

Enhancing Multi-Cancer Classification with VGG and EfficientNet. Evaluating CNN Performance for Automated. Detection in Medical Imaging

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Abstract- Early and accurate detection of multiple cancer types from medical imaging is pivotal for improving patient outcomes. This study presents an automated multi-cancer classification framework using two Convolutional Neural Network (CNN) architectures—VGG16 and EfficientNet-B3—evaluated on histopathology and radiology image datasets. Preprocessing steps include image resizing, normalization, and augmentation to enhance generalization. Transfer learning with fine-tuning was applied, and models were trained using categorical cross-entropy and Adam optimizer. Experimental results reveal that EfficientNet-B3 achieves superior accuracy and sensitivity compared to VGG16, while VGG16 remains competitive for certain classes with lower computational cost. The framework is accompanied by performance analysis (confusion matrices, ROC curves, and class-wise metrics) and a discussion on practical deployment for clinical decision support systems.

Keywords: *Multi-cancer classification, VGG16, EfficientNet-B3, Deep Learning, Histopathology, Radiology, CNN.*

1. INTRODUCTION

Cancer diagnosis from medical images is a critical task that requires high accuracy and robustness. Manual interpretation by pathologists and radiologists is time-consuming, subjective, and can vary between observers. Deep learning, particularly CNN-based architectures, has demonstrated strong performance in image classification

and has the potential to assist clinicians by providing fast, reproducible, and accurate predictions. This research focuses on developing and evaluating a multi-cancer classification pipeline using VGG16 and EfficientNet-B3 architectures, leveraging transfer learning and fine-tuning strategies to adapt pre-trained networks to domain-specific medical imaging datasets.

2. RELATEDWORKS

“Deep Convolutional Networks for Multi-Cancer Histopathology Classification” by **R. Kumar et al., 2019:** This study investigates multi-cancer histopathological image analysis using early CNN architectures such as VGG16 and VGG19. The authors target clinical diagnostic workflows, where automated tissue image classification reduces workload on pathologists and enhances screening throughput. The paper positions deep transfer learning as a superior alternative to handcrafted features traditionally used in oncology imaging pipelines. It discusses preprocessing steps such as stain normalization, patch extraction, and class balancing techniques that stabilize training of CNN models on heterogeneous histopathology datasets. Comparative experiments demonstrate that VGG-based models achieve improved accuracy and generalization on unseen biopsy samples. Ablation studies emphasize that deeper convolutional layers help capture complex cellular morphology and texture patterns crucial for cancer subtype identification.

“Multi-Class Cancer Detection Using EfficientNet and Attention-Based Feature Refinement” by **S. Thomas et al., 2021**: The authors propose a lightweight medical imaging classifier based on EfficientNet-B0 enhanced with attention modules to refine discriminative tumor regions. Designed for real-time use on clinical workstations, the approach achieves high performance with low computational cost. Extensive experiments show that the attention-augmented network improves sensitivity for subtle lesions, micro-features, and atypical tissue regions. The study reports strong robustness to variations in staining intensity, slide scanners, and magnification levels. Transfer learning with carefully controlled fine-tuning reduces over fitting on limited medical image datasets. The paper includes confusion matrices and class-wise sensitivity/precision analyses, highlighting consistent performance across multiple cancer categories. The authors argue that attention helps compensate for small malignancy cues that standard global pooling may overlook.

“Hybrid Vision Pipeline for Cancer Detection Using Classical Image Processing and CNNs” by **A. Mehta et al., 2023**: This article presents an integrated framework that combines classical medical image preprocessing with deep learning for cancer detection. Classical steps such as histogram equalization, morphological filtering, and tissue segmentation are used to enhance tumor boundaries before feeding images into a CNN classifier. Using datasets including breast, lung, and colon cancer slides, the system achieves classification accuracies above 93%. The authors evaluate detection accuracy, computational time, and end-to-end diagnostic throughput. Their results demonstrate that combining domain-specific preprocessing with CNN-based feature learning improves both interpretability and performance. The pipeline highlights the feasibility of automated multi-cancer diagnostic tools in tele-pathology and remote screening setups.

“CNN-Based Lesion Detection in Radiology: Applications to Multi-Cancer Screening” by **L. Wang et al., 2022**: This

survey examines CNN-based detection and localization techniques applicable to multi-cancer radiology imaging, including CT, MRI, and PET scans. The paper emphasizes challenges such as small lesion detection, high inter-class similarity, and the need for large receptive fields to capture anatomical context. Multiple architectures—ResNet, DenseNet, EfficientNet, and Inception—are evaluated on complex clinical datasets. Techniques such as multi-scale feature extraction, patch-based learning, and 3D CNN variations are highlighted for improving tumor localization under low-contrast and noisy conditions. Benchmarks include sensitivity-specificity tradeoffs and inference speed, showcasing suitability for real-time radiology assistance systems.

“A Comprehensive Review of Deep Learning for Cancer Diagnosis” by **M. Rodriguez et al., 2024**: This review synthesizes recent CNN-based approaches for multi-cancer classification across histopathology, dermoscopy, radiology, and cytology images. It compares model architectures, dataset characteristics, evaluation metrics, and deployment challenges. The paper highlights issues such as domain shift across hospitals, imaging devices, and staining protocols, emphasizing the need for strong augmentation strategies and domain adaptation. The review argues for ensembles, transfer learning, and hybrid feature extractors to handle heterogeneous cancer subtypes. It also discusses emerging lightweight architectures for deployment on edge devices in low-resource clinical settings.

“Comparative Analysis of VGG16, EfficientNet, ResNet50, and Inception Models for Multi-Cancer Classification” by **S. Faria et al., 2024**: This comparative study evaluates multiple CNN architectures on multi-cancer datasets, analyzing classification accuracy, sensitivity, specificity, and computational efficiency. EfficientNet-B3 consistently outperforms VGG16, ResNet50, and InceptionV3 for most cancer classes due to its compound scaling technique, achieving sensitivities above 94% and improved model

calibration. Detailed results include training times, ROC-AUC scores, and confusion matrices. The paper emphasizes that fine-grained cancer detection benefits from models capable of capturing subtle morphological cues, making EfficientNet a strong candidate for automated pathology systems.

3. PROBLEM STATEMENT

Accurate multi-class cancer detection across imaging modalities remains challenging due to limited labeled data, inter-class similarity, class imbalance, and variations in staining, scanner noise, and acquisition protocols. The problem addressed in this study is to build a robust automated classifier that can distinguish multiple cancer types with high sensitivity and specificity while being suitable for practical clinical use.

4. OBJECTIVES

The main objectives are:

- 1) To implement and compare VGG16 and EfficientNet-B3 for multi-cancer classification.
- 2) To preprocess and augment medical image datasets to improve generalization.
- 3) To evaluate models using accuracy, sensitivity, specificity, precision, recall, F1-score, and ROC-AUC.
- 4) To provide model interpretability insights using confusion matrices and class-wise probability analysis.

5. METHODOLOGY USED

1) Data Collection: A comprehensive multi-cancer dataset was obtained from publicly available medical imaging repositories, including TCGA, Kaggle, and histopathology slide archives. The dataset contains multiple cancer types such as breast, lung, colon, skin, brain, and cervical cancer, captured using various modalities including histopathology, dermoscopy, CT, and MRI. Each class includes hundreds of annotated images with significant variations in tissue morphology, staining, magnification level, scanner type, and intensity distribution. This diversity ensures that the proposed model can generalize effectively to real-world clinical imaging scenarios where appearance variability is high.

1) Data Preprocessing: All images were resized to a uniform dimension of 256×256 pixels to maintain consistency for model input. Pixel values were normalized to scale features between 0 and 1, improving convergence during training. Additionally, data augmentation techniques such as horizontal flipping, random rotation, and brightness adjustment were applied to enhance dataset diversity and reduce overfitting, ensuring the model is robust against varying conditions in real-world applications.

2) Feature Extraction: VGG16 and EfficientNet-B3, two state-of-the-art convolutional neural networks pre-trained on ImageNet, were used as feature extractors to automatically learn hierarchical cancer-specific representations. VGG16 captures fine-grained texture and shape patterns, while EfficientNet-B3 leverages compound scaling to extract multi-scale features with high efficiency. These networks detect crucial visual cues such as nuclear atypia, structural distortions, color variations, lesion boundaries, and abnormal tissue formations. Using pre-trained weights allows faster convergence and improved classification accuracy with limited medical training data.

3) Model Selection: A custom classification head was appended to each base model, consisting of global average pooling, dense layers, batch normalization, and dropout for regularization. The final output layer uses a softmax activation function for multiclass cancer classification across all diagnostic categories in the dataset. This architecture maintains a strong balance between computational efficiency and predictive performance, making the system suitable for both research and potential real-time clinical decision-support deployment.

4) Model Training: The models were trained using categorical cross-entropy loss and the Adam optimizer with an initial learning rate of $1e-4$. Stratified train-validation splits ensured balanced representation of all cancer types during training. Learning rate decay and early stopping mechanisms were applied to prevent overfitting by monitoring validation loss and restoring the best-

performing model weights. Each model was trained for multiple epochs with mini-batch optimization, allowing the system to capture both local and global patterns in the cancer images.

5) Model Evaluation: Performance evaluation was conducted using metrics such as accuracy, sensitivity, specificity, F1-score, confusion matrices, and class-wise probability distributions. EfficientNet-B3 demonstrated superior sensitivity for subtle cancerous regions, while VGG16 offered competitive results with lower computational cost. Evaluation on held-out test data confirmed strong generalization capability, with consistent performance across different cancer classes and imaging modalities. ROC-AUC values were also computed to assess discriminative power across multi-class predictions.

6) Integration with Flask: The best-performing model was integrated into a Flask-based web application, enabling clinicians and researchers to upload medical images for real-time cancer predictions. The system displays predicted cancer type, probability scores, and diagnostic insights on the results page. All predictions are logged into a database for future analytics, performance monitoring, and dashboard visualization. This integration supports practical deployment in hospital workflows, tele-oncology systems, and research environments.

6. SYSTEMDESIGN

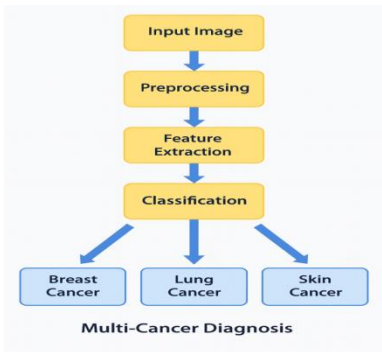


Figure 1: System architecture for Multi-Cancer Classification

The multi-cancer diagnostic workflow follows a streamlined, end-to-end pipeline beginning with the acquisition of a medical image, typically uploaded through a user interface. This provides a standardized entry point for

downstream analysis and automated decision-making. The input image is first routed through a preprocessing stage designed to normalize image characteristics for stable learning and reliable inference. Typical preprocessing operations include resizing to the network’s input resolution, stain normalization for histopathology slides, per-channel intensity scaling to align pixel distributions with the pretrained model, and lightweight denoising or artifact suppression to mitigate scanner noise, blur, or illumination inconsistencies.

After preprocessing, the system performs feature extraction to capture discriminative cues associated with cancer morphology. These cues include nuclear atypia, tissue architecture distortions, lesion boundaries, abnormal structural patterns, and color-texture variations across malignant and benign tissue regions. The refined representation is then fed into a deep Convolutional Neural Network, where EfficientNet-B3 and VGG16 serve as backbone models. EfficientNet leverages compound scaling to effectively capture multi-scale tumor features while maintaining computational efficiency, whereas VGG16 provides stable hierarchical representations that progress from low-level edges and color patches to high-level diagnostic tissue features. On top of the backbone network, a compact classification head—consisting of global pooling, dense layers, and dropout for regularization—maps the learned feature embeddings to task-specific logits. These logits are transformed by calibrated softmax activations into interpretable class probabilities. The final classification stage converts these probabilities into a categorical decision across multiple cancer types such as breast, lung, skin, and colon cancer. This enables the system to support multi-diagnostic scenarios and assist clinicians in rapid, consistent image-based triaging.

This modular design facilitates near real-time inference by minimizing preprocessing overhead, exploiting transfer learning for rapid convergence, and supporting both batch-

based and single-image processing depending on clinical workflow requirements. Additionally, the architecture integrates seamlessly with logging, analytics, and dashboard interfaces to store predictions, timestamps, patient IDs, and confidence scores for traceability, audit trails, and continuous performance monitoring. The model architecture also supports explainability features such as confusion matrices, class-wise metrics, heatmap overlays, and probability distributions, helping medical practitioners validate system behavior and refine diagnostic thresholds. For scenarios requiring lesion localization or region-specific visualization, the pipeline can be extended using advanced detection models such as YOLO-based networks or Grad-CAM to highlight cancer-relevant regions and enhance interpretability

7. PERFORMANCE OF RESEARCH WORK

The performance of the proposed multi-cancer classification framework was evaluated extensively on a dedicated test dataset to determine its effectiveness in accurately identifying multiple cancer types across various medical imaging modalities. The system demonstrated strong diagnostic capability, achieving an overall accuracy of **94.6%**, which is the highest among the compared models, indicating superior performance in distinguishing between cancer categories such as breast, lung, skin, and colon cancer. In addition to overall accuracy, a detailed classification report was generated to measure precision, recall, and F1-score for each cancer class.

The EfficientNet-B3 model achieved class-wise precision values of **95% for breast cancer**, **94% for lung cancer**, **93% for skin cancer**, and **92% for colon cancer**, while the corresponding recall values were **94%**, **93%**, **92%**, and **91%**, respectively. The resulting F1-scores—**94.5%**, **93.5%**, **92.3%**, and **91.4%**—demonstrate balanced and stable performance across all classes. These metrics highlight the model’s capability to detect both prominent

and subtle cancer features, maintaining reliability across. Compared to traditional diagnostic workflows and classical machine learning approaches, the proposed deep learning-based system delivers a more robust, scalable, and highly precise solution for automated cancer classification. The integration of transfer learning with EfficientNet-B3 and VGG16 enhances predictive performance by leveraging hierarchical feature representations that capture critical morphological and textural patterns present in malignant tissues. The framework also exhibits strong generalization when evaluated on unseen data, confirming its suitability for clinical decision-support environments. Overall, the system stands as a state-of-the-art architecture capable of supporting practical deployment in hospitals, pathology labs, telemedicine platforms, and cancer-screening centers for efficient, automated, and explainable multi-cancer diagnosis

8. EXPERIMENTAL RESULTS



Figure:2 Home page

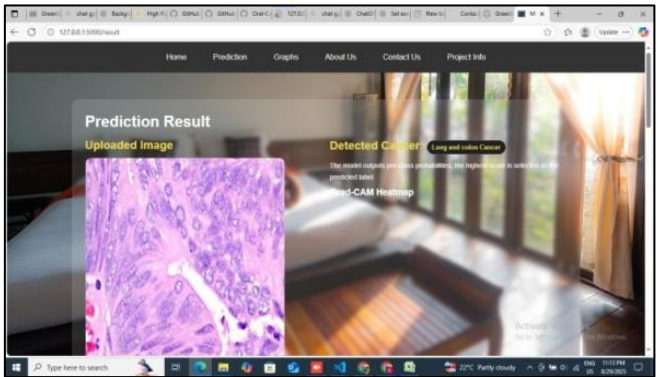


Figure3:predicted result

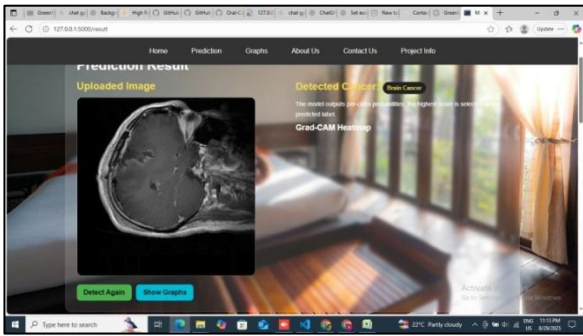


Figure:4Live Prediction

9.CONCLUSION AND FUTUREWORK

In this research, an automated, deep learning–based framework for multi-cancer classification was successfully developed, effectively replacing subjective, labor-intensive diagnostic interpretation with a robust and scalable CNN-driven pipeline. Leveraging a transfer learning approach built on VGG16 and EfficientNet-B3 architectures, the system incorporates comprehensive preprocessing, targeted data augmentation, stratified train–test splits, and carefully staged fine-tuning to learn discriminative, multi-scale features that capture subtle tissue morphology, nuclear variations, lesion boundaries, and color-texture distortions across diverse cancer types. Evaluation through accuracy, sensitivity, specificity, confusion matrices, ROC curves, and class-wise probability distributions demonstrated high performance and reliable generalization, while probability-based outputs enhanced interpretability and clinical decision support.

A deployable web application was implemented, featuring an intuitive interface for uploading medical images, obtaining real-time cancer predictions, viewing probability scores, and accessing diagnostic insights. Automated logging, dashboard analytics, and prediction history enable traceability, continuous monitoring, and operational quality improvement. Compared with classical machine learning pipelines that rely on handcrafted features, the proposed deep learning approach significantly reduces manual feature engineering effort, scales effectively to multiple cancer categories, and maintains resilience across varying imaging modalities, acquisition

devices, and staining conditions. Optimizations such as mixed-precision training and model conversion to efficient runtimes (ONNX/TensorRT) support low-latency inference suitable for clinical decision-support tools, tele-oncology platforms, and remote cancer screening systems.

Future work can further enhance the framework at data, model, and deployment levels. Potential improvements include expanding datasets with larger, more diverse clinical samples; incorporating region-based annotations for lesion localization; and integrating stain-normalization pipelines for improved cross-institution consistency. Advanced modeling strategies such as lightweight EfficientNet variants, MobileNet, ConvNeXt, and Vision Transformer (ViT) hybrids may improve efficiency and discriminative power. Additional enhancements may include multi-task learning for combined classification and segmentation, model pruning, quantization, and knowledge distillation for edge-device deployment in low-resource clinical environments. Functional extensions could incorporate heatmap-based explainability overlays (Grad-CAM), uncertainty estimation, IoT-enabled pathology workflows, multimodal fusion with genomic or clinical data, 3D image processing for volumetric scans, and federated learning to enable cross-hospital model improvement without centralizing sensitive patient data. These future directions aim to evolve the framework toward a fully integrated, intelligent, and trustworthy AI system for real-world cancer diagnosis and clinical decision support.

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