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Automated Steel Surface Defect Classification Using Deep Learning

Abstract

This project investigates automated steel surface defect classification using deep learning techniques. Classical machine-learning baselines and convolutional neural networks were evaluated on the NEU Surface Defect Database. Experimental results show that CNN-based models significantly outperform traditional approaches by learning spatial defect patterns, demonstrating the effectiveness of deep learning for industrial quality-control applications.

Introduction

Steel surface inspection is a critical step in manufacturing processes, as surface defects can impact product quality, safety, and downstream costs. Traditional manual inspection methods are time-consuming and prone to subjectivity, motivating the use of automated vision-based systems. This project explores whether deep learning models, particularly convolutional neural networks, can effectively classify steel surface defects and outperform classical machine-learning baselines.

Dataset and Preprocessing

Experiments were conducted using the NEU Surface Defect Database, which contains grayscale images across six defect classes. Images were resized and normalized prior to training. To improve generalization and reduce overfitting, data augmentation techniques—including rotation, horizontal flips, and zoom—were applied exclusively to the training set.

Methods

Several models were evaluated to establish a performance hierarchy:

- Logistic regression and a shallow multilayer perceptron using flattened pixel input
- Custom convolutional neural networks with increasing regularization
- A transfer learning model leveraging pre-trained convolutional features

Model performance was assessed using a train/validation/test split. Learning curves and qualitative error analysis were used to diagnose overfitting and misclassification patterns.

Results

Classical machine-learning models performed poorly due to the loss of spatial information inherent in flattened pixel representations. In contrast, CNN-based models demonstrated strong generalization by learning hierarchical texture features. Regularization and data augmentation reduced overfitting, while transfer learning achieved the highest test accuracy among all evaluated models.

Conclusion

The results demonstrate that deep learning, particularly convolutional architectures, provides an effective solution for automated steel surface defect classification. These findings highlight the potential of CNN-based systems to improve industrial inspection accuracy and scalability. Future work includes explainability analysis and deployment-oriented validation.