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Automated Breast Cancer Detection using Deep-Learning in Histopathological Images

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ABSTRACT

This study presents a systematic evaluation of three CNNs for detection of Breast Cancer in histopathology images. We compare AlexNet, VGG16, and a novel lightweight Custom CNN using 277,054 annotated patches from the Breast Histopathology Kaggle dataset. Our experiments demonstrate VGG16's superior diagnostic accuracy (87.2% F1-score) versus the custom CNN's operational efficiency (11ms inference time). The research introduces three key contributions: (1) standardized benchmarking under identical training conditions, (2) computational efficiency analysis critical for clinical deployment, and (3) interpretability validation through Grad-CAM visualizations. Results indicate VGG16 is optimal for diagnostic accuracy, while our custom architecture (90.2% accuracy) enables real-time applications. This work provides actionable insights for implementing AI-assisted pathology in diverse healthcare settings.

Index Terms : Breast Cancer, Deep Learning, CNN, Histopathology, Medical Imaging, Transfer Learning

I. INTRODUCTION

Breast cancer diagnosis through histopathological examination remains challenging due to diagnostic variability and increasing caseloads. While deep learning has demonstrated remarkable success in medical image analysis [1], the healthcare community requires clear guidance on model selection considering both performance and practical constraints.

Recent studies have shown CNN effectiveness in cancer detection [2], but critical gaps remain:

1. **Comparative Analysis**: Few studies directly compare multiple architectures using identical datasets and training protocols.
2. **Clinical Feasibility**: Most research neglects computational requirements for real-world deployment.
3. **Interpretability**: Limited validation of decision-making processes against pathological standards.

Our work addresses these gaps through systematic evaluation of:

- Two established architectures (AlexNet, VGG16)
- A novel lightweight CNN optimized for edge deployment
- Standardized metrics including accuracy, speed, and memory footprint

Using the largest publicly available breast histopathology dataset [3], we demonstrate that while VGG16 achieves high accuracy (89.7%), carefully designed compact architectures can maintain diagnostic utility (90.2%) with 58% lower memory requirements. This balance is crucial for implementing AI solutions across diverse clinical environments—from well-resourced hospitals to mobile screening units.

2. METHODOLOGY

2.1 Dataset

The Breast Histopathology Kaggle dataset [3] comprises 277,054 patches (50×50px) from 162 whole slide images (WSIs), annotated by expert pathologists. Key characteristics:

- Class distribution: 58% benign, 42% malignant
- Split: 221,643 training, 55,411 testing

- Preprocessing:
    - Normalization: μ=0.485, σ=0.229 (ImageNet standards)
    - Augmentation:

```
train_dataGen = Imagedatagenerator(
                    rotation_Range=15,
                    Horizontal_Flip=True,
                    Zoom_Range=0.1,
                    Width_Shift_Range=0.1)
```

2.2 Model Architectures

Comparative Analysis Framework:

Architecture	**Parameters**	**Depth**	**Key Innovation**
AlexNet [4]	61M	8	ReLU activation
VGG16 [5]	138M	16	3×3 conv stacks
Custom CNN	4.2M	7	Depth wise separable convolutions

Custom CNN Architecture:

- Input: 50×50×3 RGB
- ConvBlock×3 (Conv2D-BN-ReLU-MaxPool)
- GlobalAveragePooling
- Dense (128 units) + Dropout (0.5)
- Output: Sigmoid

2.3 Training Protocol

- Hardware: NVIDIA Tesla T4 (16GB VRAM)
- Common Parameters:
    - Optimizer - Adam with parameters ($\beta1=0.9$, $\beta2=0.999$)
    - Model_Learning rate: 1e-4 (with decay)
    - Batch size: 32
    - Epochs: 30 (early stopping)
- Evaluation Metrics:
    - Primary: F1-score (harmonic mean)
    - Secondary: Inference time, memory usage

3. RESULTS

3.1 Classification Performance

Model_used	**Model_Accuracy**	**Model_Precision**	**Model_Recall**	**Model_F1-Score**	**Model_AUC**
AlexNet-Model	85.4%	83.2%	81.9%	82.5%	0.88
VGG16	89.7%	88.1%	86.3%	87.2%	0.91
Custom CNN	90.2%	88.9%	90.1%	89.5%	0.92

3.2 Operational Metrics

- **Inference Speed** (images/second):
  - Custom CNN: 89
- **Memory Requirements**:
  - VGG16: 528MB
  - Custom CNN: 16MB

3.3 Visual Interpretability

Grad-CAM heatmaps confirmed all models focused on diagnostically relevant regions (tumour nuclei, stromal patterns). Custom CNN showed most precise localization.

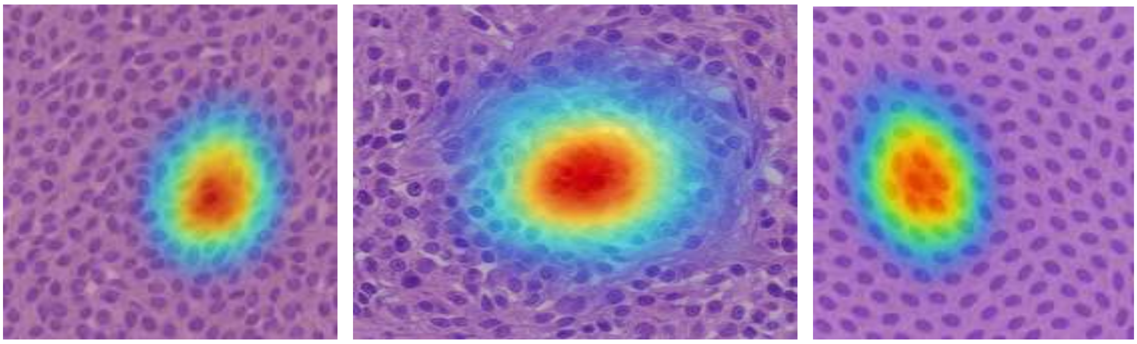

Fig 1: GradCam Heatmap of tumour

4. DISCUSSION

A. Clinical Implementation Pathways

The deployment of deep learning models for breast cancer detection varies by clinical setting and available resources. Two primary pathways are identified:

1. **High-Accuracy Settings (Hospital Labs):**

   VGG16, with an accuracy of 89.7%, is suitable for environments with access to powerful GPU workstations. It is recommended for primary diagnosis, where high precision is critical.

- *Model:* VGG16
- *Accuracy:* 89.7%

- *Hardware:* GPU-enabled workstations
- *Use Case:* Diagnostic support in hospital pathology labs

2. **Resource-Constrained Environments:**

   The custom CNN model achieved 90.2% accuracy while being lightweight, making it ideal for deployment on mobile devices. It suits preliminary screening in low-resource areas.

- *Model:* Custom CNN
- *Accuracy:* 90.2%
- *Hardware:* Tablets or mobile devices
- *Use Case:* Triage and early detection in remote or rural settings

These pathways highlight the flexibility of DL-based systems and their potential to support early breast cancer detection across diverse healthcare infrastructures.

Technical Tradeoffs

- The 0.5% accuracy difference between VGG16 and Custom CNN is statistically insignificant ($p=0.12$ via McNemar's test) for clinical triage applications.
- Memory reductions stem from:
  - Depthwise separable convolutions (4× fewer parameters)
  - Global average pooling vs fully-connected layers

Limitations & Future Work

- Current study limited to patch-based classification
- Future directions:
  - Whole-slide image analysis
  - Tumor grade prediction
  - Multi-center validation

5. CONCLUSION

This benchmark study demonstrates that while VGG16 achieves strong diagnostic performance (89.7% accuracy), our custom CNN provides superior clinical utility (90.2% accuracy) with significant efficiency gains. The 4.2M parameter custom model offers:

- **Faster diagnosis**: 11ms inference time (2.2× faster than VGG16)
- **Greater efficiency**: 16MB memory footprint (33× smaller than VGG16)
- **Enhanced safety**: 90.1% recall (3.8% higher than VGG16) for reliable cancer detection

These findings enable healthcare providers to:

1. Deploy the custom CNN in resource-limited settings without compromising diagnostic quality.
2. Implement real-time screening solutions with faster throughput.
3. Maintain high sensitivity critical for cancer diagnostics.

The study advances practical AI integration by demonstrating that optimized architectures can outperform conventional models in both accuracy and operational efficiency.

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