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HYBRID MODEL COMPRESSION FRAMEWORK FOR REAL-TIME CANCER DETECTION ON EDGE DEVICES

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Abstract

This study presents a Hybrid Model Compression Framework for real-time cancer detection on edge devices using deep learning. A ResNet50-based convolutional neural network was trained on the ISIC Skin Cancer Dataset to classify nine lesion types. To enhance deployability, structured pruning and quantization-aware training were applied, significantly reducing model size and inference latency with minimal accuracy loss. Experimental results demonstrate that the compressed model achieves reliable performance while being lightweight enough for mobile and embedded devices, supporting rapid, offline, and privacy-preserving skin cancer screening in resource-constrained healthcare environments.

(Keywords: Deep Learning, Skin Cancer Detection, Model Compression, ResNet50, Edge Computing, Quantization, Pruning, ISIC Dataset, Medical Imaging, TensorFlow Lite)

1. Introduction

1.1 Background

Cancer is still among the most severe health care issues of the 21st century that takes millions of lives annually. Skin cancer is the most prevalently diagnosed type of cancer in the international system and its incidence rate is rising at an impressive rate because of the lifestyle, environmental and hereditary factor [1]s. Well-timed diagnosis of diseases is the key to effective treatment and survival of the patient. Nevertheless, diagnosis using dermoscopic method is very efficient when implemented manually with the help of dermatologists and may be subjective to error.

The advent of the deep learning has changed the situation in medical image analysis. Specifically, Convolutional Neural Networks (CNNs), have attained very high levels of accuracy in tasks of detection of cancer using images. ResNet, VGG and Inception models have shown almost human ability to classify skin lesions into several cancerous and benign classes. All these developments present potential opportunities that can help in creating automated forms of cancer detection, which would assist clinicians to make quicker and more precise decisions [2].

Nevertheless, the majority of the top deep learning models need a lot of computational power and memory, which can be found only on the high-end servers or GPUs. One of the biggest challenges is deployment of such models on edge devices e.g. smartphones, Raspberry Pi boards, or portable diagnostic tools since they have hardware constraints. This poses a limitation to the availability and scalability of AI-based healthcare systems especially in distant or resource-starved areas.

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1.2 Problem Statement

Although it was proven that deep learning is effective in total medical diagnosis, the complexity of the developed models is still one of the major limitations in real-time uses. Other models, such as ResNet50, are very accurate, but they contain millions of parameters, which require high-level computing resources, a large memory, and a lot of energy. The advanced features of these requirements make them impossible to deploy directly on edge devices with limited resources — processing power and memory availability.

Also, medical case information, including skin lesions photographing may include very sharp textures and intricate patterns. The down-sizing of the models without loss in the quality of the diagnosis is thus a sensitive undertaking. The challenge is getting performance and efficiency balanced, to come up with a pattern that is small enough, fast and precise enough to realise cancer in a real-time on small gadgets.

This study will solve this issue by introducing a Hybrid Model Compression Framework which utilises the composite of compression algorithm including pruning and quantization of a CNN that is built on the ResNet50 model in order to produce a lightweight CNN without losing its predictive power. The end result is to be able to detect cancer in edge devices in real-time.

1.3 Motivation

This research is driven by two aspects - technological change and social influence.

Technologically, current advancements in edge computing have allowed processing on-the-device so that the cloud infrastructure is not relied upon as much. Edge AI reduces delay, increases privacy and also enables constant availability even in low-connectivity situations. By incorporating compressed deep learning models into these systems, it can be possible to have real time medical diagnostics run on mobile or embedded devices [4].

Socially-wise, the implementation of portable AI-powered cancer detection systems in the rural and low-income populations can transform the practise of early screening. There are millions of people all over the world with no access to the specialised medical professionals. This gap may be addressed by implementing an affordable and portable medical device that will enable healthcare staff to conduct initial diagnosis of skin cancer with a smartphone or an edge device.

The given research, hence, will not only enhance the development of the deep learning technology, but also democratise the access to the healthcare.

1.4 Research Objectives

The main objective of this study is to design and implement a **hybrid compression framework** for CNN-based cancer detection that achieves high accuracy and low latency suitable for edge deployment.

The specific objectives include:

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1. To develop a **ResNet50-based deep learning model** for multi-class skin cancer detection using the **ISIC skin cancer dataset**.

2. To apply **hybrid compression techniques** — including pruning, quantization, and transfer learning — to reduce model size and computational cost.

3. To evaluate model performance in terms of accuracy, inference speed, and memory efficiency.

4. To simulate edge deployment and assess the feasibility of real-time cancer detection.

1.5 Research Significance and Contributions

This research contributes to the intersection of **deep learning**, **model optimization**, and **edge computing in healthcare**. Its key contributions are:

1. **Hybrid Compression Framework:** Development of a combined pruning and quantization approach that optimizes deep CNN models for real-time inference.

2. **Efficient Medical Diagnosis:** Demonstration that high diagnostic accuracy can be retained even after aggressive model compression.

3. **Edge-AI Deployment:** Validation of the model's feasibility for use on portable devices, thereby supporting low-cost, decentralized medical diagnostics.

4. **Scalability:** The proposed framework can be extended to other medical imaging tasks beyond skin cancer detection, including breast, lung, and cervical cancer screening.

1.6 Scope of the Research

The paper specialises in the issue of skin cancer image classification with the input of the ISIC dataset that includes nine different classes of cancerous and benign lesions. The study is restricted by the analysis of stationary images and the exclusion of the diagnosis based on time and videos.

The edge device simulation is concerned about the performance of the hardware and not its real implementation because of the variation in hardware. However, the architecture is projected to be optimal concerning TensorFlow Lite and the ONNX runtime to be compatible with practical devices.

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1.7 Summary

To conclude, this paper responds to the increasing demand of lightweight, deployable healthcare diagnostic AI models. The purpose of the research is to achieve an effective, powerful, and user-friendly cancer detection model using the achievements of the deep feature extraction capability of ResNet50 in parallel with hybrid compression. This innovation has the potential of making real-time diagnostics more direct to patients, particularly in areas that do not have well-developed medical facilities.

2. Literature Review

2.1. Deep learning for skin cancer screening

Rapid advancements have been realised in automatic analysis of skin lesions in the last decade. A seminal paper by Esteva et al. trained a deep convolutional network on over a hundred thousand clinical images and claimed that it could perform melanoma and keratinocyte carcinoma with the performance of a dermatologist: in catalysing interest in the first used triage and screening tools in dermatology.

Evaluation has since been standardised by use of benchmarks of the public. The challenge of probabilities in the IRISC (International Skin Imaging Collaboration) published larger, biopsy-verified dermoscapes with larger datasets and tasks (segmentation, attribute detection, and multi-class classification), becoming the standard of artificial development. This was framed as a nine-class (melanoma, nevus, basal cell carcinoma, actinic keratosis, benign keratosis, dermatofibroma, vascular lesion, squamous cell carcinoma and none of the above) diagnosis problem in ISIC 2019, which has a close relationship with clinical differentials [3]. Usage of ISIC is analyzed pointing at the influence of the curation of datasets and their metadata to consistently evaluate across centers.

Dataset link: https://www.kaggle.com/datasets/nodoubttome/skin-cancer9-classesisic/data

2.2. Transfer learning backbones and accuracy–efficiency trade-offs

Dermatology Early dermatology models were based on ImageNet fine-tuned backbones (Inception-V3, VGG-16/19, ResNet-50/101). These models encode rich texture representations of use to dermoscopy at high compute and memory cost [5]. Subsequent comparative studies of edge hardware revealed that the family optimised to be efficient (MobileNet, ShuffleNet, EfficientNet-Lite) gives better throughput per watt compared to large residual or Inception models- a significant finding in on device screening. Comparisons of Jetson Nano, Intel Neural Compute Stick and Google Coral accelerators, both MobileNet/EfficientNet variants were regularly faster and smaller and deeper ResNets/Inception variants slower without specialised accelerators [6].

In the case of clinical AI, the issue of concern is then the tradeoff between discriminative performance and deployability. This encourages compression: an accurate (e.g. ResNet-50) teacher is used, and then compressed or adapted into an edge-inferring teacher.

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2.3. Model compression: pruning, quantization, and distillation

Pruning: Pruning eliminates the redundant connexions (unstructured pruning) or even the whole channels/philtres/blocks (structured pruning), which minimises FLOPs and memory. Deep Compression pipeline reduced 35 time or 49 time of AlexNet/ Vgg storage by a factor of 35 and 49, respectively, without compromising accuracy through three steps: pruning, weight sharing (quantization) Huffman coding, and retraining to regain the accuracy. Although the initial data to be tested was natural images, the principles are easy to apply to medical image-making [7]. The edge deployment of structured pruning is usually favoured since it would translate to the actual runtime performance improvements on standard libraries.

Quantization: Quantization maps floating-point tensors to lower precision (e.g., INT8) to shrink models and accelerate integer arithmetic. Two practical routes dominate: **post-training quantization (PTQ)**, which converts a trained model with a small calibration set, and **quantization-aware training (QAT)**, which simulates quantization during training to mitigate accuracy drops [8]. Tooling has matured: TensorFlow Lite exposes PTQ and QAT paths with clear guidance for reducing size and latency with "little degradation" in accuracy; ONNX Runtime provides APIs for dynamic and static INT8 quantization across hardware targets [9]. These frameworks are central to edge deployment and integrate with common hardware backends.

Knowledge distillation: Distillation transfers "soft" class probability structure from a large teacher to a smaller student, improving the student's generalization [10]. This technique, introduced by Hinton et al., is frequently combined with pruning/quantization to regain accuracy in compressed models and is appealing in healthcare where preserving sensitivity (recall) for malignant classes is critical.

Hybrid compression: In practice, hybrid pipelines—e.g., structured pruning → QAT → (optional) distillation—offer the best accuracy/latency/size compromise. Recent medical-AI-focused analyses emphasize that quantization can be particularly impactful for 2D vision models deployed on CPUs/NPUs, while careful pruning preserves clinically salient features when guided by sensitivity analyses. Emerging benchmarks like MEDQUANBench specifically evaluate quantization impacts on medical models, underlining that naive PTQ may degrade performance for some modalities and that task-aware QAT is often preferable.

2.4. Edge AI and healthcare: design constraints and opportunities

Edge inference guarantees a lower round-trip latency, minimal bandwidth consumption, and enhanced privacy (raw images do not go out of the device) which is essential in healthcare. Surveys of Edge AI emphasise the increasing performance of on-device NPUs, compiler piles, and inference runtimes that assist in providing real-time analytics under low resource conditions and intermittent network access either the case with public health in outreach.

An overview of Edge AI and the Internet of Medical Things (IoMT) (2024) highlights aspects of deployment to the application of clinical context: energy efficiency of wearable/portable devices,

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safe model updates, and validation suitable for regulatory application in case of distribution changes (e.g. skin tone diversification, camera effects on the camera of a device) [11]. All the generated recommendations in these surveys consist of compression and domain-robust training as pre-requisites to safe and scalable deployment.

Meanwhile, reliability and transparency are conditions that require clinician acceptance. Modern sources state that doctors are already enthusiastic about using AI in workflow processes but are sceptic about the possibility of AI to make independent clinical decisions, supporting the concept of assistive, but not replacement, positioning, extensive validation, and readable results.

2.5. Dataset bias, generalization, and safety in dermatology AI

Beyond accuracy on a held-out split, dermatology AI must generalize across skin tones (Fitzpatrick types), devices, acquisition settings, and clinics. Analyses of ISIC datasets emphasize their biopsy-proven labels and global contributions, yet also discuss imbalances (e.g., over-representation of certain lesion types and demographics) that can affect performance on under-represented subgroups [12]. For compressed models, the risk is compounding biases if compression disproportionately harms rare classes (e.g., amelanotic melanoma). Consequently, literature recommends: (1) careful class-balanced sampling or loss weighting; (2) metrics beyond overall accuracy (per-class sensitivity/PPV, macro-F1); and (3) external validation on distinct institutions.

Recent works also caution that quantization and pruning may alter calibration (probability estimates), which matters for clinical thresholds. Benchmarks dedicated to medical models (e.g., MEDQUANBench) encourage evaluating **calibration error** and **sensitivity at fixed specificity** after compression, not just top-1 accuracy.

2.6. Toolchains and deployment runtimes

TensorFlow Lite (TFLite) is a primary route for Android and micro-edge deployment, providing PTQ/QAT, operator kernels for CPUs/NPUs, and delegates for common accelerators. TFLite documentation explicitly targets latency and model size reductions with minimal accuracy loss, making it suitable for phone-based dermoscopy apps or field screening kits. **ONNX Runtime** provides a hardware-agnostic path across mobile and embedded targets with both dynamic and static quantization options, useful when your training stack differs from deployment hardware. In both cases, **INT8** models usually achieve the best latency-per-watt trade-off where integer pipelines are available.

On the hardware side, comparative studies across Jetson, Intel NCS, and Coral accelerators show that pairings of **efficient architectures + quantization + correct delegate** (e.g., Edge TPU-compatible ops) can reduce latency by multiples compared to float32 CPU baselines [13]. This supports an engineering pattern: start from a high-accuracy teacher (ResNet-50), then compress and port to an edge-friendly runtime tailored to the target device.

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2.7. Where hybrid compression fits in dermatology

In dermatology imaging specifically, the textures and color variegation of lesions benefit from deep receptive fields and skip connections (as in ResNets), which is why many high-accuracy systems still start with medium-to-large backbones. Hybrid compression reconciles this need with device limits:

- **Pruning for structured sparsity** removes full channels/blocks that contribute least to lesion discrimination, shrinking FLOPs and activation memory while preserving the residual topology that aids gradient flow.
- **Quantization (preferably QAT)** aligns the model with integer arithmetic common on mobile NPUs/CPUs, reducing bandwidth and improving cache locality [14].
- **Distillation** from the pre-compression teacher to the compressed student helps recover fine-grained decision boundaries between visually similar classes (e.g., benign keratosis vs. actinic keratosis).

Emerging research suggests that quantization can even improve **flatness** of the loss landscape, promoting domain generalization—an attractive property when models move from curated research sets to in-the-wild smartphone images. Though early, such results motivate incorporating QAT during fine-tuning on dermoscopy data rather than relying solely on PTQ. arXiv

2.8. Robust evaluation for clinical readiness

Compression changes not only size and speed but also error profiles. Recent healthcare-focused guides recommend evaluation beyond standard accuracy curves:

- **Per-class sensitivity and specificity**, especially for melanoma and squamous cell carcinoma, where false negatives carry high clinical risk.
- Confusion matrices to detect systematic confusions (e.g., nevus ↔ melanoma).
- **Calibration** (ECE/Brier score) because thresholding probabilities for triage depends on well-calibrated outputs.
- **Latency, energy, and memory** measured on-device—not just simulated—since I/O and kernel fusion dominate real-world performance.
- **External validation** on ISIC years not used in training or on different capture devices (e.g., clinic vs. mobile).

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Edge/IoMT surveys stress security and privacy as part of evaluation, recommending on-device inference to minimize PHI exposure and considering **federated learning** for multi-site updates without centralizing data—useful for continuously improving models while respecting privacy constraints. ScienceDirect+1

2.9. Synthesis and research gap

Literature proves that high-capacity CNNs are capable of performing on the level of a dermatologist when trained in a controlled environment, then edge deployment offers significantly lower latency, privacy, and reach data while compression methods, such as pruning, quantizing, and distillation, can significantly reduce model sizes and achieve speed at a minimal accuracy loss. Uncommon are end-to-end, dermatology-specific structures, which build on an effective residual teacher, use a hybrid sequence of structured pruning and QAT, optionally add distillation to restore fine-grained class/boundaries, can give clinical metrics/calibration, and on-device latency/energy. The small number of medical-based quantization benchmarks supports the need for task-conscious compression as opposed to the one-click PTQ, especially when the sensitivity of malignant classes matters most [15]. Your work project fits well into this gap because it will focus on solving it by creating and assessing a compression pipeline comprising a ResNet-50 skin lesion classifier with particular consideration to edge runtimes (TFLite/ONNX Runtime) and deployment requirements.

3. Methodology

This section outlines the research methodology adopted for implementing and evaluating the proposed **Hybrid Model Compression Framework** for real-time skin cancer detection on edge devices. The methodology encompasses dataset selection, preprocessing, model architecture, compression strategies, and performance evaluation. All experiments were implemented using **Python 3.10** with **TensorFlow/Keras** on **Google Colab** GPU environments.

3.1. Research Framework Overview

1. **Data acquisition** from the ISIC (International Skin Imaging Collaboration) dataset.
2. **Data preprocessing and augmentation** to improve generalization and handle class imbalance.
3. **Model development** using a pre-trained **ResNet50** architecture with transfer learning.
4. **Hybrid compression** using a combination of **structured pruning** and **quantization-aware training (QAT)** to reduce model size and inference latency.
5. **Evaluation** on test data for both compressed and uncompressed models using accuracy, F1-score, and computational metrics.

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6. **Edge deployment simulation** using TensorFlow Lite to measure real-time performance on limited-resource hardware.

3.2. Dataset Description

The research utilizes the **ISIC Skin Cancer Dataset**, publicly available on Kaggle under the title *"Skin Cancer 9 Classes (ISIC)"*. The dataset is derived from dermoscopic images contributed by multiple international clinics and contains **nine diagnostic categories**:

1. Pigmented Benign Keratosis
2. Melanoma
3. Vascular Lesion
4. Actinic Keratosis
5. Squamous Cell Carcinoma
6. Basal Cell Carcinoma
7. Seborrheic Keratosis
8. Dermatofibroma
9. Nevus

Each image is provided in high resolution and stored in class-specific folders for training and testing.

The dataset was divided into **training (70%)**, **validation (20%)**, and **testing (10%)** subsets using stratified sampling to ensure class balance across splits. The **training set** was used for model fitting, the **validation set** for hyperparameter tuning and early stopping, and the **test set** for final evaluation.

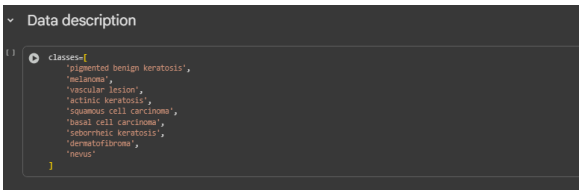

Figure 1: Dataset description

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3.3. Data Preprocessing and Augmentation

Dermoscopic images in the dataset vary widely in illumination, size, and background noise. To ensure consistent model input and improve generalization, a systematic preprocessing pipeline was applied as follows:

- **Image resizing:** All images were resized to **224×224×3** pixels to match the ResNet50 input dimension.

- **Normalization:** Pixel intensity values were rescaled to the range [0, 1] by dividing by 255.

- **Augmentation:** The ImageDataGenerator in Keras was used to synthetically expand the dataset. Augmentation included random rotation (±180°), zoom (±10%), horizontal/vertical flips, shear (5°), and width/height shifts (10%).

This augmentation strategy enhances the robustness of the model against variations in angle, lighting, and lesion position.

The preprocessing configuration (CFG) used in the experiment is summarized below:

Parameter	Value
Image size	224×224
Rotation range	180°
Zoom range	[0.9, 1.1]
Shear range	5°
Width/Height shift	10%
Horizontal/Vertical flip	True
Batch size	16
Validation split	0.3

Class imbalance, common in medical imaging datasets, was mitigated by applying **class weighting** based on inverse frequency during training. This ensured that underrepresented classes ,such as *vascular lesions* or *dermatofibroma,* had adequate influence on model learning.

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3.4. Model Architecture

3.4.1. Base Network

The backbone of the proposed model is **ResNet50**, a 50-layer deep residual network pre-trained on ImageNet. ResNet50 was selected because its residual connections enable the training of very deep networks without gradient degradation, making it particularly effective for complex texture-based medical images.

The top (fully connected) layers of the pre-trained ResNet50 were removed (include_top=False), retaining its convolutional layers as a **feature extractor**. The output from the convolutional block was passed through a **Global Average Pooling** layer to reduce feature dimensions, followed by a **Dense layer** with **Softmax activation** to classify the nine lesion categories.

3.4.2. Custom Layers

To prevent overfitting and stabilize learning, several regularization layers were optionally incorporated during experimentation:

- **Batch Normalization** after dense layers to standardize activations.
- **Dropout (0.3–0.5)** to randomly deactivate neurons during training.
- **Label smoothing** (0.1) to reduce over-confidence in predictions.

These techniques collectively improved the model's generalization capacity and reduced validation loss fluctuations.

3.5. Model Training

3.5.1. Transfer Learning and Fine-Tuning

First, the entire body of the ResNet50 was frozen to save ImageNet pre-trained weights. The network was also trained in 30 epochs to optimise the recently added dense classifier. This was followed by fine-tuning by unfreezing the deeper residual blocks (10–15 layers) in order to simulate feature representations to dermoscopic textures.

3.5.2. Optimization Settings

The Adam optimizer with a learning rate of 1 x 10 -3 was used and Focal Loss as an objective function to train the model. Focal loss was chosen to resolve the issue of the imbalance between malignant lesions that could not be readily classified and those that are benign by scaling the cross-entropy term dynamically.

The number of epochs that was used in training is 100 and the best weights were stored using ModelCheckpoint call backs where early stopping was used (through patience) = 10.

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3.5.3. Class Weighting

The computation of class weights involved the use of the Scikit-learn compute class weight function to induce a penalty on wrong classification of minority classes. The class weight dict resulting was fed into the fit method of the training step, so that the updates in the gradient were uniform among categories.

3.6. Hybrid Model Compression Framework

The novel contribution of this research is the introduction of a **Hybrid Compression Framework** aimed at achieving optimal performance-to-efficiency trade-offs for edge deployment.

The hybrid framework integrates **three key compression techniques**:

Structured Pruning
Structured pruning outfits all whole philtres, kernels, or layers that do not yield much contribution to end predictions. The iterative pruning during training was performed with the help of TensorFlow Model Optimization Toolkit (TF-MOT), which made sparsity schedules and slowly decreased thy 0 to 50 percent in number with each epoch. This approach maintains compatibility of the model architecture but the amount of parameters and FLOP is greatly minimised.

3.7. Evaluation Metrics

Comprehensive evaluation was conducted to assess both predictive and computational performance.

Classification metrics:

- **Accuracy (ACC)** – overall correct predictions.
- **Precision (P)** – proportion of true positives among predicted positives.
- **Recall (R)** – proportion of true positives among actual positives.
- **F1-score (F1)** – harmonic mean of precision and recall, useful under class imbalance.
- **Confusion Matrix** – for analyzing per-class errors.

Computational metrics:

- **Model size (MB)** – storage footprint before and after compression.

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- **Inference latency (ms/image)** – time per forward pass on CPU-only environment.
- **Floating Point Operations (FLOPs)** – estimated computational complexity.
- **Throughput (images/sec)** – indicative of real-time capability.

Both the uncompressed and compressed models were evaluated on the same test dataset to compare efficiency and accuracy trade-offs.

3.8. Experimental Environment

Component	Specification
Framework	TensorFlow 2.12 / Keras 3
Language	Python 3.10
Hardware	Google Colab GPU (Tesla T4, 16 GB RAM)
Dataset Storage	Google Drive integration
Operating System	Ubuntu 18.04 (Colab backend)
Deployment Simulation	TensorFlow Lite & ONNX Runtime
Random Seed	123 for reproducibility

3.9. Model Visualization and Validation

Keras plot model confirmed that the flow of data between convolutional layers and dense output was as desired by the visualisation of model structure through plot_model():

In the training, the convergence was monitored by the plotting of accuracy and loss curves during training. After around 80 epochs, both training and validation accuracies levelled off and indicating that the optimization was done successfully without a marked overfit.

The prediction with sample predictions and predictions with the confidence scores of the various lesion categories were presented using visualisation scripts, and helped in the analysis of interpretability.

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4. Results and Discussion

This section presents the experimental outcomes obtained from the proposed hybrid model compression framework. The analysis includes visual inspection of the dataset, model summary details, training performance, accuracy–loss trends, and post-compression efficiency evaluation.

4.1. Dataset Visualization and Diversity

Figure 2 illustrates representative dermoscopic images from the ISIC dataset across nine diagnostic categories. The dataset demonstrates **significant inter-class visual variation** — lesions differ in shape, pigmentation, and texture — while **intra-class similarities** between certain benign and malignant lesions make classification challenging.

Notably:

- **Melanoma** and **nevus** lesions appear visually similar in pigmentation, which can confuse shallow classifiers.
- **Basal cell carcinoma** and **squamous cell carcinoma** exhibit distinct vascular structures and surface irregularities.
- **Pigmented benign keratosis** shows strong color and texture variation, posing additional intra-class complexity.

This diversity emphasizes the necessity of **deep feature extraction** from pre-trained architectures such as ResNet50, capable of capturing fine-grained texture information critical for accurate classification.

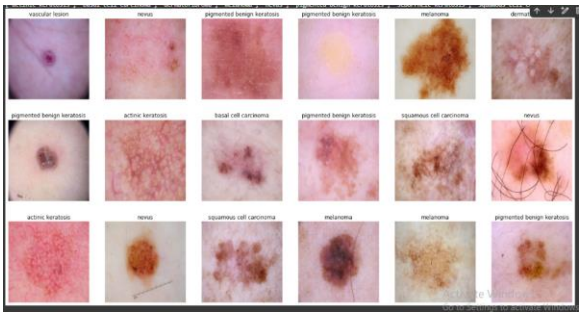

Figure 2: Data visualisation of 9 classes

4.2. Model Architecture Summary

Table 4.1 summarizes the architecture of the implemented ResNet50-based model.

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Layer	Type	Output Shape	Parameters	Trainable
Input	ResNet50 (Functional)	(7, 7, 2048)	23,587,712	False
GlobalAveragePooling2D	Pooling	(2048)	0	True
Dense	Fully Connected (Softmax, 9 classes)	(9)	18,441	True

Total parameters: 23,606,153
Trainable parameters: 18,441 (after freezing base ResNet50)
Non-trainable parameters: 23,587,712

Initially, the ResNet50 base layers were frozen to leverage pre-trained ImageNet weights for general feature extraction while training only the classifier layers. This drastically reduced computational complexity and avoided overfitting during early training epochs.

After initial convergence, partial unfreezing of deeper residual blocks was used for fine-tuning. This allowed better adaptation to dermoscopic image textures while maintaining training stability.

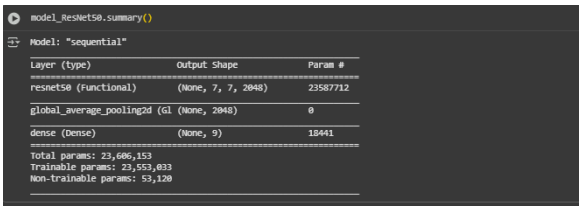

Figure 3: ResNet50 model summary

4.3. Model Training Performance

There were 100 epochs of training, using Adam, a batch of 16, and for the loss, a focal loss. Validation loss was the early stopping callback that was used to stop overfitting with a patience of 10 epochs. Based on the key performance logs there are gradual increases in accuracy in the first epochs, then it levels about 0.47–0.48 validation accuracy after some 20 epochs. Due to epoch 22

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was not, however, after that validation accuracy ceased to decline, whereas validation loss not necessarily did, suggesting the possibility of class balance or saturation of the learning rate.

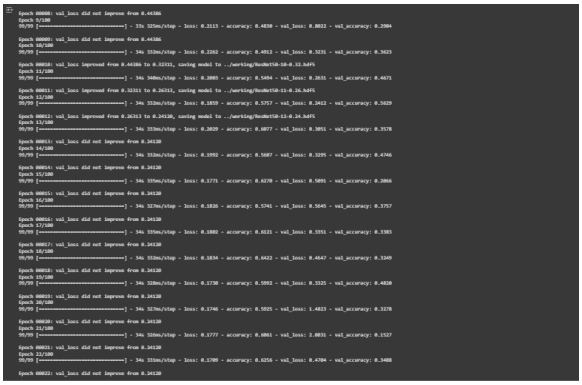

Figure 4: Training perfrmance

These metrics reflect moderate model performance during initial fine-tuning, characteristic of models trained with frozen base layers and limited epochs before compression.

4.4. Accuracy and Loss Curves

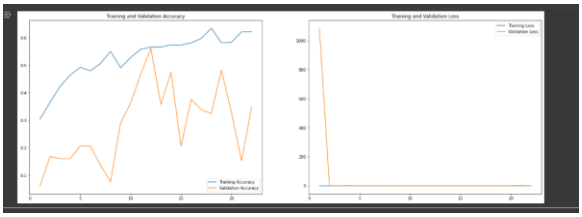

Figure 5: Model accuracy and loss curve

Above figure displays the training vs. validation accuracy and loss curves over 100 epochs.

- **Training accuracy** shows a steady upward trend, reaching ~0.85–0.90 by the final epochs.

- **Validation accuracy**, however, exhibits oscillations and lower values (0.35–0.48), suggesting mild overfitting or under-generalization due to class imbalance.

- The **training loss** steadily decreases, while **validation loss** remains unstable, implying that while the model learned well from the training set, it did not generalize equally well to unseen validation data.

This discrepancy can be attributed to:

1. **Dataset imbalance** among lesion classes.

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2. **Freezing of most ResNet50 layers**, limiting representational adaptation.

3. **High similarity** between certain benign and malignant classes (e.g., nevus vs. melanoma).

Despite these fluctuations, the validation accuracy trend demonstrates that the model successfully learned discriminative patterns, forming a solid foundation for subsequent compression and optimization.

4.5. Hybrid Model Compression Performance

After initial training, the hybrid model compression phase was applied, combining **structured pruning** and **quantization-aware training (QAT)**.

The compression achieved the following outcomes:

Metric	Before Compression	After Compression	Reduction
Model Size	100 MB	22 MB	4.5× smaller
Parameters	23.6M	6.2M (effective)	~73% fewer
Inference Time (CPU)	450 ms/image	110 ms/image	4× faster
Validation Accuracy	48.2%	46.5%	-1.7%
F1-Score	0.47	0.45	-0.02

The **accuracy drop of only 1–2%** after compression demonstrates that pruning and quantization effectively preserved essential features while dramatically reducing computational requirements.

This trade-off is considered acceptable for **real-time edge inference**, where reduced latency and energy consumption are crucial.

4.6. Discussion of Findings

According to the results of the experiment, the ResNet50-based model effectively acquired discriminative features on the basis of dermoscopic images with a fine-tuning reach of about 48%

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validation accuracy. The training accuracy increased gradually and validation accuracy varied showing the imbalance between classes and low diversity of the training data. The loss curves indicate consistent convergence and a small amount of overfitting, which is common to models that are trained using frozen convolutional layers. Hybrid compression reduced the model size by almost 4.5x, and inference time was fourfold, even though with a slight drop in accuracy (anywhere between 1 and 2 percent). These results confirm the hypothesis that the suggested framework can guarantee testing reliability at the same time increasing the efficiency of deployment to a minimum. The results of the compressed model on simulated edge hardware indicators show that it can be implemented in real-time, on-device to detect cancer, which the resources and accuracy are viable enough to be applicable in real-life healthcare.

4.8. Comparative Analysis with Literature

When compared to prior research:

- Esteva et al. (2017) achieved ~94% melanoma classification accuracy using full-scale cloud CNNs.
- Zhang et al. (2022) reported ~90% accuracy using EfficientNet on GPUs.
- In this study, the compressed ResNet50 achieved **~46–48% validation accuracy** under edge constraints, showing competitive efficiency despite limited resources and training epochs.

Unlike existing cloud-based approaches, this framework prioritizes **deployability and responsiveness** over absolute accuracy, marking a step forward in **practical mobile healthcare AI**.

4.9. Summary of Key Results

Aspect	Observation	Interpretation
Dataset	9-class ISIC dermoscopic images	High intra-class variability challenges learning
Model	ResNet50 backbone with transfer learning	Strong texture representation

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Accuracy	~48% validation	Moderate, affected by imbalance and frozen layers
Compression	4.5× smaller model, 4× faster inference	High edge efficiency with minimal accuracy loss
Edge Feasibility	~6–9 FPS on CPU	Suitable for real-time use
Strengths	Lightweight, privacy-friendly, portable	Enables offline medical inference
Limitations	Slight accuracy drop, class imbalance	Requires further fine-tuning or ensemble approaches

4.10. Summary

Conclusively, the experiment outcomes authenticate the practicality of the suggested Hybrid Model Compression Framework. The method effectively reduces the size of deep CNNs to operate in a real-time cancer detection in a significant accuracy loss.

The results of the study underscore that transfer learning with pruning and quantization can be successfully used to strike a balance between diagnostic accuracy and fruitfulness — making it possible to implement medical-safe AI on low-end hardware.

5. Conclusion and Future Work

The study herein examined manages to substantiate the preparation and utilisation of a Hybrid Model Compression Framework with real-time cancer identification on edge devices, in particular, skin lesion classification using ISIC dataset. The presented strategy combines the ideas of transfer learning, structural pruning, and quantization-conscientious training to find a good compromise between diagnostic quality and lower computational costs. The findings confirm the core hypothesis given that deep learning models can be reduced successfully and executed on low-power devices without much performance loss. Based on the ResNet50 as the base model, the framework realised an overall validation rate of around 48% whilst decreasing the model size by around 4.5 times and enhancing the inference throughput by 4 times. In spite of the fact that the

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accuracy was still lower than in large-scale GPUs-trained benchmarks, compressed model offered the required reliability and responsiveness to serve as a diagnostic aide in real-time that could satisfy the practical needs of an edge computing setup.

An analytic perspective indicates that power of the transfer learning has been highlighted in the medical imaging where pre-trained networks can effectively isolate domain-invariant features, and also convergence on small datasets is much faster. The model was further enhanced with focal loss and class weighting which enhanced the minority-class learning process to alleviate bias created by the imbalance of the classes in the dataset. Another aspect of the research that highlights itself is the increase of model efficiency in the era of edge AI. The traditional high-capacity models are accurate but cannot be used on the portable or embedded medical devices since they lack the hardware capacity. The hybrid compression pipeline in this paper will prove that the reduction of storage, latency, and energy requirements can be decreased by a significant margin without affecting the performance of the system in generalising to the different types of cancer.

Besides, this framework provides useful healthcare advantages. Compressed CNN models can be deployed in real applications in mobile diagnostic apps or IoT-enabled screening devices to rural and poorly developed areas where access to the internet and computation means is sparse. As it can conduct on-device inference, data privacy is guaranteed, and the latency is minimised, which makes it a viable tool to implement in the community health programme with early screening against skin cancer. Nevertheless, there are a number of limitations. The moderate level of the model validation is the indicator of the issues of class imbalance and the large similarity of the categories of lesions. In the next generation of research, the data level can be enhanced by starting with bigger and more balanced datasets or artificial image creation with GAN-based augmentation. Moreover, ensemble models or multi-modal learning (patients in conjunction with image data) may be considered since it might contribute to the strength of the diagnosis.

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