Sustainability Strategies and Evaluation for

*Green AI for Medical Image Classification with Explainable AI*

Nachiket Mehendale (x23272473)

Emerging Artificial Intelligence Technologies and Sustainability – H9ETS

MSCAI1\_SEP24

School of Computing

National College of Ireland

# Background Research

The growing dependence of healthcare sector on artificial intelligence technology for diagnostic scans or images has caused major sustainability issues. Medical imaging classification tools typically use computationally demanding deep learning models that require large amounts of energy and need extensive hardware infrastructural resources (Strubell et al., 2019). This computational burden adds to CO2 emissions and reduces availability in healthcare settings with limited resources.

Skin-related diseases affect millions of people worldwide, but prompt detection of the disease can significantly improve treatment outcomes, and therefore skin cancer screening is a highly relevant application area. Conventional diagnostic methods depend largely on skilled professionals causing obstacles to access in underserved areas. But AI-powered diagnostic tools have the potential to broaden access to quality healthcare despite the fact that medical imaging systems have a greater environmental impact (Esteva et al., 2017).

Sustainable AI development is now a major focus, primarily in medical contexts where applying models requires a trade-off between precision and ecological impact. The notion of "Green AI" focuses on building computationally efficient algorithms that decrease energy and hardware consumption without sacrificing diagnostic accuracy (Schwartz et al., 2020). This approach addresses ecological concerns alongside practical application hurdles within healthcare systems.

International regulatory organizations have started setting sustainability criteria for AI systems in healthcare technologies. The EU AI legislation has clauses about evaluation of environmental effects of high-risk AI systems, especially those applied to diagnostic processes. Medical instrument clearance processes more often consider overall ecological costs together with safety and effectiveness criteria. Medical associations are working on formulating guidelines for environmentally friendly AI implementation in clinical settings. These new guidelines highlight the importance of transparent reporting of hardware and software resources together with greenhouse gas assessments. Hospitals and clinics are expected to ensure compliance with standards with operational efficiency without compromising patient treatment standards (Martinez & Lee, 2022).

In medical scenarios, where confidence and openness are vital for diagnosis, the use of explainable AI(XAI) methods becomes crucial. To enable sound clinical decision-making, Doctors and specialists must be able to interpret how AI systems arrive at their conclusions. However, explainability and computational efficiency often clash because interpretability techniques tend to require additional computing power. (Adadi & Berrada, 2018).

# Sustainability AI Technologies

This research uses a comprehensive approach for environmentally friendly medical image classification by integrating efficient model designs paired with explainable AI techniques. The methodology is based on three core strategies: efficient architecture, model compression, and resource-conscious training protocols.

## Efficient Model Architectures and Compression Techniques

The selection of resource-efficient base architecture is the first step in the ecologically friendly green plan. As for Sandler et al. (2018), MobileNetV2 acts as the foundation model due to its refined architecture, and which makes it suitable for environments with limited resources. In comparison with conventional CNN models, MobileNetV2 uses some specialized convolution operations that significantly minimize the number of training parameters and processing needs. The model maintains acceptable accuracy levels while further lowering computational demands by using a width multiplier of 0.5. Model compression techniques are the next major key component of the sustainability strategy. Weight magnitude pruning eliminates less significant network connections, usually resulting in 50–80% sparse models without substantial accuracy degradation (Han et al., 2015). Post-training compression technique transforms 32-bit floating-point weights to 8-bit integers thereby lowering model memory usage by almost 75% and enabling faster model execution on mobile hardware. These compression methods collaborate to optimize resource consumption throughout the model lifecycle.

## Resource- conscious Training and Explainable AI Integration

The training model uses early stopping and low learning rate to avoid extra computing cost during model development. Batch size adjustment maintains efficient training considering hardware memory, ensuring consistency on various hardware setups. Transfer learning from pre-trained ImageNet weights minimizes training time and processing needs while utilizing existing feature representations (Tajbakhsh et al., 2016). Explainable AI prioritizes resource-efficient techniques that provide valuable insights without excessive overhead. Gradient-weighted Class Activation Mapping (Grad-CAM) creates explanatory heatmaps by marking specific parts of the image with minimal additional computation. Local Interpretable Model-agnostic Explanations (LIME) offers local model insights using perturbation methods and supplements Grad-CAM explanations alongside Grad-CAM visual maps (Ribeiro et al., 2016).

# Experiment Details

This study uses the MNIST:HAM10000 dataset which contains 10,015 dermatoscopic or skin lesion images. After we cleaned the data by getting rid of missing values and duplicate samples, we worked with 7,418 images of seven different skin conditions: actinic keratoses, basal cell carcinoma, benign keratosis-like lesions, dermatofibroma, melanoma, melanocytic nevi, and vascular lesions. All images were resized to 224×224 pixels using LANCZOS4 interpolation and normalized to values between 0 and 1.

We split the data carefully to avoid data leakage by keeping unique lesions separate for validation while using all other images for training. This gave us about 2,000 training images and 500 validation images. Since some skin conditions had very few examples, we used data augmentation with different rates for each class to balance the dataset. The augmentation techniques included rotation up to 30 degrees, shifting images by 15%, brightness changes, and flipping images horizontally and vertically.

We tested three different CNN models. The Green Baseline CNN is a simple model with 60,935 parameters using only 0.23 MB of memory. The Step-wise CNN is comparatively more intricate with batch normalization having 212,007 weights with a size of 0.81 MB.

A screenshot of a computer screen

AI-generated content may be incorrect.

**Figure1: Model architecture comparison showing the three CNN implementations used in this study.**

The EfficientNet-B0 uses transfer learning with 4,714,154 parameters and 17.98 MB of memory. All models were trained using the AdamW optimizer with a learning rate of 0.0001 and categorical crossentropy loss. We used early stopping, low learning rate, and model checkpointing to get the best results. To evaluate sustainability impact, we computed carbon footprint using energy consumption estimates of 0.5 kWh per training hour and 0.5 kg CO2 per kWh. For explainable AI, Grad-CAM method was used to highlight image regions targeted by the models. Plus, LIME to explain individual predictions. We evaluated models using accuracy, precision, recall, and F1-score. All experiments used fixed random seeds to ensure consistent results.

# Sustainability Evaluation

Students must report the results of their experiments and provide analysis and discussion around their results. Furthermore, students should detail some critiques on AI applications, in particular their chosen method, with respect to Sustainability. The critiques should include, but not limited to, the limitation of AI technologies, the limitation of application, the ethical conducts, and human-machine interactions in decision making.

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# Conclusion

Students should conclude their report with a brief summarisation of AI technologies for sustainability in the domain of their choice. Furthermore, students should outline the impact the experimented AI approaches have on the sustainable development, and several future directions one can develop AI technologies to achieve sustainable development goals.

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