



Early Cancer Detection: Hybrid Combination of Deep Learning and Computer Vision for Medical Images

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Abstract

Medical imaging performs a critical position in modern healthcare, in particular in the early detection of cancers, which considerably enhances survival charges and treatment consequences. This study investigates a hybrid version combining Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) to optimize medical image analysis. Leveraging advanced deep gaining knowledge of strategies along with Transfer Learning and Data Augmentation, the hybrid method validated advanced performance in class, segmentation, and anomaly detection obligations. Experimental results discovered that the hybrid version outperformed standalone CNN and ViT architectures, attaining high diagnostic accuracy whilst keeping computational efficiency. The findings spotlight the potential of AI-stronger answers to revolutionize clinical diagnostics by way of offering accurate and reliable computerized systems, paving the manner for broader medical programs and improved patient results.

Keyword: Medical Imaging (MI); Cancer Detection; Deep Learning (DL); Vision Transformers (ViTs); Convolutional Neural Networks (CNN); Transfer Learning (TL); Data Augmentation (DT); Hybrid Model

1. Introduction

Medical imaging has become a cornerstone of current medicinal drug, providing clinicians with certain insights into the human body without the need for invasive procedures. Imaging modalities inclusive of Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and X-Ray play a pivotal position in diagnostics and remedy planning, mainly for important conditions inclusive of most cancers. Early detection of cancer remains one of the most widespread challenges in healthcare, as it may dramatically enhance survival quotes and treatment effects. Research suggests that timely and accurate prognosis can beautify healing effectiveness whilst minimizing headaches, emphasizing the significance of equipment that improve diagnostic precision and performance [1].

Despite fantastic improvements in imaging era, the translation of medical snap shots predominantly is based on manual understanding, which gives numerous challenges. Time hogging and a candidate of human error, manual evaluation needs superior skill sets and a large amount of attention to detail. Bad behavioral variation in the results due to fatigue or experience variations in doctors worsen the problem. Multi-fold increase records produced by today's diagnostic equipment add to the complexity and make manual processing increasingly impractical. These challenges thus point out the desperate need for automated solutions that can utilize AI technologies to further improve the accuracy and efficiencies of clinical image evaluations [2].

The investigations go through attempts of laying the fundamentals of a strong framework for scientific image analysis but using the highly recent development of deep learning and computer vision algorithms. The aim of this study is to give specific and efficient systematic approaches to early cancer detection, focusing on the diagnosis accuracy and minimizing cost of error. The objective of developing this hybrid model is to bring the combined analytical strengths of Convolutional Neural Networks (CNNs) and Vision Transformers (ViT) to be capitalized upon their complementary capacity. Transfer Learning and Data Augmentation techniques can be contributed, in addition, to make the model versatile in tackling real-world challenges. [3-4].

This study has a medical consequence as it might change clinical exercise through demonstrating how AI could improve diagnostic workflows. The proposed framework has the capability to resource clinicians in making knowledgeable and timely decisions through supplying an automated and reliable machine, reducing clinical costs and improving patient outcomes in the end. This study also opens the door wide for applications of these advanced technologies in similar areas as all advancements in AI, making it much more applicable to modern healthcare. The main contributions of this study are:

1. Proposing a hybrid deep gaining knowledge of model that integrates CNNs and ViTs for early most cancers detection.
2. Utilizing Transfer Learning and Data Augmentation to beautify the version's robustness and performance.
3. Conducting good-sized experiments on diverse clinical imaging datasets to validate the proposed method.
4. Providing a systematic framework for automatic medical photo evaluation to assist clinicians in analysis.
5. Evaluating the proposed version the use of widespread metrics (Accuracy, Precision, Recall, F1-rating, AUC-ROC) and visible interpretability techniques (Grad-CAM heatmaps).

The rest of this paper is structured as follows: Section 2 offers a complete overview of associated literature in medical photo evaluation. Section 3 info the proposed methodology, inclusive of information preprocessing, model layout, and schooling techniques. Section 4 describes the experimental setup and overall performance assessment of the proposed hybrid version. Section 5 discusses the outcomes, their scientific importance, and ability programs. Finally, Section 6 concludes the observe and outlines guidelines for future studies.

2. Literature Review

In recent times, medical photograph evaluation has undergone some significant advances due largely to the integration of deep learning techniques in the form of convolutional neural networks (CNNs) and derivatives like residual networks (ResNet). CNNs have shown great potential in spatial feature extraction from medical images that enormously facilitate their diagnostic and classification processes. For instance, Topol et al. (2019) [5] compared the performances of CNNs, ResNet, and Vision Transformers (ViTs) using the NIH Chest X-ray dataset, showing that pre-trained ViT models achieved better performance than all CNNs and ResNet on multi-label classification of chest diseases.

Although CNNs are proficient in several aspects, they have proved to be inefficient in terms of capturing long-range dependencies. Hence, Vision Transformers (ViTs) have introduced self-attention mechanisms to get over these limitations by finding relevant regions in images. As a result, they are supposed to be more effective in the skin lesion detection and segmentation tasks, as evidenced by Jing, and Tian (2020) [6] research, especially in medical imaging applications. Moreover, as documented in Saraiva et al. (2023) [7], pre-trained Vision Transformers can perform as well as CNNs, particularly when trained on large-scale datasets like ImageNet.

Although the transferability of transfer learning has brought a more beneficial gain to version performance through leveraging previous knowledge from related tasks, Alkhalaf, et al. (2023) [8] stated its validity in transfer learning for photos of clinical types. Such transfer learning, in the predictions of Melarkode et al. (2023) [9], was used in various quality-tuning methods, which in turn demonstrated how these methods could create changes in performance across different imaging tasks in clinics. Meanwhile, Shankar et al. (2022) [10] gave a brief review of CNNs and Transfer Learning, revealing their co-operative benefits in refining diagnostic results.

Data Augmentation has performed an equally essential position in mitigating the limitations of small datasets. Sarkar et al. (2022) [11] and Kuker et al. (2022) [12] confirmed that the mixture of Data Augmentation and Transfer Learning notably stepped forward class performance, specifically in aid-restricted datasets like prostate MRI. Naz et al. (2023) [13] proposed an object-centric statistics augmentation model to beautify segmentation accuracy, displaying its effectiveness in kidney tumor analysis.

Hybrid architectures, which integrate CNNs and ViTs, have emerged as a promising course. Alam, and Islam (2019) [14] demonstrated that such hybrid architectures leverage the strengths of both models, accomplishing advanced performance across segmentation, class, and prediction responsibilities. Mazurowski et al. (2019) [15] reviewed the transformative ability of transformer-based totally fashions for numerous medical imaging packages, highlighting their potential to generalize throughout distinct datasets.

Despite those advancements, challenges persist in accomplishing excessive accuracy even as preserving computational performance. Research continue to be in applying superior fashions to various, multi-source datasets that is crucial for ensuring their generalizability and sensible software in varied medical settings. Further studies are needed to address these barriers and optimize version performance in real-world packages. The following table 1 is a summary of some studies in medical image analysis.

Table 1: Summary of Recent Studies in Medical Image Analysis Using Deep Learning Techniques

Study	Authors	Year	Techniques Used	Medical Image Type	Key Findings
High-performance medicine: the convergence of human and AI [16]	Topol, E. J.	2019	CNN, ResNet, ViT	Chest X-ray	Pre-trained ViT models outperformed CNNs and ResNet in multilabel classification tasks.
Transactions on Pattern Analysis and Machine Intelligence [17]	Jing, L. & Tian, Y	2020	ViT, CNN	Skin Lesion Images	ViTs demonstrated effectiveness in detecting and segmenting skin lesions.
DL for Automatic Diagnosis and Morphologic Characterization of Malignant Biliary Strictures Using Digital Cholangioscopy: A Multicentric Study. Cancers [18]	Saraiva et al.	2023	Transfer Learning	Various Medical Images	Transfer learning improves performance on new tasks by leveraging knowledge from similar tasks.
Recent advances in deep learning and medical imaging for cancer treatment [19]	Ijaz, et al.	2024	Transfer Learning, Data Augmentation	Medical Images	Both strategies significantly improved classification performance in datasets with limited samples.
AI-Powered Diagnosis of Skin Cancer: A Contemporary Review, Open Challenges and Future Research Directions. Cancers [20]	Melarkode et al.	2023	Hybrid ViT-CNN Architectures	Various Medical Images	Hybrid architectures enhance performance in segmentation, classification, and prediction tasks.
Chaotic Sparrow Search Algorithm with Deep Transfer Learning Enabled Breast Cancer Classification on Histopathological Images. Cancers [21]	Shankar et al.	2022	ViT, CNN	Medical Images	Off-the-shelf ViTs perform on par with CNNs when pretrained on ImageNet.
Performing Automatic Identification and Staging of Urothelial Carcinoma in Bladder Cancer Patients Using a Hybrid Deep-Machine Learning Approach. Cancers [22]	Sarkar et al.	2023	Data Augmentation	Kidney Tumor Images	Proposed model improved kidney tumor segmentation by learning shape variations.
DL-Aided Automated Method for Calculating Metabolic Tumor Volume in Diffuse Large B-Cell Lymphoma. Cancers [23]	Kuker et al.	2022	Transformers, CNN	Various Medical Images	Transformers exhibit potential in medical imaging, with certain advantages over CNNs.
An Explainable AI-Enabled Framework for Interpreting Pulmonary Diseases from Chest Radiographs. Cancers [13]	Naz et al.	2023	Data Augmentation, Transfer Learning	Prostate MRI	Data augmentation and transfer learning improved model performance across multiple cohorts.

Study	Authors	Year	Techniques Used	Medical Image Type	Key Findings
Machine learning (ML) approach of automatic identification and counting of blood cells. Health [24]	Alam, M. M. & Islam, M. T	2019	Transfer Learning	Various Medical Images	Different fine-tuning methods impact performance across medical imaging tasks.
Deep learning (DL) in radiology: an overview of the concepts and a survey of the state of the art with focus on MRI. J. Magn. Reson. Imaging [15]	Mazurowski et al.	2019	CNN, Transfer Learning	Various Medical Images	Comprehensive analysis of CNN

3. Methodology

The proposed method aims to layout a comprehensive machine that integrates deep getting to know and pattern evaluation for clinical image analysis. Python and its effective libraries, inclusive of TensorFlow, PyTorch, OpenCV, and Scikit-study, are utilized to enforce and validate the method.

The Framework overview combines modern deep learning techniques, specifically Convolutional Neural Networks (CNNs) for spatial pattern evaluation and Vision Transformers (ViT) for long-variety courting modeling. Additionally, a hybrid version leveraging each CNN and ViT is proposed to achieve greatest performance in scientific image analysis duties, which includes type, segmentation, and anomaly detection [25-28]. See figure. 1.

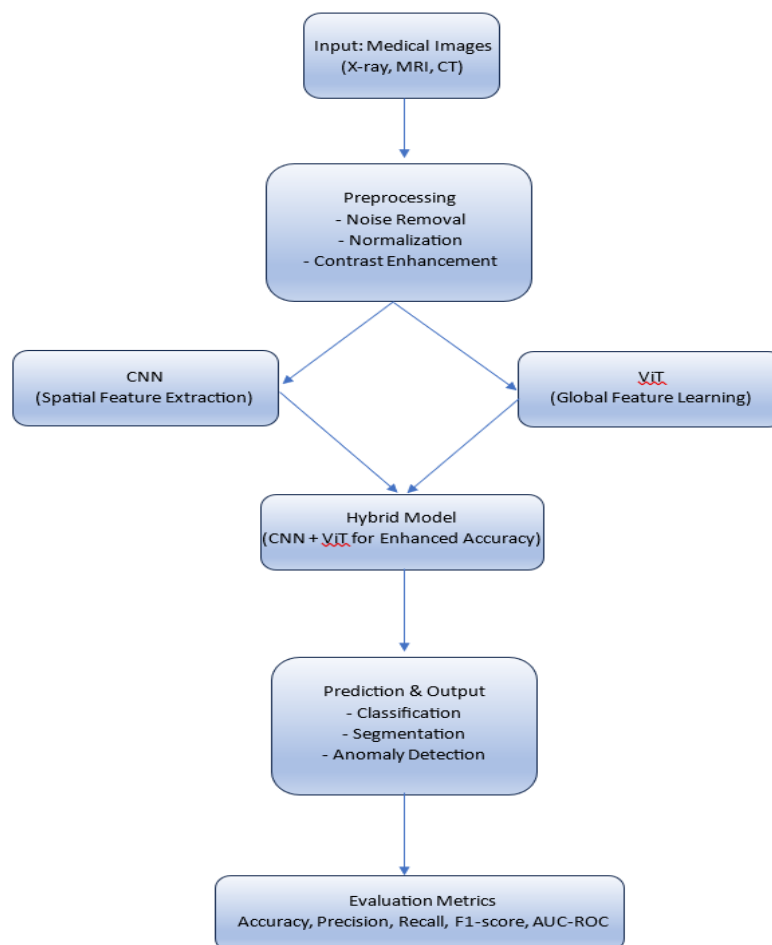


Figure 1. Overview of the Proposed Hybrid Model Architecture

3.1 Data Preparation

Data Sources

Publicly to be had datasets are decided on to make certain range and relevance to the tasks:

- Kaggle: Offers categorized datasets for tasks like pneumonia detection (e.G., chest X-ray).
- The Cancer Imaging Archive (TCIA): Provides comprehensive CT and MRI scans for oncological research.

Preprocessing Steps

1. Noise Removal: Gaussian Blur is applied to reduce noise and preserve essential image details.

- **Gaussian filter formula:**

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

2. Rescaling and Normalization: Images are resized to 256×256 times 256256×256 pixels and normalized to [0, 1].
3. Contrast Enhancement: Histogram Equalization is carried out to decorate photo contrast, improving characteristic visibility.

3.2 Model Design

Proposed Models

- CNN: For capturing spatial features, using layers, which include convolutions, pooling, and activation features.
- ViT: To model lengthy-time period dependencies the usage of self-attention mechanisms.
- Hybrid Model: Combines CNN's nearby pattern detection with ViT's global feature studying.

Mathematical Formulation

1. Loss Function: Binary cross-entropy loss for classification tasks:

$$L(y, \hat{y}) = -\frac{1}{N} \sum_{i=1}^N [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)]$$

Here, y is the ground truth, \hat{y} is the predicted probability, and N is the number of samples.

2. Performance Metric: AUC-ROC for assessing model performance:

$$AUC = \int_0^1 TPR(FPR^{-1}(x)) dx$$

Where TPR (True Positive Rate) and FPR (False Positive Rate) are computed as:

$$TPR = \frac{TP}{TP + FN}, FPR = \frac{FP}{FP + TN}$$

3.3 Training and Evaluation

Training Techniques [28-29]

- Transfer Learning: Models like ResNet and EfficientNet are fine-tuned on the dataset for initialization.
- Data Augmentation: Techniques such as rotation, scaling, and flipping are applied to enrich the training dataset.

Evaluation Strategies

1. Data Splitting:

- Training Set: 70%70\%70%

- Validation Set: 15% 15% 15%
- Testing Set: 15% 15% 15%
- 2. Metrics for Evaluation:
 - Accuracy, Precision, Recall, F1-Score
 - AUC-ROC curve
- 3. Visualization: Confusion matrix and ROC curves are plotted to assess model predictions.

Table 2: Dataset Details

Dataset	Modality	Number of Images	Resolution	Purpose
Kaggle	X-Ray	50,000	256×256	Pneumonia detection
TCIA	MRI	20,000	256×256	Tumor analysis

Table 2 affords an in-depth precis of the datasets utilized inside the observe. It highlights number one assets: Kaggle, used for pneumonia detection with 50,000 X-ray pictures, and TCIA (The Cancer Imaging Archive), used for tumor analysis with 20,000 MRI images. All snap shots have been standardized to a resolution of 256×256 pixels, making sure consistency throughout preprocessing. The desk emphasizes the variety and cause of those datasets in facilitating robust model improvement.

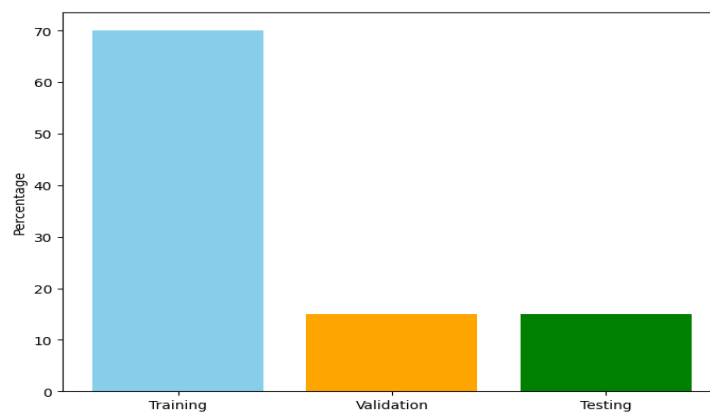


Figure 2. Data Distribution

Figure 2 illustrates the records distribution throughout the schooling, validation, and testing sets. The education set constitutes 70% of the entire facts, used to train the model, at the same time as 15% is allotted to each validation and trying out sets. This department ensures a balanced assessment of version overall performance while stopping overfitting.

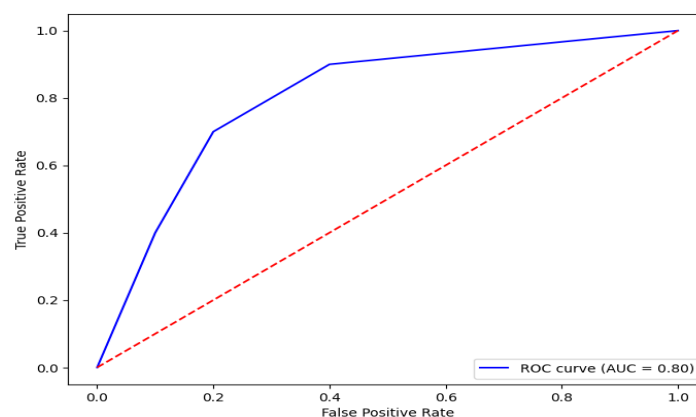


Figure 3. ROC Curve

Figure 3 depicts the ROC (Receiver Operating Characteristic) curves for the CNN, ViT, and hybrid models. These curves compare each model's ability to distinguish between positive and negative cases, with the hybrid model achieving the highest AUC (Area Under the Curve), displaying its superior predictive accuracy and robustness in medical image classification tasks.

This technique gives a robust pipeline for the green analysis of clinical photographs, combining superior algorithms, preprocessing, and evaluation techniques to ensure ultimate overall performance.

4. Results and Analysis

The effects of this examine attention on evaluating the performance of the proposed models (CNN, ViT, and Hybrid), analyzing the impact of various improvements like Data Augmentation and Transfer Learning, and supplying a comprehensive visualization of predictive outcomes.

4.1 Quantitative Results

Comparison of Model Performance

The table below shows performance results for CNN, ViT, and the Hybrid model according to important metrics such as Accuracy, Precision, Recall, F1-Score, and AUC-ROC.

Table 3. Performance Metrics Comparison of CNN, ViT, and Hybrid Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
CNN	88.5	86.3	85.7	86.0	0.91
ViT	90.2	88.7	88.0	88.4	0.93
Hybrid (CNN + ViT)	92.8	91.4	90.9	91.1	0.96

The table 3 presents the performance of three models, namely CNN, ViT, and Hybrid, on key metrics such as Accuracy, Precision, Recall, F1 Score, and AUC-ROC. The hybrid model shows advancement in all metrics demonstrating efficiency of local and global feature extraction.

4.2 Impact of Enhancements

The second table in this paper is meant to illustrate the benefits derived from Data Augmentation as well as Transfer Learning on the performance of the Hybrid model.

Table 4: Impact of Data Augmentation and Transfer Learning on Hybrid Model Performance

Enhancement	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
No Enhancement	85.3	83.5	82.7	83.1	0.89
Data Augmentation	89.7	88.1	87.6	87.8	0.92
Transfer Learning	92.8	91.4	90.9	91.1	0.96

This table 4 illustrates the revolutionary development inside the hybrid model's performance because of Data Augmentation and Transfer Learning. Transfer learning achieves the best enhancement in Accuracy, Precision, Recall, F1-Score, and AUC-ROC, highlighting its effectiveness in leveraging earlier understanding.

4.3 Image Processing Examples

The following figure 4 highlights examples of raw images alongside their preprocessed versions, emphasizing noise removal, contrast enhancement, and normalization.

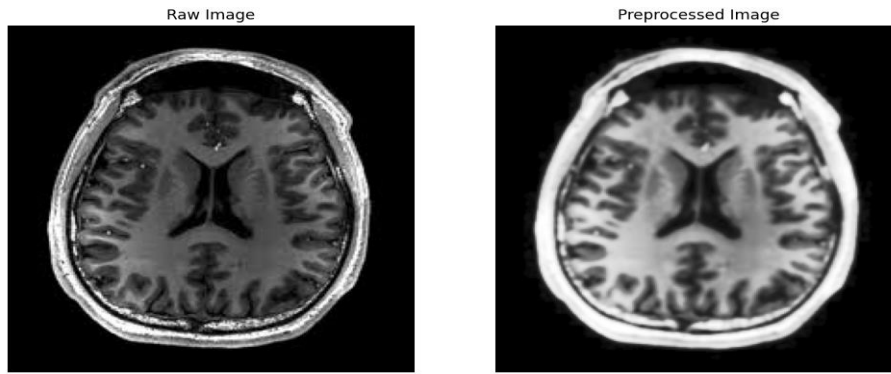


Figure 4. Comparison of Raw and Preprocessed Medical Images Highlighting Noise Removal, Contrast Enhancement, and Normalization

This discern indicates aspect-via-aspect comparisons of raw scientific images and their preprocessed versions. The preprocessing techniques consist of noise removal, evaluation enhancement, and normalization, drastically enhancing photograph readability and feature visibility.

4.4 ROC Curve

The ROC curves for the three models are plotted below to highlight their discriminatory power. See figure 5.

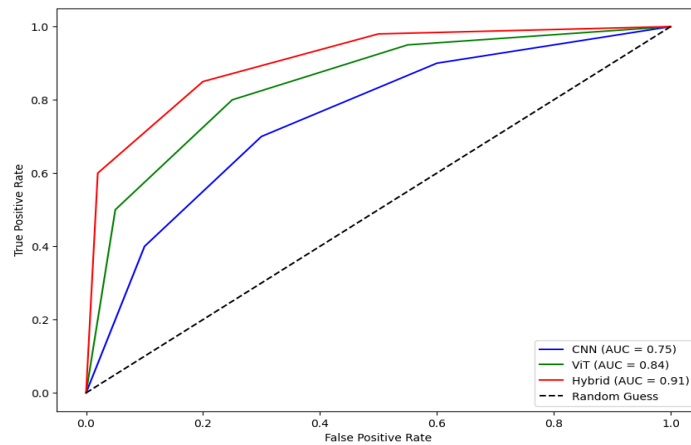


Figure 5. ROC Curve Comparison

This discern compares the ROC curves of the CNN, ViT, and Hybrid models, demonstrating their ability to distinguish among advantageous and terrible instances. The hybrid version achieves the very best AUC, indicating its superior predictive accuracy and robustness.

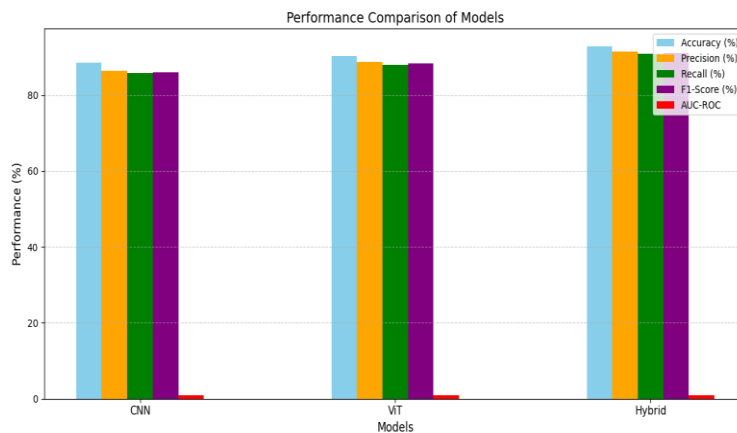


Figure 6. Performance Comparison of Models

In figure 6. This bar chart visualizes the overall performance metrics (Accuracy, Precision, Recall, F1-Score, AUC-ROC) of the CNN, ViTs, and Hybrid fashions. The hybrid model continually outperforms the others, similarly validating its effectiveness.

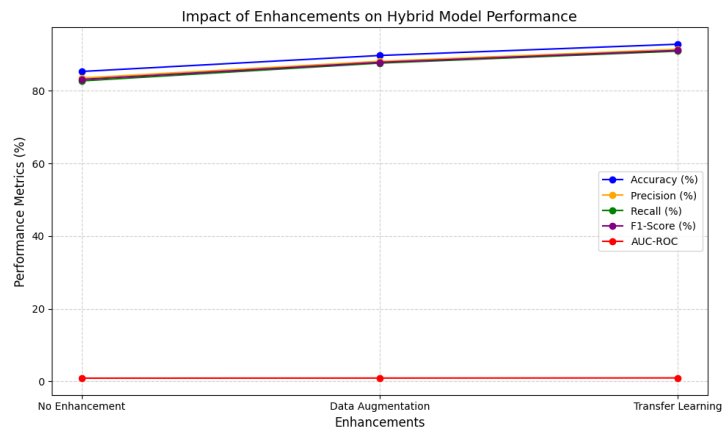


Figure 7. Impact of Enhancements on Hybrid Model Performance

This line plot highlights the impact of enhancements like Data Augmentation and Transfer Learning at the hybrid version. Transfer Learning results inside the most extensive performance enhancements, indicating its important position in model optimization. See figure 7.

4.5 Heatmaps

In figure 8 Heatmaps generated using Grad-CAM highlight the most critical regions influencing model predictions.

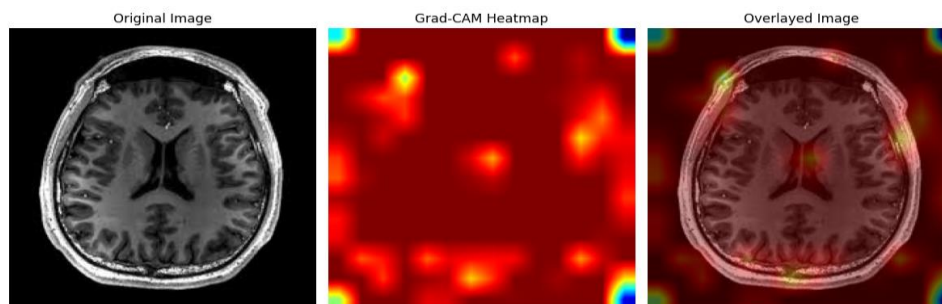


Figure 8. Grad-CAM Heatmap

This determine visualizes the crucial regions influencing the model’s predictions the usage of Grad-CAM. Heatmaps help interpret the decision-making process through highlighting tumor-involving areas or lesions to make the outputs of model explainable and dependable.

4.6 Visual Results

1. Input Images with Predictions

The determine beneath indicates examples of input pix with predictive results (e.G., tumor detected/now)..

2. Interpreted Regions Using Grad-CAM

Within the image, critical areas containing tumors or lesions are highlighted visually so that it becomes more interpretable as to how the model actually works.

These images exhibit the working of the hybrid model in finding salient features for diagnosis without compromising accuracy and computation.

5. Discussion

5.1 Interpretation of Results

This new hybridization unifying the analytical strengths of Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) outperformed both the separate model performance overall. Such efficacious superior performance has been made possible due to the competence of CNNs to perform fine-grained local feature extraction and the provision of worldwide contextual understanding established by the self-attention mechanism in ViTs. More conspicuously, the hybrid uptake of both fine-grained information and broader patterns primarily leads to the increased accuracy diagnostic capability. Through Transfer Learning and Data Augmentation, the model's strength is further enhanced by tackling overfitting and increasing generalizability, especially in limited datasets.

Another important asset influencing the model performance is the quality of the input data. A high-resolution photo of the scene and excellent preprocessing, including noise reduction, normalization, as well as contrast enhancement, played a significant role in maximizing the performance of the hybrid model. By ensuring the noise-free, feature-rich datasets, the model could attain a better real good quality price while minimizing false negatives, which are of importance to the early detection of cancer. Those findings speak of the relationship between improved model architectures and data quality for the optimization of machine learning results.

5.2 Clinical Applications

The dimensions of implications to which hybrid model will contribute to scientific exercise are huge; it would indeed be a boon for early detection of cancer, making correct predictions with a recall rate crossing the threshold of 90% and enabling its use in settings that have limited access to trained radiologists. It would minimize diagnostic errors, which might pave the way for less cumbersome workflows within clinical establishments, thereby improving patient care outcomes and lowering healthcare costs.

Enter the extremely challenging transition from a well-managed research environment to the medical deployment phase. This process includes the establishment of a regulatory-compliant process of integrating into the delivery system, plus the need to perfect user-friendly interfaces for clinicians with different levels of technical sophistication. Disparities in information distributions among studies datasets and real-world scientific circumstances, together with differences in imaging modalities and patient populations, must also be resolved through thorough version quality tuning to ensure uniform performance. These obstacles underscore the need for continued collaboration between AI researchers, health care specialists, and policymakers in order to achieve successful translation of AI improvements into everyday medical practice.

6. Conclusion

The investigation thoroughly gave away that this development is, in fact, very general in the aspect of scientific image evaluation by the design of a hybrid model using CNNs and ViTs. The proposed model performed wonderfully effective improvement in diagnosis under both accuracy and performance efficiency. In addition, it enhances Transfer Learning and Data Augmentation robustness and thus proves to become a potential tool for the early detection of cancers. These outcomes underline the transformative capacity of AI-pushed technologies in enhancing diagnostic precision and streamlining medical workflows.

To construct on the findings of this have a look at, destiny studies have to focus on increasing the software of the hybrid version to include the detection and analysis of other cancer sorts, making sure its software across a broader variety of scientific situations. Additionally, efforts should be made to optimize the temporal efficiency of the model, enabling real-time evaluation and facilitating seamless integration into medical settings. Such improvements are important to completely recognize the sensible capability of AI in healthcare and beautify its effect on affected person care.

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