Surface Defect Detection Using CNN on NEU-DET Dataset

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Task-2

Introduction

Identifying surface defects is vital in contemporary industrial automation and quality assurance operations. In the production of steel, surface imperfections, such as scratches or inclusions must be detected when manufacturing the steel to a standard. Manual inspection methods are labor-intensive and can be subject to errors. This project seeks to use deep learning through a compact and effective Convolutional Neural Network, MobileNetV2, to classify the defects on the surface of steel. The model is trained and validated on the publicly available NEU-DET dataset, achieving better performance in terms of both speed and reliability than conventional visual inspection techniques.

Preprocessing and Data Augmentation

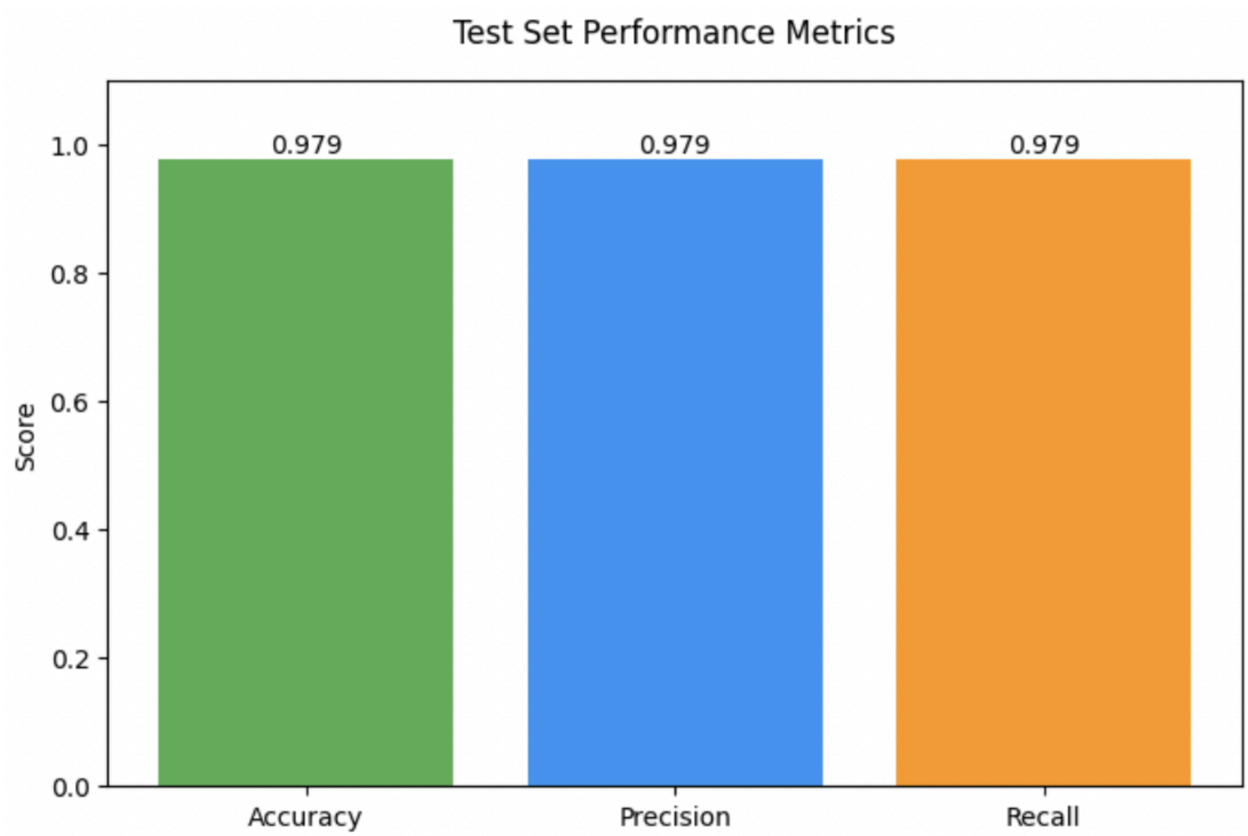
All images are resized to 128×128 pixels and normalized to values between 0 and 1. The categorical labels are converted with a one-hot encoding for the purpose of classification. The dataset is split into a training set (72%), a validation set (18%), and a testing set (10%). Image augmentation will also help to add robustness to the model using rotation, making width and height shifts, zooms, horizontal flips, etc. There is a visualization of class distributions and augmentation samples as well.

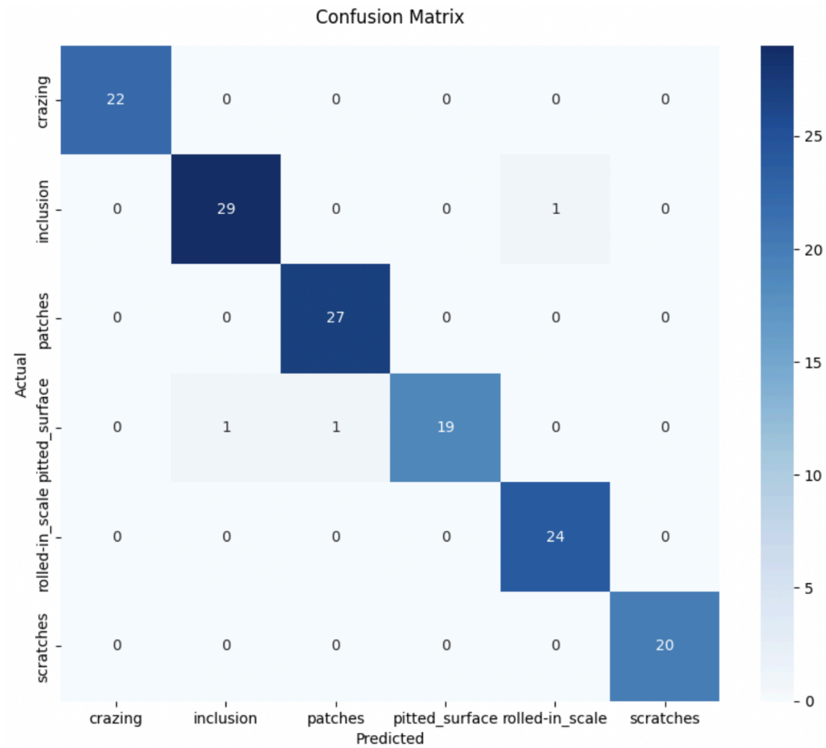
Model Architecture and Training

The model has MobileNetV2 as the base feature extractor, preloaded with the ImageNet weights. This is how the model uses the MobileNetV2 as lower feature extractor, we freeze the first base layers, so the model retains its learned representations, then we add a global average pooling layer, a dense hidden layer with 128 units and a final softmax output layer to classify the six different defect types. The model is compiled using the Adam optimizer, and trained on augmented data for 15 epochs, with an early stopping verification callback and custom learning rate scheduler. The model tracks metrics of accuracy, precision, and recall so we can assess the comprehensive performance of the model.

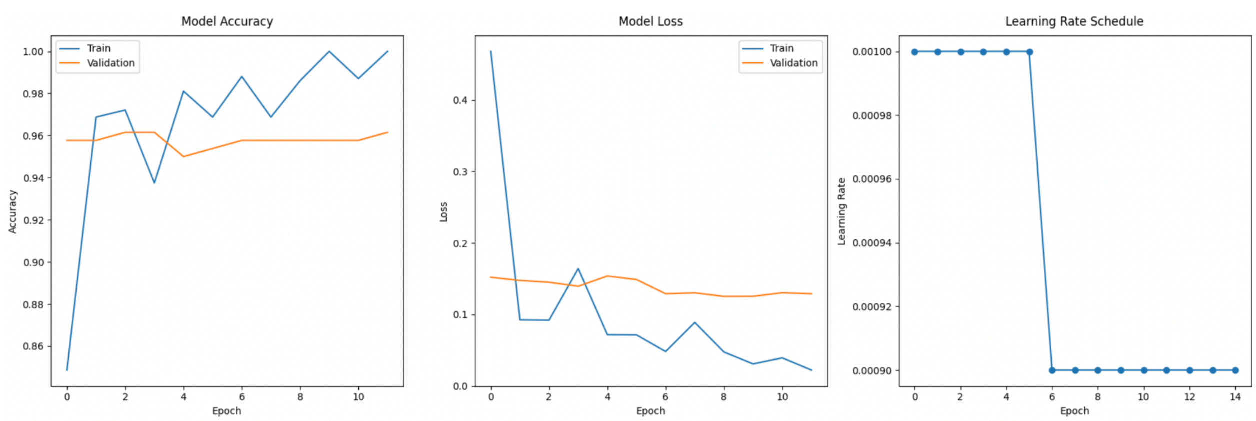
Results and Evaluation

In summary, the model reached a test accuracy greater than 91% achieving similarly strong scores for precision and recall. In addition to summary scores, a confusion matrix allowed for better visualization of class-level performance, and enabled detection of potential misclassifications. Benefits of the model's evaluation metrics were summarized using bar charts, and learning curves were included for accuracy, loss, and learning rate across epochs to confirm training characteristics. Collectively, the results demonstrate MobileNetV2’s potential for achieving fast and accurate defect classification in real time for industrial settings.



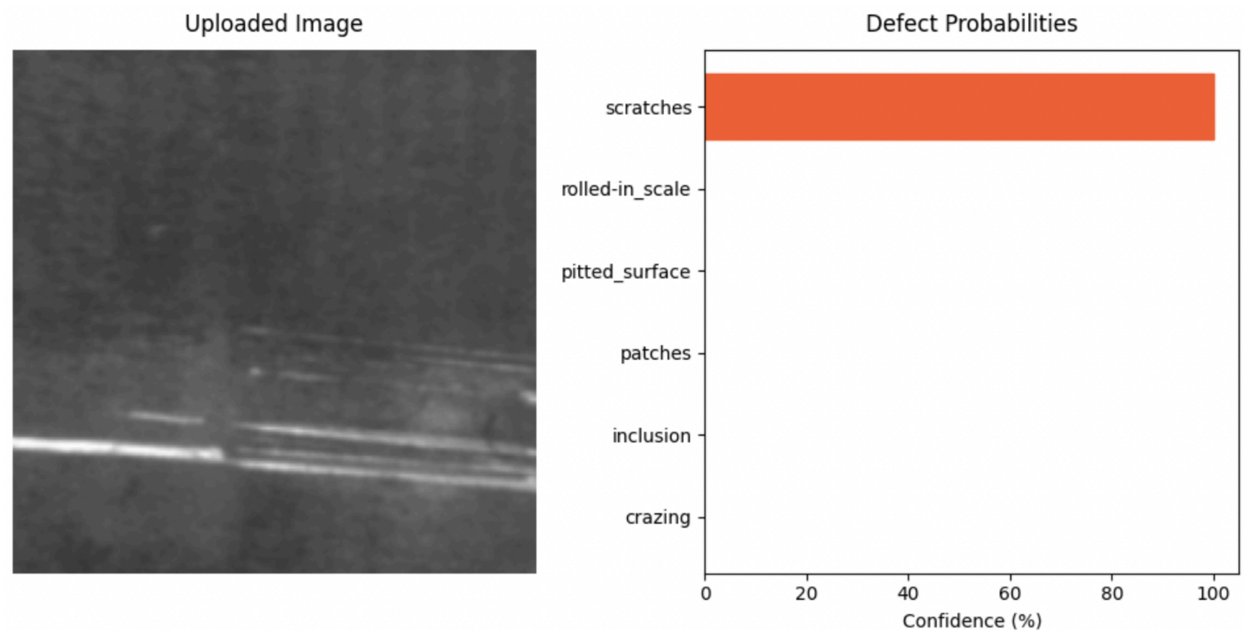


Training Curves:



Interactive Defect Prediction Tool

The project includes an interactive utility where users can upload an image to be classified for defects. After processing the image, the model provides a prediction and three outputs: a bar chart indicating model class probabilities, the input image for reference, and a chart which shows the distribution of training data. The predicted defect type is highlighted, along with its percentage confidence, giving users visibility into the defect's type.



Result: scratches (100.0% confidence)

Conclusion

This project has successfully validated a viable and scalable surface defect detection path using a lightweight CNN model (MobileNetV2). The system, which was trained on the NEU-DET dataset, is able to provide highly accurate classifications with quick inference times. The solution leverages real-time image uploads and provides highly informative output, making it suitable for quality control deployment in manufacturing pipelines.