

A Comprehensive Study of MobileNetV2 and Its Application in Breast Ultrasound Cancer Detection

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I. Introduction

MobileNetV2 is a lightweight Convolutional Neural Network (CNN) developed for mobile and embedded vision applications. It significantly reduces model size and computational cost using two key architectural innovations: **inverted residual blocks** and **linear bottlenecks**. This allows MobileNetV2 to maintain good accuracy while running efficiently on low-resource devices such as smartphones, IoT boards, and web browsers.

In the context of breast cancer diagnosis, deep learning models must handle limited datasets, noisy ultrasound images, and real-time constraints for clinical deployment. MobileNetV2's small model footprint and efficient computation made it an ideal baseline architecture during the early experimentation phase of our project, an AI-powered diagnostic system for breast ultrasound cancer classification.

Our experiments used MobileNetV2 primarily to test feasibility, benchmark accuracy, and compare lightweight CNN performance against deeper architectures. This report discusses how MobileNetV2 works, how we used it in our project, and how its performance compares to other CNNs.

II. Literature Review

Sandler et al. introduced MobileNetV2 in 2018, improving upon MobileNetV1 by using inverted residuals that connect thin bottleneck layers with wider expansion layers. Global studies show MobileNetV2 achieves competitive accuracy on classification tasks while requiring only a fraction of the computation used by heavier CNNs.

Several existing works utilize MobileNetV2 for medical imaging:

- **Breast ultrasound classification** using MobileNetV2 achieved 85–92% accuracy in previous studies.
- **Low-resource healthcare systems** benefit from MobileNetV2 due to its small model size and fast inference.
- **Transfer learning** using ImageNet weights has been shown to improve performance on medical images with small datasets.

However, MobileNetV2 alone often struggles with complex ultrasound noise patterns, which motivated researchers to combine it with attention modules or hybrid feature fusion networks.

III. Methodology

In our project, MobileNetV2 was used for:

1. **Early-stage benchmarking**
To evaluate whether lightweight CNNs could classify BUSI + local ultrasound data effectively.
2. **Transfer Learning**
 - Pretrained on ImageNet
 - Final dense layer replaced with **3-class output (Normal, Benign, Malignant)**
 - Softmax activation
3. **Training Strategy**
 - Image size: **224 × 224**
 - Optimizer: **Adam (lr=0.0001)**
 - Loss: **Categorical cross-entropy**
 - Augmentation: rotation, flip, zoom, brightness
4. **Evaluation**
MobileNetV2 was evaluated against Xception and EfficientNetB3 using the same dataset split.

IV. Implementation

The implementation followed these steps:

A. Model Preparation

- Loaded `MobileNetV2(include_top=False)`
- Added `GlobalAveragePooling2D`
- Added `Dense(128)` with ReLU
- Added dropout for regularization
- Final `Dense(3)` with Softmax

B. Dataset

- Total images: **760**
- Includes BUSI dataset + Kaggle + additional Bangladeshi images
- Mask images (+45.5%) removed before final experiments

C. Training

- Batch size: 32
- Epochs: 20–25
- Validation based on early stopping
- Model stored in H5 format for comparison

V. Results & Analysis

A. Accuracy

Model	Training Accuracy	Testing Accuracy	Notes
MobileNetV2	65%	70%	Underfitting; shallow depth

B. Interpretation

MobileNetV2 struggled due to:

- Limited representational power for noisy ultrasound textures
- Small dataset size
- Lack of ability to extract deeper high-level semantic features

However, it provided valuable early insights:

- Lightweight models can run faster
- Preprocessing and dataset cleaning significantly affect accuracy
- EfficientNetB3 was justified as the superior model for deployment

VI. Discussion

Although MobileNetV2 performs well on everyday image classification, breast ultrasound images are more challenging because:

- Lesions have irregular boundaries

- Noise and artifacts vary across hospitals
- Tumor shapes differ between patients

Thus, MobileNetV2 demonstrated:

Strengths

- ✓ Very fast inference
- ✓ Small model size (3.4 MB)
- ✓ Suitable for mobile devices

Limitations

- ✗ Lower accuracy
- ✗ Struggles with complex textures
- ✗ Cannot capture deep high-level features

This led our project to migrate toward **EfficientNetB3**, which uses compound scaling, deeper layers, and squeeze-and-excitation optimizations.

VII. Conclusion

MobileNetV2 served as an important baseline for our research. It helped verify that lightweight CNNs can classify breast ultrasound images but also revealed the need for more powerful architectures to achieve clinical-grade performance.

Although MobileNetV2 achieved only **70% testing accuracy**, the experiments confirmed:

- Dataset quality heavily influences model success
- Lightweight models alone are not enough for medical-grade accuracy
- More sophisticated CNNs (EfficientNetB3) are needed for deployment

VIII. Future Work

Future improvements may include:

- Using MobileNetV2 as a **feature extractor** combined with attention layers
- Training a MobileNetV2-Tiny variant for mobile offline diagnosis
- Testing MobileNetV3 and MobileNetV4 for performance comparison
- Exploring knowledge distillation from EfficientNetB3 into MobileNetV2

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