INC23

LIFE ASSESSMENT OF RADIANT COILS UISNG MICROSCOPIC IMAGES

SIT PAING HTUN

ADVISORS: ASST. PROF. DR. SARAWAN WONGSA | ASSOC. PROF. DR. ISARATAT PHUNG-ON

1. BACKGROUND & PROBLEM

What are radiant coils?

- Radiant coils serve as essential components within cracking furnaces.
- They are constructed from HT E alloys, such as Cr35Ni45Nb.
- Their efficiency diminishes over time, largely due to the extreme operating conditions that can reach temperatures of approximately 1,100 °C.
- Carburisation is the primary factor leading to the failure of radiant coils.

What is carburisation?

- Carburisation is a process in which carbon diffuses into a material at elevated temperatures.
- This process can alter various properties of the material, including increasing hardness and transforming its magnetic state from paramagnetic to ferromagnetic.

Current inspection tools

- Eddy current testers, Vickers hardness test, and magnetic sensors are employed to assess the condition of radiant coils.
- However, these methods require human intervention and could be unreliable sometimes due to human error.

2. METHODOLOGY

DATASET CONSTRUCTION

Microscopy Imaging | Image Acquisition | Sample Images

TRANSFER LEARNING

- **Pretrained models** • **Feature extraction & Fine-tuning** • **Classification**

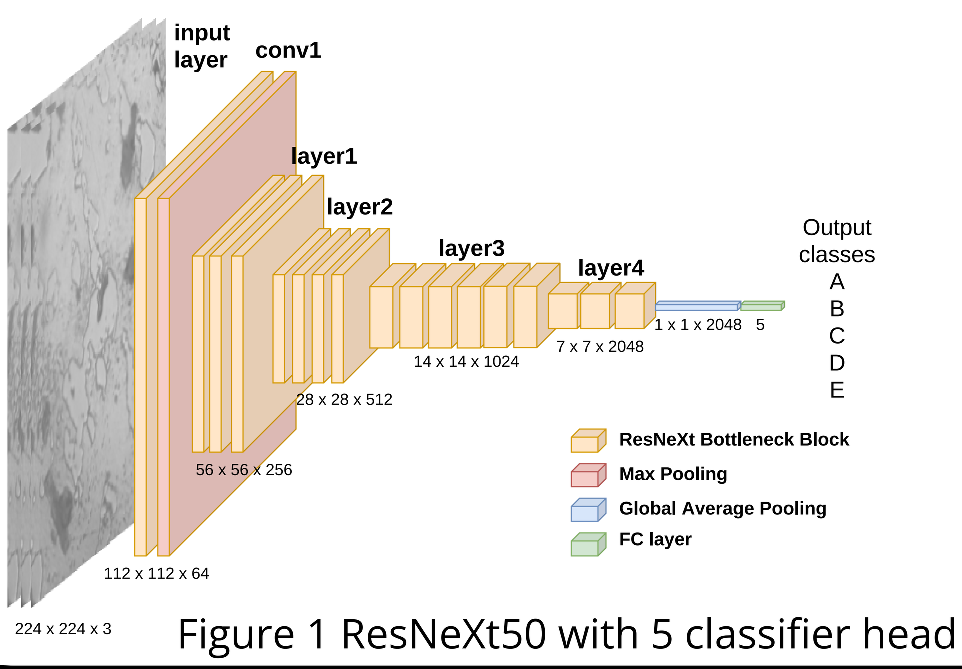
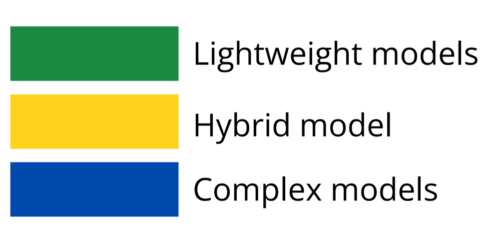


Figure 1 ResNeXt50 with 5 classifier head

- ImageNet1k pretrained models got replaced by custom FC layer.
- two stage training
  - feature extraction (only FC layer training)
  - fine-tuning (full layers training)
- 5 classes (A, B, C, D, E)

MODELS COMPARISON

Model Architecture	Parameters Count
ShuffleNetV2 (x1.0)	1,258,729
MobileNetV2	2,230,277
MobileViT-S	4,940,873
EfficientNetV2-S	20,183,894
ResNeXt50 (32x4d)	22,990,149



DOMAIN SHIFT MITIGATION

Sequential Fine-tuning

Models previously trained on circular domain dataset were **fine-tuned using curved domain dataset**.

Joint Training

Models previously trained on circular domain dataset were retrained using **both domains of dataset with weighted random sampling.**

3. EXPERIMENTAL RESULTS

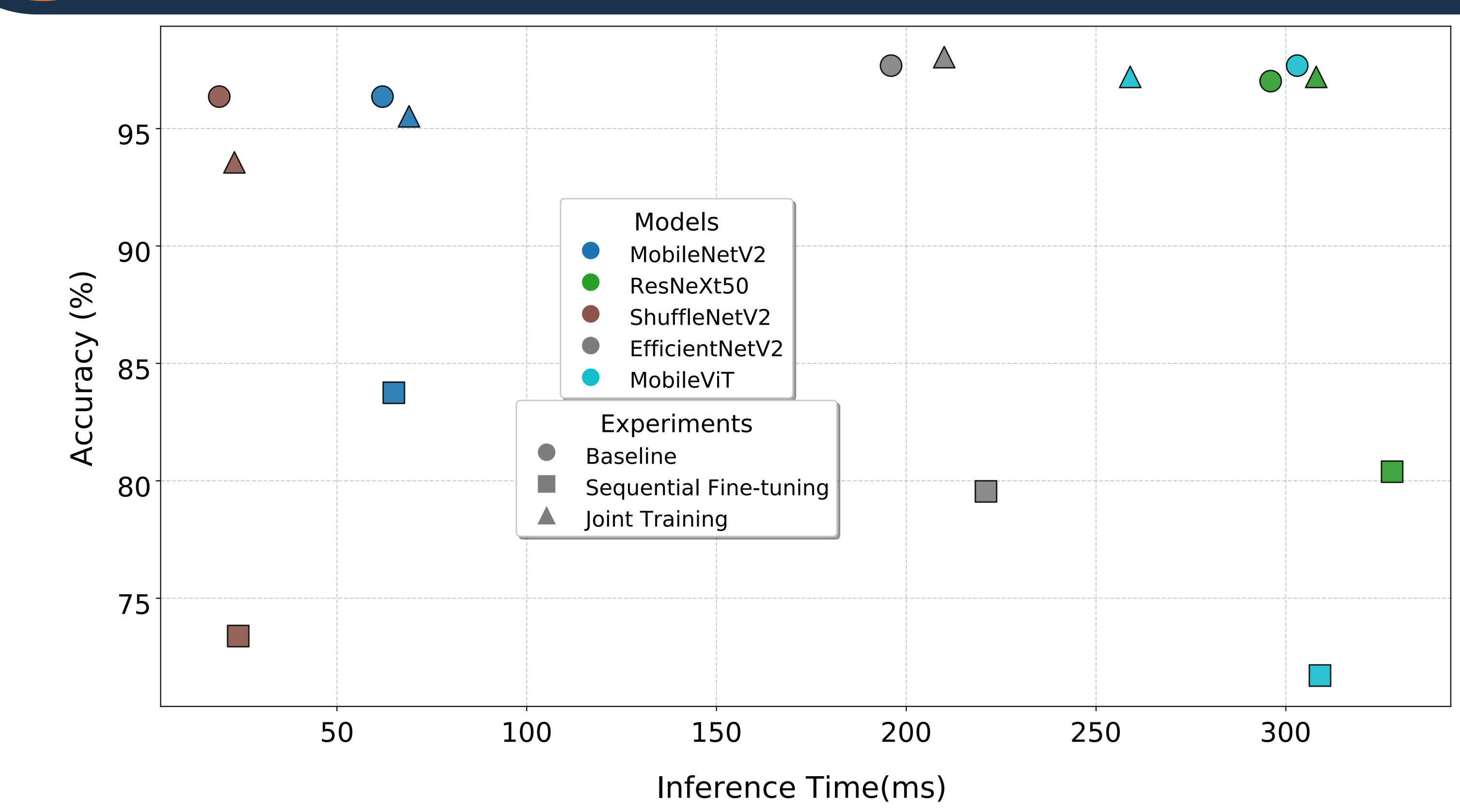


Figure 2 Accuracy Vs. Inference Time across Experiments

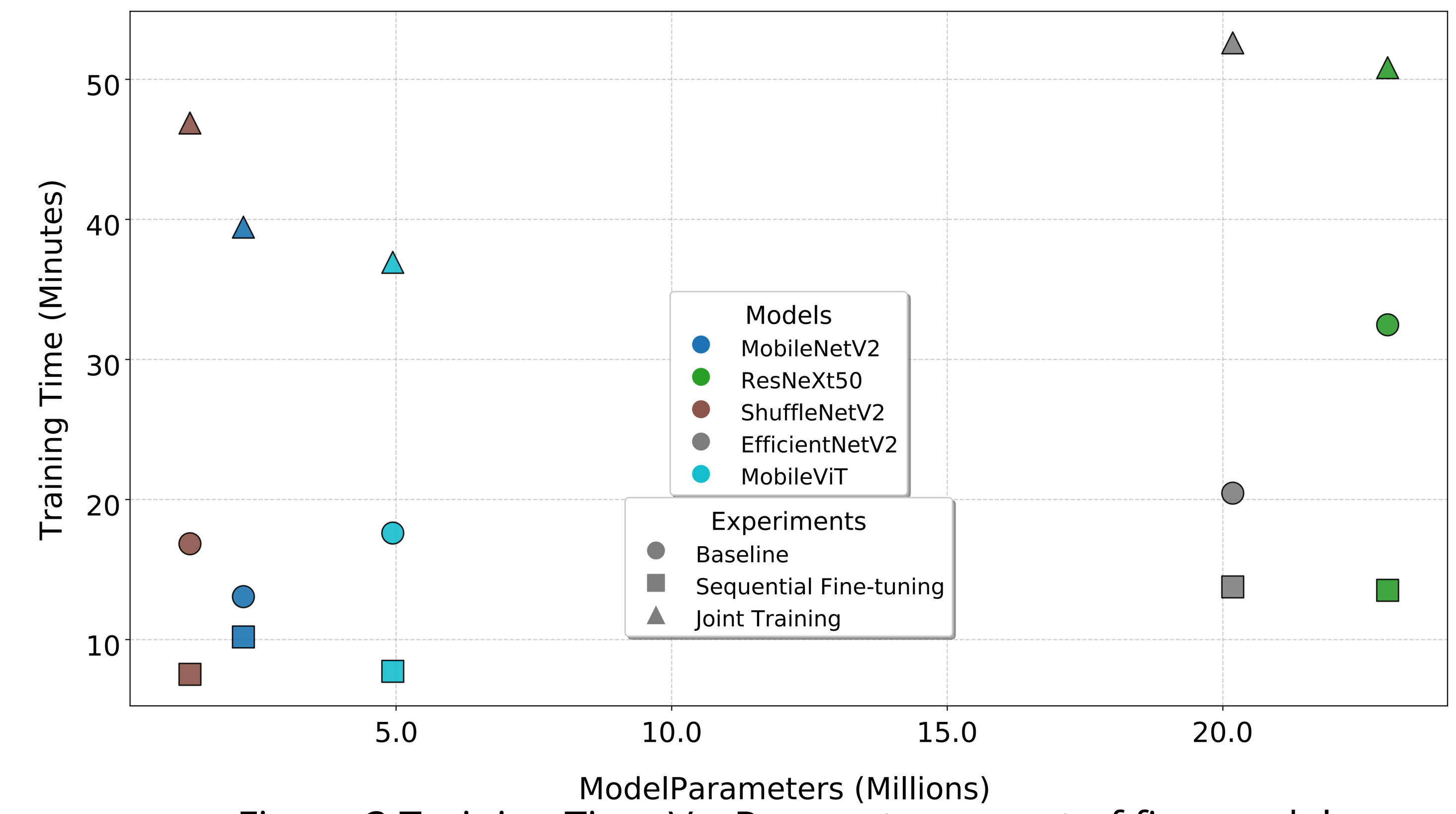


Figure 3 Training Time Vs. Parameters count of five models

Baseline - Trained only on cross-section dataset
Sequential Fine-tuning - Retrained the baseline models with curved dataset
Joint Training - Retrained the baseline models with both datasets

4. DISCUSSION & CONCLUSION

- There is a **direct correlation between the number of trainable parameters and the time required for five-fold cross-validation**. More parameters demand longer training sessions.
- **A higher parameter count does not guarantee better accuracy**. For example, MobileViT achieves performance comparable to ResNeXt50 despite having nearly 79% fewer parameters.
- While related to parameter count, FLOPs and memory access, **inference speed is also heavily influenced by architecture**. Notably, MobileViT (a lightweight vision transformer) has a slower inference speed than EfficientNet, even with fewer parameters.
- **Training strategy significantly impacts the trade-off between efficiency and precision**: SFT requires less training time with the cost of catastrophic forgetting, joint training takes more time but provides more accurate classification.

This study has successfully established **an automated classification system for the degradation of radiant coils** using microscopic images with transfer learning algorithm on hugging face platform. Future research may focus on real-time classification of radiant coil degradation employing a handheld digital microscope camera.

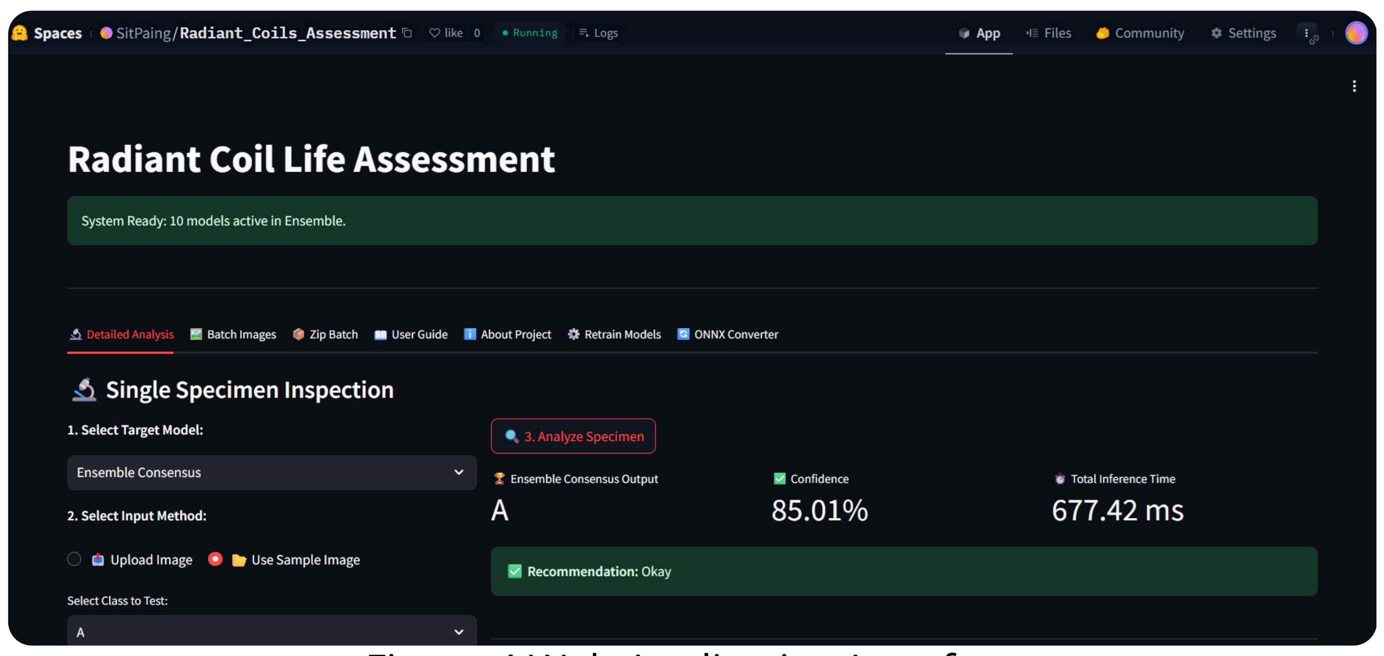


Figure 4 Web Application Interface

SCAN HERE TO USE THE APP

REFERENCES

- Phochan, S., 2024, **Study on Relationship between Carburisation Layer Thickness and Variation of Magnetic Field of Product Transfer Tube in Fired Tubular Reactor**, Independent Study, Master of Engineering (Welding Engineering), King Mongkut's University of Technology Thonburi.
- R. Liu et al., "AIMIC: Deep Learning for Microscopic Image Classification", **Computer Methods and Programs in Biomedicine**, Volume 226, November 2022, 107162.
- A. Musa et al., 2026, "A Systematic Review of Cross-Population Shifts in Medical Imaging Analysis with Deep Learning", **Big Data and Cognitive Computing**, Vol. 10, No. 3, pp. 76.