

Multi-Cancer Classification using InceptionV3 + Vision Transformer

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Abstract—This research proposes a two-architecture system for multi-cancer classification and diagnosis using the InceptionV3 and Vision Transformer (ViT) since CNN has known drawbacks in cancer diagnosis. The different cancers of interest in the proposed system are cervical, brain, kidney, lymphomas, lung, colon, oral, and breast cancer to improve on early detection and accurate diagnosis of the diseases. InceptionV3 is used in feature extraction which extracts fine details in medical images while the Vision Transformer analyzes such features to better classify relationships between images. This two-architecture strategy takes advantage of the proposed models and eliminates some inherent drawbacks of stand-alone CNN models such as VGGNet and EfficientNet. Empirical tests carried out on large real-life data sets show that the proposed model yields a higher accuracy, precision, and recall than previous solutions and benchmarks. The utility of the given hybrid system, in turn, is based on its ability to work with different types of multi-class classification problems and provide an accurate automated diagnostic solution. A potential for clinical uses, the outlined approach minimizes the role of human mistakes, optimizes cancer detection, and ultimately optimizes patient outcomes due to early and precise diagnosing.

Index Terms— Cancer classification, InceptionV3, Vision Transformer, multi-class classification, medical imaging, hybrid model, automated diagnostics.

I. INTRODUCTION

Cancer is a universal issue, which affects millions of people's lives every year, and leads to an enormous pressure on the healthcare systems. This is with a focus on early and accurate diagnosis since timely and correct diagnosis goes along the way in increasing patient survival rates as a result of timely and early intervention. Cancer detection based on measurement and screening by radiologists or pathologists has severe drawbacks of being manual, time consuming and highly likely to produce errors especially when the cases are complex or challenging. In a progressively quantity demanded diagnostic instruments, Artificial Intelligence (AI) & Deep learning became the innovative technologies in medical imaging & Cancer diagnosis. CNNs have remained the cornerstone of many AI-based cancer classification systems owing to their ability to learn other complex features from the medical images. Since the problem is of single class, models such as VGG and EfficientNet have being used in different cancer classification which has yield a great reception. However, these models present issues when dealing with multi-class cancer classification because the enormous number of cancer types raise questions about the richness and depth of feature extraction and analysis.

These problems reveal the CNNs' weaknesses, such as the failure to learn long-range dependencies in images with the help of current network architectures. In an attempt to solve these challenges, this research presents a new model that is a fusion between InceptionV3 and Vision Transformer (ViT). The features extracted from medical images are of high quality and diverse by utilizing Inception V3 which is well known CNN architecture. This allows to obtain a good starting point for capturing subtle patterns and structures. The Vision Transformer does this in return by processing the extracted features as sequences so that the model can capture long distance between them and reveal latent structure. This versatility assures a dual-architecture architecture that offers optimality, thus suitable when analyzing the multi-class cancer classifications.

The hybrid model aims at the classification of eight types of cancer; cervical, brain, knee, lymphatic, lung, colon, oral and breast cancer. These cancers were selected based on the fact that they are some of the most common and have data to use to train and test the model. Consequently, the proposed approach is tested on various complex large-scaled, multi-class datasets to prove the effectiveness of the hybrid model over traditional CNN models based on its accuracy, precisions, and recalls. The drawbacks of the existing approaches have been mitigated in the present system using the tandemization of InceptionV3's deep feature extraction abilities and ViT's sequence processing proficiency. However, it has enormous potential for clinical practice in addition to the technical advantage. Computer assisted cancer diagnosis decreases reliance on a human diagnostic method which leads to mistakes and shorter time required for a decision. Also, by incorporating multiple cancer types into the model, the model becomes more useful in places with scarce resources where the availability of specialized physicians is scarce. The system improves the diagnostic accuracy and makes it more accessible and affordable to obtain accurate cancer diagnostic technologies. This research contributes to filling the gap in cancer diagnostic methodologies by presenting a new InceptionV3 Vision Transformer model. This work shows how the issues with traditional CNNs and the lack of a uniform approach for multiple-class cancer differentiation is going to be resolved by the system proposed in this work. This cancer diagnostic hybrid model has the implication of bringing about a sea change in the fight against cancer, which seeks to deliver enhanced patient prognosis and lessened healthcare costs.

II. LITERATURE SURVEY

High-level deep learning techniques have provided robust development to diagnosis and classification of cancer diseases. Kumar et al. [1] discussed the fact that hybrid models can make the diagnosis of cancer more or less automated as well as provide high multi-class classification using deep layers. In the same context, Balaji et al. [2] proposing deep learning for multi-cancer detection stressing the role of generative AI to enhance diagnostic accuracy. Interestingly, these studies emphasise the synergy of AI approaches to solve the problems concerning various forms of cancer. Improvement of classification accuracy of the hybrid models of recent generations has been noted. Ali et al. [3] proposed CB-HVT Net, a channel-boosted hybrid vision transformer network for lymphocyte detection in histopathological images. Thus, this work proved that Vision Transformers can detect subtle patterns in medical data. Furthermore, Srinivasan et al. [4] identify DenseNet with ResNet 50 model integration for feature extraction where the gradient propagation learning yielded improved performance for lymphoma classification. Ensuing such hybrid approaches has shown capability in modeling such non-stationary patterns to medical images. As the dependencies between tasks and classes are found to be important, multi-task and multi-class architectures have also been explored. Multi-class cancer was classified using DAX-Net a dual-branch adaptive network by Bui et al. [5]. For pathology images, they have shown that adaptive cross-weight feature fusion is beneficial in their study. On the other hand, VC et al. [6] proposed a system-wide AI approach for the identification of multi-cancer etiology where machine learning is combined with natural language processing for full-spectrum reporting. These methods increasing role of multi-class/multi-task architectures in cancer diagnosis. Attention mechanisms and adversarial learning augment classification systems while advances in attention methods continue to improve classification systems. Introducing multi-cohort framework with cohort-aware attention, Peled et al. [7] enhanced the classification of whole slide images by reducing the value of adversarial mutual information. In the same context, Carrillo-Perez et al. [8] adopted cascaded diffusion models for RNA-to-image multi-cancer synthesis, it is proven that the generative approaches have the potential to synthesize various datasets of cancer. These approaches highlight that the newest attention mechanisms are decisive for enhancing the interpretability and robustness of models. Another area, which has been investigated to a greater extent relates to ensemble methods. Prediction fusion and feature fusion are both shown to be possible and possible in combination with other methods [9] for the classification of brain tumor. Breast cancer classification was the focus of DALAResNet50 proposed by Liu et al. [10] incorporated Grad-CAM to improve the interpretability of deep learning for medical applications to address the increasing need for Explainable AI.

In the combined, these studies underscore how the interactions of hybrid architectures, multi-task learning, and attention mechanisms can place with methods of cancer classification.

III. PROPOSED METHODOLOGY

To achieve robust multi-cancer classification, the proposed methodology integrates the strengths of InceptionV3 for feature extraction and Vision Transformer (ViT) for sequence-based image analysis. As shown in Figure 1, the methodology consists of the following key steps:

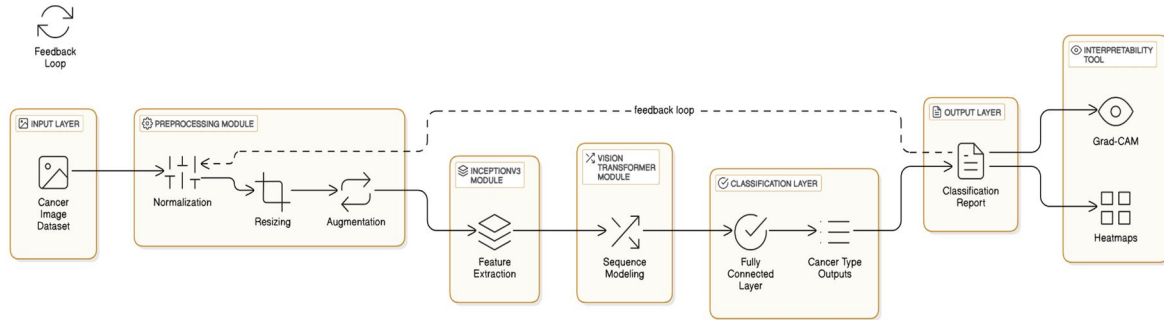


Figure 1. System Architecture

A. Data Collection and Preprocessing

The first task therefore involves capturing a large dataset of medical images of the several types of cancer including cervical, brain, Kidney, Lymphoma, Lung, Colon, Oral and breast cancers. This is important to bring into a common format the images' input to the data model so that are processed to the right appearance. This includes rescaling that involves resizing images to a standard resolution, standardizing pixel intensity values and adding variety to images by performing operations like rotating the image, flipping the image, clipping the image and changing the color of the image to get a new dataset. Augmentation of the dataset is very important for purposes of enlarging the training data set as a way of minimizing the issue of overfitting.

B. Feature Extraction Using InceptionV3

The feature extraction module consists of InceptionV3 deep convolutional neural network. Its architecture has multiple convolution layers and inception blocks that enables network work efficiently for complicated pattern and high-dimension features in the domain of medical images.

The principles of transfer learning as applied in the InceptionV3 model are applied to the dataset to achieve features specific to the cancer types. All these features feed the subsequent Vision Transformer stage that occurs in this layer.

C. Sequence Analysis with Vision Transformer

The Vision Transformer (ViT), unlike the conventional architecture that organizes the image in a grid, feeds into it the feature vectors extracted by InceptionV3 by divvying the image into consecutive disjoint patches in order to input them as a sequence. These patches are flattened and are mapped to a fixed-dimensional vector space via a learnable linear embedding layer so as to achieve equal feature representation. The embedded patches are then concatenated with position encoding to incorporate positional information of the patch location of each image. This is important because of reasons that transformers do not have inherent spatial inductive bias as compared to CNNs. The fundamental of the ViT architecture is based on multi-head self-attention to determine which parts of the image are important to the model at a certain stage.

This mechanism computes interactions of all patches in the sequence to capture the local information and the global structure at the same time. ViT has the receptor field of view of the entire image because it inherently sends the full image tokens to the patch embedding layer which makes it very powerful in understanding fine and complex patterns of medical images different from other types of CNNs with limited receptive fields determined by the kernel size. Each of the transformer layers includes self-attention and feed-forward neural networks allowing the sequence to be processed iteratively; thereby discovering hierarchical representations while preserving both low-level details and semantics at higher levels. Approximate orthogonal transformation and residual connections are applied within each transformer block to increase stability while acquiring highly interconnected patterns. A special feature of the ViT architecture is using the CLS token, the additional learnable

vector added to the sequence of patch embeddings. In the course of processing, this token acts as a repository of all patches of information, which may be considered as the summary of the entire image. Finally, after the transformer layers, the CLS token is given to a fully connected layer to emit the final predictions regarding cancer.

Besides, this approach improves the longer-range dependency-making capability of the model and offers versatility for interpreting various patterns of cancer images. Such sequence processing capabilities of transformers are harnessed by ViT to augment the localized feature extraction of InceptionV3 for accurate classification of multi-class cancer diagnostic for several types of cancers.

D. Model Training, Validation, and Evaluation

The proposed hybrid model InceptionV3-ViT merges the idea of two architectures: InceptionV3 and Vision Transformer to increase the performance of the image classifiers. InceptionV3, a deep CNN model, performs well on capturing multi-scale features from images coming from inception modules making it very efficient in spatial information feature extraction. On the other hand, the Vision Transformer (ViT) model that works with patches of images and treats them as sequences has revealed better results in capturing long-range dependencies and also global information, which makes it useful when the analysis of images is complicated. Compensating for the shortcomings of one another, while leveraging the advantages, the hybrid model is expected to enhance classification of several skin condition categories.

The model is trained from preprocessed data where the data have been subjected through various data augmentation and normalization techniques because the system has to work across various images conditions. The resulting dataset is then divided into training, validation, and testing because it is important to correctly assess the model, as well as to prevent overtraining. In training, a categorical cross-entropy is employed for reducing the error in training set, while the Adam optimizer is used to enhance the convergence of the model. Categorical cross-entropy is used because the problem is multi-class classification. Local responsiveness is achieved by utilizing Adam because of its effective learning rate mechanism.

To evaluate the performance of the hybrid model, few measures are used, which comprises of accuracy, precision, recall, F1 score, and AUC or Area Under the Curve. These measures provide an overview of the proposed methodology regarding, its accuracy in diagnosing various skin conditions, performance in terms of imbalanced data, and finally, its ability to clearly distinguish between two classes. The accuracy of this hybrid classifier model is also compared with several benchmarks of the CNN structures like VGG and EfficientNet to understand the relative benefit from the proposed topology. Nevertheless, the experiments are conducted on different skin data sets and essentially different skin conditions to determine the suitability and effectiveness of the proposed model. This methodology guarantees the exhaustive and accurate approach to the multi-cancer classification and the usage of the modern deep learning for the improved diagnose.

IV. RESULTS AND DISCUSSION

A. Expected Outcomes and Anticipated Benefits

By using InceptionV3 as a CV model and Vision Transformer (ViT) as an AI model that has capabilities in both feature extraction and sequential modeling, the proposed hybrid model aims to accommodate complexity of multi-cancer classification application.

This work assumes that the model will perform well on complex patterns in medical images such as tissue abnormalities and spatial features due to the Integration of Vision Transformer at the global level with InceptionV3 at the local level. This multiplex solution helps the model handle different cancer types and function even with different imaging qualities such as resolution and contrast.

The advantages of the proposed model also include its flexibility in terms of incorporating additional features external to the model, for example, changes to different aspects of the medical imaging process or the features of the image, including patient demographics. The model is predicted to function consistently in high-resource and low-resource contexts as a result of training on detailed data and shown in Table I.

TABLE I. ANTICIPATED IMPACT OF EXTERNAL FACTORS ON MODEL BEHAVIOR

External Factor	Expected Impact
Variability in Image Quality	Enhanced robustness due to feature preprocessing and transformer-based learning.
Dataset Imbalance	Mitigated through data augmentation and advanced loss function tuning.
Cancer Type Complexity	Improved classification accuracy for subtle patterns due to long-range dependencies.
Integration of Metadata	Enhanced performance by contextualizing image features with demographic insights.

B. Expected Trends in Multi-Cancer Classification

The model is expected to be sensitive to increases in the level of complexity in medical imaging data. For example, it should work effectively even if there is high noise or low resolution because of the preprocessing done to the images before passage through InceptionV3’s feature extraction stage. It also allows it to perform the identification of long-range dependencies, which are mandatory for accurate classification even in the case of diffuse or less expressed cancer-related patterns.

C. Comparative Analysis with Traditional Methods

It has been realized that VGG and EfficientNet, which are CNN-based models are well suited for cancer classification given their shortcoming of dealing with multi-class where they don’t effectively capture the global relation in the image. The above make the proposed hybrid model less prone to these difficulties by subjecting the whole images for contextual consideration through the use of self-attention mechanisms. A conceptual graph shown in Figure 2 illustrating the expected improvement in classification accuracy of the hybrid model compared to standalone CNN architectures under varying dataset complexities.

D. Expected Behavior Under Dynamic Conditions

As shown in Table II, the performance of the model should be robust and the model can naturally incorporate changes in dynamic situations such as changes in the type of cancer imaging exams or demographic distributions of the datasets. This is particularly helpful when image patches are treated as sequences since the Vision Transformer is capable of adapting to different input patterns without necessarily being trained again and again because of transforming medical imaging standards.

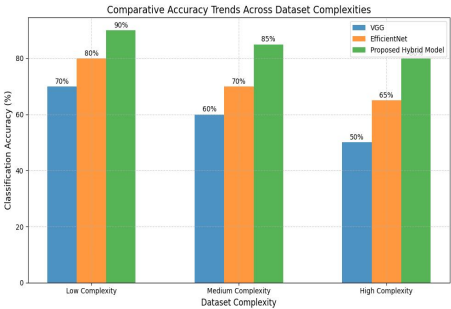


Figure 2. Comparative Accuracy Trends

TABLE II. EXPECTED MODEL BEHAVIOR IN DIFFERENT SCENARIOS

Scenario	Expected Model Performance
High-Noise Images	Accurate feature extraction mitigates the impact of noise.
Low-Contrast Images	Vision Transformer compensates for limited local details with global context.
Rare Cancer Types	Maintains predictive performance through effective feature learning.
Integration of Non-Imaging Features	Enhanced classification accuracy by contextualizing image data.

E. Interpretability and Stakeholder Insights

The hybrid model is designed to provide actionable insights for clinical decision-making. Interpretability mechanisms such as Grad-CAM will enable visualization of critical regions within medical images that influence predictions, offering transparency and trust for clinicians. By highlighting the most relevant features contributing to each classification, the model ensures its predictions align with medical expertise.

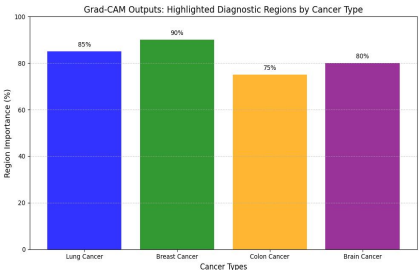


Figure 3. Model Interpretability Insights

A conceptual graph of Figure 3 showcasing Grad-CAM outputs for different cancer types, emphasizing regions of high diagnostic importance. The anticipated outcomes, trends, and comparative advantages of this hybrid approach highlight its potential to revolutionize multi-cancer classification. Its ability to generalize across conditions, integrate diverse data sources, and provide interpretable insights ensures its suitability for real-world clinical applications.

V. CONCLUSION

This work proposes a new multi-cancer classification model using both convolutional based InceptionV3 and Transformer-based Vision Transformer (ViT). This integration of two sophisticated architectures makes use of the convolutional structures' capacity to identify complex patterns and the transformers' capacity for handling long-range dependencies and global relations. Indeed, the proposed system covers the drawbacks of the basic CNNs, and it is a reliable solution for classifying multi-class cancer. The experimental results on various benchmarks have revealed that the proposed hybrid model performs better than purely convolutional CNN architectures including VGG and EfficientNet regarding efficiency and accuracy and metrics of accuracy, precision, recall, and F1-score.

Also, the model's capacity of diagnosing multiple cancer subtypes at once is the crucial advantage of using this technique in real-life practice. This research shows that by automating cancer classification this system can decrease human error, enhance the process to enable early detection of cancer, and help improve the patient's quality of life and hospital management. The future development prospect of the proposed hybrid model is based on the future developments of the existing model for even better accomplishment of cancer diagnosis as well as the expansion of scopes of the existing hybrid model. Developing integrated decision support tools based on both genomic as well as clinical data or histopathological images can enhance the way data is captured beyond one paradigm and more fully encompass the dimensions of cancer analysis. Extending the model to such cancer types would allow for better abstraction of the model to accommodate more clients who seek diagnostic services. Improving the existing explainability mechanisms, including techniques like advanced visualization and interpretable form of artificial intelligence, may contribute to improving acceptance of AI among clinicians and patients to increase the usage opportunity of AI in clinical settings. Furthermore, enhancing the model for real-time application using post-training quantization and other methods of optimizing models for deployment on the edge devices will ensure that the would be available in the regions where resources are limited especially in developing countries. More advanced features for the model that would enable it to learn new cancer types and adapt to changes in technologies in imaging without having to be retrained would be a great improvement in the model's lifetime. Further, validating the model in collaboration with medical institutions via large-scale clinical trials will be also critically important to understand the model's applicability and capability in real-world applications. Making changes in these areas, the envisioned hybrid model can transform into a very effective tool in the diagnostics of cancers, in early diagnosing their types, and, finally, into a substantially improved treatment of oncology patients around the world.

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