with machines is required.
- **Continuous Data Collection**: Enables constant monitoring without interruptions.
- **Early Detection**: Even the smallest deviations, often imperceptible to the human ear, can be identified quickly.

Conclusion: Audio-based anomaly detection allows for predictive maintenance, reducing downtime and lowering maintenance costs.

Summary of sections in the paper:

1. The Idea: Simulating and Testing Crack Detection.

2. Available Methods for Anomaly Detection.
3. How My System Works – Results and Precision.
4. Black-and-White vs. Color Images: A Comparison.
5. From Experiment to Industrial Practice.
6. Practical Implementation Options:
    - Option 1: Robot Automation for Manual Systems.
    - Option 2: Fully Automated Solution with Conveyor Systems.
7. The Future of Crack Testing.
8. Extending AI Techniques to Other Applications, such as Audio-Based Anomaly Detection.