Turbine Vane Defect Detection With Computer Vision

Howmet Aerospace

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PURDUE UNIVERSITY | The Data Mine Corporate Partners Program

HOWMET AEROSPACE

OVERVIEW

- Manufacturing aerospace parts is challenging due to strict tolerances and requirements. Therefore, identifying defects is crucial. We partnered with Howmet Aerospace to develop a machine learning model to quickly and reliably flag defective engine turbine vanes from x-ray images.
- We modified an open-source image classifier and train it on data provided by Howmet Aerospace.
- It is important to identify defects in the manufacturing process to improve product reliability, reduce cost and enhance safety,

Image processing

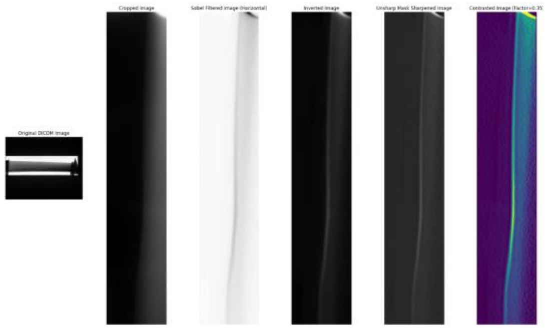

Fig 1. Applying filter to images

Program takes direct X-Ray image and processes it into a filtered image for classification (creating a complete data pipeline)

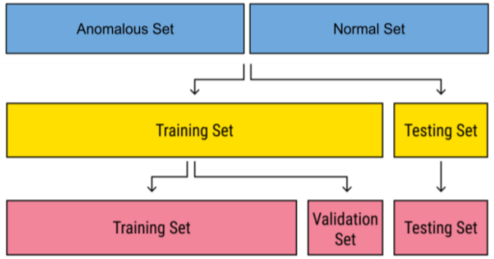

Fig 2. Oversampling data split structure

Anomalous and normal data are split into training, validation, and testing set with a ratio of 7:2:1.

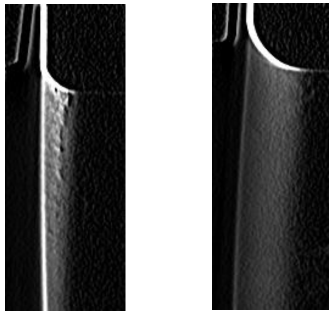

Fig 3. Anomalous and Normal vane filtered pic.

~3000 human-flagged images to build dataset for model training and ~2000 artificial images from data augmentation

Model

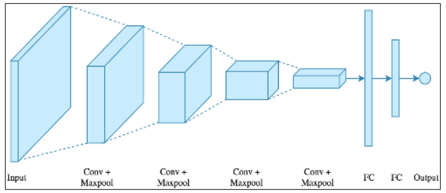

Fig 4. Overview of a model structure

Convolutional Neural Network (CNN) model architecture for its strength in extracting image features.

Hyperparameter	
Learning rate	Loss function
Optimizer choice	Model depth
Other optimizer params (e.g., Adam beta1)	Layer size
Batch size	Layer params (e.g., kernel size)
Weight initialization	Weight of regularization
	Nonlinearity

Fig 5. Hyperparameters

By modifying small metrics inside the model, called hyperparameters, the model could be optimized to yield higher accuracy

The model takes the image and classifies it into normal or anomalous based on the previously human flagged data

Pretrained models and architecture such as VGG and ResNet were utilized along with a custom head to create the classifier with model tuning and transfer learning

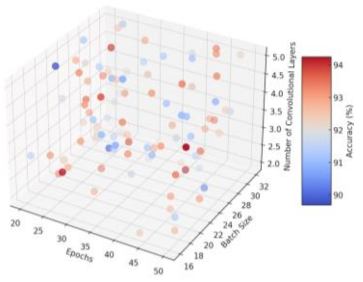

Fig 6. Hyperparameter optimization of CNN model

Results

Model achieve increasingly high accuracy over training epoch but no improvement on negative predictive value. Additionally, loss increases over time between training and validation, highlighting model overfitting training data.

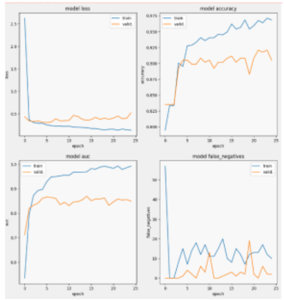

Fig 7. Model performance over epoch

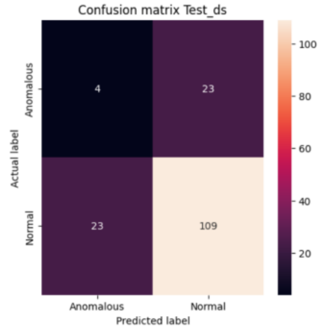

Fig 8. Confusion matrix with test dataset

Conclusions

The accuracy achieved is ~94%, which is an improvement over the 87% accuracy of human-only classification. However, the model suffers from low negative predictive value.

In conclusion, the model is not yet suitable for implementation in the aerospace industry. Its ability to accurately detect defective parts remains a challenge. Addressing this challenge requires additional training data, which pose as a bottle neck to the success of this project due to the lack of available of such data.

Future Works

I. Increase model's defect detection accuracy rate.
II. Broadening the model's detection to encompass diverse defect types.
III. Extending the model's applicability to encompass varied turbine vane designs.
IV. Implement image segmentation and bounding box around defective areas.

References

Chintanda, A., Ju, P., Winchester, J., Yao, D., & Zhang, K. (2023, April). *Automatic X-Ray Anomaly Detection of Turbine Vanes*. The Data Mine. https://datamine.purdue.edu/corporate/HowmetAerospace/TDM_Symposium2023_Poster_Howmet_turbine.pdf

Fergusson, M., Ak, R., Tsun, Y., Lee, T., & Law, K. H. (2018, August 7). *Detection and Segmentation of Manufacturing Defects with Convolutional Neural Networks and Transfer Learning*. arXiv. https://arxiv.org/pdf/1808.04018

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