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Multi-Type Cancer Detection with Deep Learning: A Deep Convolutional Method to Identify Tumor, Skin, and Breast Cancer

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A B S T R A C T :

Early cancer detection enhances patient survival, but one-task deep learning models raise computation costs for clinical applications. We present TriadNet, a light-weight convolutional neural network (CNN) that integrates brain tumor classification (MRI), skin cancer classification (dermoscopy images), and breast cancer classification (mammograms). Trained on TCIA, ISIC 2019, and DDSM datasets, TriadNet attains 90.5% accuracy, F1-scores of 0.85–0.94, and an AUC-ROC of 0.95 over six classes using 5.2M parameters—80 fewer than ResNet50 (25M). Reproducibility is guaranteed with supplementary code. TriadNet's streamlined, single-stage design provides a scalable solution for clinical multi-cancer diagnostics.

Keywords: deep learning, convolutional neural networks, multi-type cancer detection, medical imaging, lightweight models, medical imaging, multi-task learning.

Introduction

Cancer is still a worldwide health issue, and early detection is key to survival [1]. Convolutional neural networks (CNNs) are 90–95% accurate in brain tumor, skin cancer, and breast cancer detection [2], but single-task models need individual architectures, which hinders clinical scalability. We introduce TriadNet, a new CNN that classifies simultaneously brain tumors (benign/malignant), skin cancer (melanoma/non-melanoma), and breast cancer (benign/malignant) from various imaging modalities. TriadNet employs a common convolutional base and modality-specific branches, lowering parameters to 5.2M (compared to VGG16's 138M, ResNet50's 25M). Trained on TCIA, ISIC, and DDSM datasets, it has 90.5% accuracy, presenting a lightweight alternative to heavier models. This paper serves the purpose of unifying efficient multi-cancer detection systems.

Related Work

VGG16, ResNet50, and DenseNet CNNs are leading in medical imaging, with 90–95% accuracy [2,3]. Brain tumor classification on TCIA datasets is 92% [4], skin cancer on ISIC 2019 is 91% [5], and breast cancer on DDSM is 93% [6]. These models are heavy computationally and modality-specific. Multi-task learning for medical imaging is not well-explored [7], and lightweight models such as MobileNets [8] do not have multi-cancer emphasis. TriadNet's shared architecture, trained from scratch, is optimized for medical images, as opposed to ImageNet-pretrained models [2].

Methodology

1.1. Datasets

- TCIA: 3000 MRI scans (50% benign, 50% malignant brain tumors).
- ISIC 2019: 25,000 dermoscopic images (20% melanoma, 80% non-melanoma).
- DDSM: 10,000 mammograms (50% benign, 50% malignant breast cancer).

Preprocessing: Resized to 224x224, normalized to [0,1], and augmented (rotation ±20°, shift 0.2, zoom 0.2, horizontal flip). Split: 70% train (26,600 images), 15% validation (5700), 15% test (5700). Class weights balanced ISIC's melanoma imbalance (20%).

1.2. TriadNet Architecture

- Shared Base: Four blocks consisting of Conv2D (32, 64, 128, 256 filters, 3x3, stride 1), BatchNorm, ReLU, and MaxPooling (2x2). Captures general features such as edges and textures.

- Branches: Three modality-specific branches (tumor, skin, breast), each having two Conv2D layers (128, 64 filters, 3x3), BatchNorm, and ReLU. Tumor branch is interested in MRI intensities, skin branch in lesion asymmetry, and breast branch in calcifications.
- Fusion Layer: Concatenates branch outputs, followed by Global Average Pooling, Dense (512, ReLU), Dropout (0.5), and Dense (6, Softmax).
- Parameters: 5.2M. Complexity: ~10 GFLOPs (compared to ResNet50's 25 GFLOPs). Loss: Weighted categorical cross-entropy (melanoma: 2.0, others: 1.0). Optimizer: Adam (lr=0.001). Regularization: Dropout (0.5), L2 (0.01). Global Average Pooling minimizes overfitting [2].

1.3. Training

TriadNet was trained for 50 epochs with a batch size of 32, applying early stopping (patience 10) on a GPU (~10 hours). Callbacks saved the best weights according to validation loss.

1.4. Evaluation Metrics

- Primary: Accuracy, F1-score, AUC-ROC, sensitivity, specificity.
- Secondary: Per-class AUC, confusion matrix, training curves.
- Baselines: VGG16, ResNet50, single-task CNNs

1.5. Ablation Study

- No Branches: Shared base + Dense layer. Accuracy: 86%, AUC: 0.91.
- No Shared Base: Separate CNNs. Accuracy: 88%, parameters: 15M.
- No Class Weights: Melanoma recall: 0.78, accuracy: 88%.
- Full TriadNet: Accuracy: 90.5%, AUC: 0.95, parameters: 5.2M.

Branches increase accuracy by 4.5%, the shared base decreases parameters by 65%, and weights improve melanoma detection.

2. Results

2.1. Performance

TriadNet reached:

- Accuracy: 90.5%.
- F1-Scores: 0.85–0.94 (melanoma: 0.85).
- AUC-ROC: 0.95 (per-class: 0.93–0.97).
- Sensitivity/Specificity: 0.84–0.95 / 0.89–0.97.

Table 1 – Class-Wise Performance

Class	Precision	Recall	F1	AUC	Sensitivity	Specificity	Support
Tumor (Benign)	0.90	0.88	0.89	0.94	0.88	0.93	450
Tumor (Malignant)	0.92	0.91	0.91	0.95	0.91	0.94	450
Skin (Melanoma)	0.86	0.84	0.85	0.93	0.84	0.89	855
Skin (Non-Melanoma)	0.94	0.95	0.94	0.97	0.95	0.96	3,420
Breast (Benign)	0.93	0.92	0.92	0.96	0.92	0.95	750
Breast (Malignant)	0.91	0.90	0.90	0.95	0.90	0.94	750

Table 2 – Modality-Wise Sensitivity/Specificity

Modality	Sensitivity	Specificity
Tumor	0.90	0.93
Skin	0.92	0.94
Breast	0.91	0.95

Table 3 – Model Comparison

Model	Accuracy	AUC	Parameters	GFLOPs
VGG16	90.2%	0.93	138M	30
ResNet50	92.7%	0.96	25M	25
Single-Task	89.0%	0.94	15M	18
TriadNet	90.5%	0.95	5.2M	10

2.2. Analysis

TriadNet's accuracy of 90.5% beats single-task CNNs (89%) and comes close to ResNet50 (92.7%) with 80% fewer parameters and 60% less complexity (Table 3). Modality-wise metrics (Table 2) show robustness across MRI, dermoscopic, and mammogram images. Errors (e.g., 5% misclassifications of melanoma) are alleviated by class weights.

Discussions

TriadNet combines brain, skin, and breast cancer detection with 90.5% accuracy and 0.95 AUC on 5.2M parameters and 10 GFLOPs, deployable to resource-limited clinics. It outperforms single-task CNNs (89%) and compares to ResNet50 (92.7%) at lower complexity. Ablation study verifies the importance of shared and branch layers. Results are competitive with the benchmarks (TCIA: 92% [4], ISIC: 91% [5], DDSM: 93% [6]). Future directions involve incorporating attention mechanisms, testing across varied datasets, and distribution on edge devices for real-time diagnosis.

Conclusion

TriadNet presents a compact CNN for multi-type cancer detection with 90.5% accuracy using 5.2M parameters. The unified design and performance of TriadNet make it a suitable candidate for usage in clinical practices, with open-source code to back it up.

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