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Explainable Artificial Intelligence for Lung and Colon Cancer Classification

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Lung and colon cancers are among the most common and deadly cancers worldwide, and they require accurate and rapid diagnosis to decrease the mortality rate. Histopathological examination remains the gold standard for diagnosing cancer; however, it is time-consuming, prone to interobserver variability, and limited by resource constraints in many regions. Recent developments in deep learning have demonstrated enormous potential to overcome these challenges. This study examined the use of pre-trained convolutional neural network models, Xception and DenseNet201, in the classification of histopathological images of lung and colon cancer. Improved data augmentation techniques are employed to enhance model performance. The classification accuracy was approximately 99%. To obtain transparency and interpretability, explainable AI techniques, such as GradCAM of gradient-weighted classes, vanilla saliency maps of activation mapping and also SHAP, are applied. These strategies provide visual insights into the model's decision-making processes, thereby improving the understanding and trust of AI-based diagnostics. The results indicate that the deep learning model with XAI is accurate and interpretable for cancer categorization. This histopathology approach solves fundamental issues by combining the Xception and DenseNet201 models with visualization approaches to provide more accessible, efficient, and accurate diagnostic options for lung and colon cancer.

Keywords: lung colon cancer, histopathology, pre- trained cnn, deep learning, explainable artificial intelligence.

1. Introduction

Cancer is an umbrella term for various diseases that can affect any body part. Other terminology used includes malignant tumors and neoplasms. One notable feature of cancer is the rapid formation of abnormal cells that grow beyond their normal borders and eventually infiltrate into neighboring sections of the body and spread to other organs; this process is known as metastasis. The leading cause of cancer-related death is metastasis. It is anticipated that 9.7 million people will die of cancer in 2022, and 20 million new cases will be diagnosed. A total of 53.5 million people were predicted to survive five years after receiving a cancer diagnosis [1]. About one in five people will get cancer at some point in their lives; one in nine men and one in twelve women will die of the disease. Lung, breast, and colorectal cancers will be the three main types of cancer in 2022. Liver cancer (760,000 deaths, 7.8%), stomach cancer (660,000 deaths, 6.8%), colorectal cancer (900,000 deaths, 9.3%), and lung cancer (1.8 million deaths, 18.7% of all cancer deaths) were the leading causes of cancer-related deaths. By 2050, more than 35 million additional cases of cancer will be diagnosed, a 77% increase from the 20 million predicted in 2022. The rapidly rising global cancer burden is a result of changes in risk factor exposure, some of which are connected to socioeconomic development, as well as population aging and growth. In terms of the number of deaths, years of life lost, and DALYs worldwide in 2019, cancer ranked second only to cardiovascular diseases among the 22 categories of illnesses and injuries included in the GBD 2019 study.

Uncontrolled abnormal cell proliferation in the lungs is a hallmark of lung cancer. This illness is a serious health risk factor that can lead to death or severe damage. Although there are few treatment options available, lung cancer is often discovered at an advanced stage. High-risk patient screening can significantly improve survival rates and enable an early identification. The two most common types of lung cancer are small cell carcinoma (SCLC) and non-small cell carcinoma (NSCLC). SCLC is rare but often grows quickly, whereas NSCLC is more common and grows more slowly. A type of cancer that develops in the rectum or colon (large intestine) is called colorectal cancer. It is one of the most common types of cancer in the world. Treatment options for colorectal cancer are limited, and this disease is often detected at an advanced stage. Early detection and treatment of cancer reduces its mortality rate. Screening and diagnosis are the two primary pillars of early detection.

Early diagnosis: Patients with cancer are more likely to respond to treatment when the disease is discovered early, thereby increasing survival, lowering morbidities, and enabling more affordable treatment. Screening: The goal of screening is to identify individuals who may have pre-cancer or cancerous evidence before symptoms appear. Additional testing should be performed when abnormalities are discovered during screening. If cancer is discovered, treatment should also be initiated.

Convolutional Neural Network (CNN) is used to process and analysis visual data which is a type of deep learning algorithm. CNNs are very widely used in lung and colon cancer classification in order to detect patterns in medical images (such as CT scans or histopathological slides). However, they extract automatically important features such as tumor shapes, textures, and densities without manual intervention. A CNN's architecture consists of convolutional layers for feature extraction, pooling layers for dimensionality reduction and fully connected layers for classification. In these networks, they can accurately diagnose, depending on the subtlety of differences between cancerous and noncancerous tissues. CNNs are generalizable to new data, as well as unseen data, which is suitable for clinical application. However, their ability to analyse large amounts of data efficiently makes them a powerful tool in early cancer detection, and helps overcome the success of treatment planning and patient outcomes. Explainable Artificial Intelligence (XAI) is a set of methods and techniques to make the decision-making process of AI systems transparent, interpretable, and understandable to humans. XAI attempts to solve the "black box" problem of AI by providing insights into how an algorithm (model) determines its prediction or decision. Gradient weighted Class Activation Mapping (Grad-CAM) or saliency maps enable us to visualize which regions, or features in the data, have an impact on the model’s decisions. In particular, for healthcare, finance, and accountancy, where it is important to have understandable model behaviour for decision making and compliance, trust, accountability, and secure deployment of AI requires XAI.

In this study, pre-trained convolutional neural network (CNN) models, such as Xception and DenseNet201, are used to classify histopathological images of lung and colon cancer with high accuracy. To increase interpretability, this study combined explainable AI (XAI) techniques, including vanilla saliency maps, SHAP and GradCAM. These visualization strategies provide a greater level of insight into how models make decisions and, in turn, allow a higher degree of trust and transparency in AI-driven diagnostics. This study proposes a combination of robust DL architectures and XAI methods to provide accurate, interpretable, and efficient diagnostic solutions for lung and colon cancer. These are new ways to use AI to create practical and trustworthy healthcare applications that address the performance and interpretability associated with medical diagnostics.

2. Related Work

For more than 40 years, medical imaging researchers have attempted to automate cancer diagnosis by categorizing histopathological images into benign or malignant. This effort will enable the development of more accurate diagnostic instruments if we improve image analysis's effectiveness and reliability. However, the complex structure and variability of histological images make automated analysis difficult. These issues have hindered the development of a sophisticated, fully integrated diagnostic system. Despite continuous improvements, these complexities must be resolved to provide a complete tool that meets the demands of contemporary clinical applications.

In 2020 Sanidhya Mangal et al. [2] present a computer -aided diagnosis system for classifying lung and colon cancers from histopathological images using convolutional neural networks (CNNs). The authors trained a shallow CNN on 2500 images of lung and colon cancer data using the LC25000 dataset, with over 97% accuracy for lung cancer and 96% accuracy for colon cancer. Preprocessing images, applying augmentations, and applying a specific CNN layer (convolution, pooling, fully connected) were used as the methodology. However, this paper lists gaps in its applicability, such as a lack of comparative studies with more advanced architectures, and explores hyperparameter optimization and generative models for improved diagnosis. The authors Mehedi Masud et al. [3] highlight the criticality of early cancer detection as well as the potential for artificial intelligence (AI) to play the role of automated diagnoses, improving accuracy and efficiency. The methods include Unsharp Masking for image sharpening followed by feature extraction using 2D Discrete Fourier Transform (DFT) and 2D distinct Wavelet Transform (DWT). The following subsections describe the use of a multichannel Convolutional Neural Network (CNN) to classify. Despite this progress, a critical gap remains in the ability of diverse imaging modalities to be integrated into models, and large, diverse datasets are required to make models reliable and generalizable across different populations and clinical settings. The proposed method by Aya Hage Chehade et al [4]. in “Lung and colon cancer classification using medical imaging: a feature engineering approach” incorporates feature engineering to classify lung and colon cancers using medical imaging. In this, the histopathological images from LC25000 dataset are analyzed using machine learning techniques such as XGBoost, SVM, RF, LDA, and MLP. Image preprocessing, statistical measures, and GLCM-based feature extraction and recursive feature elimination for optimal feature selection are involved in the methodology. Currently, this research gap exists where we have only achieved limited simultaneous classification of lung and colon cancers using machine learning, which is superior to the black box deep learning methods, while often lacking the interpretability of the model. In 2022, Shahid Mehmood et al. [5] proposed a method to detect malignancy in lung and colon histopathological images with the help of transfer learning and Class Selective Image Processing (CSIP). The model was taken as a pretrained AlexNet, and four layers were fine-tuned over a dataset of LC25000 images on five classes. This CSIP strategy increases the accuracy of images from under classified classes to 98.4% overall, compared to 89% accuracy. The biggest problem with existing research was that it was not been able to find an efficient and computationally efficient way to detect multiple cancers without sacrificing accuracy. The paper titled "Classification of Lung and Colon Cancer Histopathological Images Using Global Context Attention Based Convolutional Neural Network" by MD. Al- Mamun Provath et al. [6] attempts to address the burning discrimination of classifying lung and colon cancer types by taking recourse to histopathologically processed images. In this model, they proposed a novel CNN model with a global context attention module that captures both channel and spatial information from the images. It first introduces a stage-based image enhancement for image quality improvement and a dataset from GANs to remedy the lack of data solicitation. This research then identifies gaps in existing studies, including small dataset sizes, interclass variation and omission of benign nodules which may cause model bias. The proposed approach seeks to enhance diagnostic accuracy through integrative approaches that take a patient level analysis alongside image and semantic information aware for non- invasive cancer screening.

Manjit Kaur et al. [7] proposed a deep learning framework, DARNet, for classifying lung and colon cancers using a Deep Attention Module and Residual Blocks, is presented. The methodology includes three core components: Capturing complex patterns using Residual Blocks (RBs), Feature extraction using Attention Modules (AMs), and Final classification using Fully Connected Layers (FCLs). Overfitting and gradient vanishing are addressed by the use of Bayesian Optimization (BO) model for hyperparameter tuning. There is a surprising degree of failure in existing models of phone speech, which is in their struggle to generalize and in hyperparameter optimization, leaving them both inaccurate and brittle. Previous studies have shown promise in cancer classification, however prior work requires enumeration of hyperparameters using trial and error that still leads to lack luster performance. To fill this gap, DARNet assembles the latest techniques to enhance the accuracy and efficiency of cancer diagnosis which successfully improves patient care. The paper titled 'Histopathological Analysis for Detection of Lung and Colon Cancer Malignancies using Hybrid Systems with Fused Features' by Mohammed Al-Jabbar et al. [8] examines the use of techniques of artificial intelligence for early cancer detection in lung and colon cancers. Using some deep learning models such as GoogleNet and VGG-19, the authors extract high-dimensional features from the histological images of the LC25000 dataset. To reduce dimensionality and extract important features, they use techniques such as Principal Component Analysis (PCA). Three strategies are developed: Features were used separately, after PCA, and hand-crafted features were combined with CNN outputs. The gap in the research is therefore the lack of accessibility and efficiency of current diagnostic measures — especially in developing countries. The need for automated, AI driven solutions to bridge the gap between advanced diagnostic capability and practical healthcare applications is a fundamental reason why traditional manual diagnosis is time consuming and subjective.

Improved Water Strider Algorithm with Convolutional Autoencoder for cancer detection on histopathological images, is presented as a new approach to detect lung and colon cancer using a hybrid algorithm by Hamed Alqahtani et al. [9] They proposed IWSACAE-LCCD, a method that combines median filtering for noise reduction, the MobileNetV2 architecture for feature extraction, and a Convolutional Autoencoder (CAE) for classification. Hyperparameter tuning is carried out using IWSA, which improves the performance of the model. This study identified the research gap between manual histopathological analysis and other medical imaging modalities which are time consuming and prone to error. Unfortunately, current automated techniques all lack high accuracy and high efficiency, particularly in real-time clinical settings. This paper attempts to enhance diagnostic accuracy and speed through using advanced deep learning methods, which meet the demand in order to develop reliable and efficient cancer detection systems in the medical practice.

In the paper ‘Biomedical Image Analysis for Colon and Lung Cancer Detection using Tuna Swarm Algorithm with Deep Learning Model’ by authors by Marwa Obayya et al. [10], they discuss a new model, BICLCD-TSADL, which uses an advanced image analysis to detect colon and lung cancer. The methodology involves several key steps: For adaptively superimposing the hyperparameter optimization by Adaptive Firefly Algorithm (AFAO) for the image preprocessing and feature extraction through Gabor filtering, and image preprocessing and feature extraction by GhostNet model. Using an Echo State Network (ESN) for classification and the Tuna Swarm Algorithm (TSA) for parameter tuning, our model employs the model. The research gap found is the poorly effective machine learning and deep learning models in accurately classifying colon and lung cancer given biomedical images’ complexity and variability. This gap is addressed by combining multiple AI techniques to increase detection accuracy to a maximum accuracy of 99.33%, thereby moving forward the state of cancer diagnostics. Another paper, titled "Prediction of Lung and Colon Cancer through Analysis of Histopathological Images by Applying Pre-trained CNN Models," by Satvik Garg and Somya Garg [11] tells us the crisis need for early cancer detection and specifically of lung and colon cancer. To analyse the histopathological images of the LC25000 dataset, the authors use eight pre trained Convolutional Neural Network (CNN) models, including VGG16, ResNet50, and InceptionV3. In the study model accuracy is enhanced with data preprocessing, data augmentation and transfer learning. Binary classification tasks are performed and model performance measured with precision, recall, F1-score, accuracy, and AUROC scores. GradCAM and SmoothGrad are used to visualize model attention on high importance image areas. In the paper, Mengash et al. [12] introduce a new method termed the Marine Predators Algorithm with Deep Learning (MPADL-LC3) to novel condition lung and colon cancer from histological images. The methodology is carried out by contrast enhancement through CLAHE, feature extraction using MobileNet, and hyperparameter optimization through Marine Predators Algorithm. Classification is done with a Deep Belief Network. This fills the research gap of needing efficient, automated cancer diagnosis methods to improve accuracy and decrease diagnostic time over traditional manual histopathological analysis to achieve better patient outcome. CLAHE is used at preprocessing stage for the classification.

3. Proposed Methodology

Dataset Description

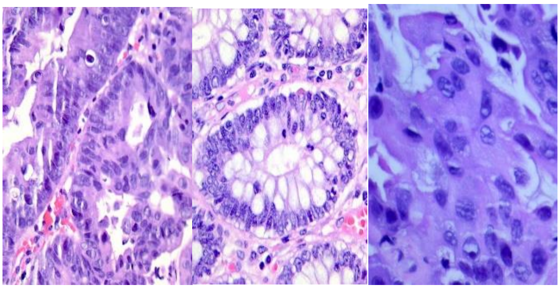
A. Borkowski and colleagues [13] introduced the LC25000 dataset in 2020, which is a useful resource for the field of medical imaging, and in particular, for histopathological image analysis. It was designed to be used in the development and evaluation of automated diagnostic systems for lung and colon cancer, two of the most prevalent and impactful cancers world-wide.

LC25000 comprises a total of 25,000 histopathological images, evenly divided into five distinct classes: lung adenocarcinoma, lung squamous cell carcinoma, normal colon tissue, colon adenocarcinoma and normal lung tissue. All classes contain 5,000 images so as to balance the training with the test images.

The dataset is high resolution and annotated, and the images, along with the annotations, will allow researchers to work with the first standardized dataset of histological complexity, whose images reflect real world complexity. In this dataset, image classification algorithms are challenged by an extremely intricate morphological features and visual variability within and between the classes. Because LC25000 includes tissue from both normal and malignant compartments in two different organ systems, broader applicability of findings provides a powerful advantage in developing generalized diagnostic models.

LC25000 has become a benchmark dataset for the field thanks to its offering of a large, diverse set of labeled images to promote machine learning based approaches to cancer diagnosis. It allows researchers to do: test out novel methodologies, improve model accuracy, and assess how robust their systems are when subjected to differences in their conditions.

In this work, we use LC25000 for evaluating our proposed automated diagnostic framework. Figure 1 describes the five classes of dataset.



(a) (b) (c)

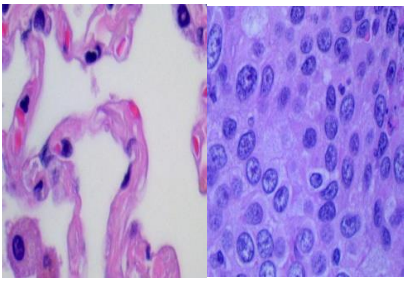

(d) (e)

Fig. 1. Histopathological images from dataset. (a) Colon Adenocarcinoma (b) Colon benign (c) Lung Adenocarcinoma (d) Lung benign (e) Lung Squamous Cell

TABLE I. DESCRIPTION OF DATASET

Class Description	Number of Images
Colon Adenocarcinoma	5000
Colon benign	5000
Lung Adenocarcinoma	5000
Lung benign	5000
Lung Squamous Cell	5000
Total Images	25000

Convolutional Neural Network

The convolutional neural network (CNN) is a deep learning architecture used to analyze visual data. Basically, it involves convolutional layers to extract features, pooling layers for dimensionality reduction, and fully connected layers for classification. CNNs have been successful in image recognition tasks, including automatically learning shape, color, texture, and even displacement information from images to diagnose cancers in medical imaging, for example.

A pre-trained CNN is a convolutional neural network trained on a large, general dataset (e.g., ImageNet) and then fine-tuned for specific tasks. A feature, learned, version avoids retraining time and is better with similar datasets, such as medical images representing lung and colon cancer classification. In this paper, we are utilizing pre- trained Xception and DenseNet 201

Xception, which is an extremely deep learning architecture based on Xception that is superior to inception, is improved upon inception using the use of depth- wise separable convolutions. This innovation splits the convolution process into two steps: pointwise convolution, which averages independent combinations of these outputs, and depth- wise convolution, which independently applies a filter to each input channel. Finally, this design provides high accuracy at reduced computational cost. Xception has three flow modules: entry, middle, and exit. Separable convolutions and skip connections are used in each flow to improve gradient flow and feature learning. The proposed method requires fewer parameters than traditional CNNs and is therefore suitable for large-scale image classification. Xception is efficient for capturing fine-grained details because it can support fine-grained features in lung and colon cancer classification. It is well suited to tasks that require precision, such as discriminating between healthy and cancerous tissues in histopathological images or radiographs, or for recognizing objects in medical imaging, due to its enhanced architecture.

DenseNet201 is a variation of the DenseNet family of deep convolution neural networks. The primary goal of this network is feature reuse. In contrast to traditional architectures, the layer in DenseNet directly connects to all other layers without skipping other layers. It provides high connectivity for the classic case, preventing duplication of features, thereby reducing redundancy and faster learning. DenseNet201 has 201 layers and makes use of densely connected blocks, where each layer takes in (or gives out to) all previous layers. First, this design enhances gradient flow; second, it solves the problem of vanishing gradients; and third, it allows for deeper networks with fewer parameters. Pooling in the network reduces the dimensionality in the transition layer between blocks and maintains computational efficiency. DenseNet201 outperformed the other networks in terms of learning complex patterns from medical images where detail is important, for example in medical applications for lung and colon cancer classification. The dense connections allow better use of features and thus more accurate differentiation between healthy and cancerous tissues across all datasets. DenseNet201 is suitable for high-precision diagnostic tasks.

Explainable Artificial Intelligence

XAI realizes the transparency by making AI models make decisions explainable. The proposed model checks complex models to prevent mistakes and ensures that all participants believe in the model. In sensitive domains, XAI is critical for stakeholders to understand, validate, and refine AI predictions to improve reliability and ethical decision making. [14]

GradCAM (Gradient-weighted Class Activation Mapping) is the visualization technique for interpreting CNN predictions. We leveraged the gradients of the target class score relative to the convolutional layer feature maps to highlight image regions whose influence on the model's decision was significant. For example, with medical images, GradCAM generates heatmaps overlayed on input images and locates suspicious lesions that are considered important. The interpretation of this method provides intuitive explanations to help understand and validate predictions, especially for high-stake cases, such as cancer detection. Because it can work with pre-trained models without architectural modifications, it is widely applicable for the application of AI in diagnosis.

Vanilla Saliency is a simple gradient approach to visualize AI model decision-making processes. The proposed method infers and calculates the gradient of the output score for the input pixels, i.e., how much change in the input pixels affects the prediction. The regions of influence are highlighted using the resulting saliency map, which is typically employed for image classification tasks. For instance, in medical imaging, it pinpoints where tumors exist using pixel-level contributions to the prediction. Vanilla Saliency is straightforward, sensitive to noise, and less interpretable than more sophisticated methods such as GradCAM. However, it provides a fertile foundation for general neural network thinking.

SHAP (SHapley Additive exPlanations) is a cooperative explainability tool based on cooperative game theory. It is capable of assigning a Shapley value to each feature, which represents the contribution of that feature to the model’s prediction. Fair and consistent attribution is achieved by SHAP because it evaluates what happens to the prediction when it is based on or off an individual feature. Thus, visualizations, such as force plots, are created to demonstrate feature importance and interactions. In healthcare, SHAP allows for the explanation of politics of AI models for cancer detection: quantifying how factors like tumor size or density affect predictions. SHAP has theoretical support and is very versatile; therefore, it has become a good tool to interpret linear and complex machine learning models.

4. Methodology

Pre-trained CNNs (Xception and DenseNet201), which were expanded by XAI are used to classify lung and colon cancer. Images were down scaled to 299x299 pixels, normalized, augmented with random rotations, horizontal flips, and contrast changes for enhancing data quality and diversity. On this dataset, we fine tunned the CNNs using transfer learning for efficient training. In particular, we used GradCAM and Vanilla Saliency for visualizing model focus and SHAP to quantify feature importance in XAI, driving interpretability. Model effectiveness was ascertained by the performance metrics such as accuracy and precision to generate a robust and interpretable cancer diagnostics. The proposed methodology in this paper is described in the following steps:

Input Image Preparation: Images were made uniform and compatible with pre-trained CNN architectures by making them standardize to 299x299 pixels. This helped with consistent preprocessing and model feeding.

Image Preprocessing: To improve training convergence, we normalized the dataset based on pixel values to the 0–1 range. The dataset was augmented with random rotations and horizontal flips to improve model generalizability. Selective cropping was applied to regions of interest to reduce background noise and computational complexity. To conquer uneven illumination, a set of brightness adjustments and contrast enhancements were used to capture key medical internals.

Model Selection and Training: We selected pre-trained Xception and DenseNet201 architectures because they perform much better in image classification.

Explainable AI Techniques: We used GradCAM and Vanilla Saliency to make the important image regions that influence predictions interpretable. Furthermore, SHAP was employed to quantify feature importance and provide complete explanations, which enriched the transparency and reliability of model outputs.

Performance Evaluation: The models were evaluated using accuracy, precision, recall, F1 score, jaccard score, and log loss as metrics. This analysis led to a highly detailed comparison of the lung and colon cancer models to identify the most effective model.

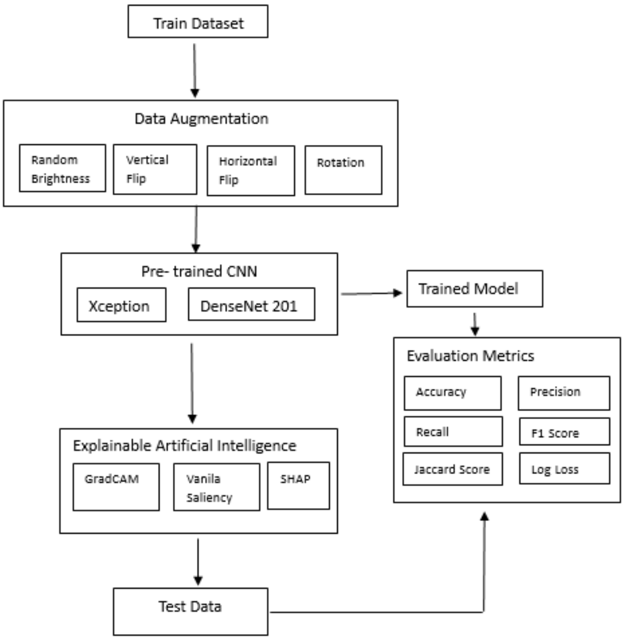


Fig. 2. Proposed methodology for lung and colon classification

Evaluation Metrics

Accuracy, precision, recall, F1-score, Jaccard score and log loss were used to evaluate lung and colon cancer classification models. Overall correct predictions was used for measuring accuracy, while precision and recall were used to measure our ability to find true positives and avoid false positives and negatives. Precisely F1 score combines the precision and recall, taken necessary when dataset is imbalanced. Overlap between predicted and actual labels was quantified using Jaccard score and thus classification consistency was revealed. The confidence of probabilistic predictions, as measured by log loss, was rewarding well calibrated outputs.

In conjunction, these metrics yielded a complete and thorough examination of model performance over multiple dimensions, which are necessary for robust and reliable diagnostic systems.

5. Results and Discussion

We then separated the dataset where 20% of images in each class were used for testing and 80% of images were training the model. In this study, we used Xception and DenseNet201 pre-trained CNN models with explainable AI paradigm to implement explainable AI based classification of lung and colon cancers. Our dataset consists of 25,000 photos broken into 5 classes each proportioned at 5,000. The models were fine- tuned on LC25000 dataset, resulting in a classification accuracies of 99.89% and 99.71, respectively. We observed that Xception showed better performance with lower log loss values, improving probabilistic prediction confidence. It shows where it focused on the left histopathological image, while GradCAM highlighted critical regions of the histopathological images. Pixel level importance was provided by vanilla Saliency maps, but also ensured the transparency of decision making. SHAP values quantified the contribution of specific features and provided the details of what is happening to model behaviour.

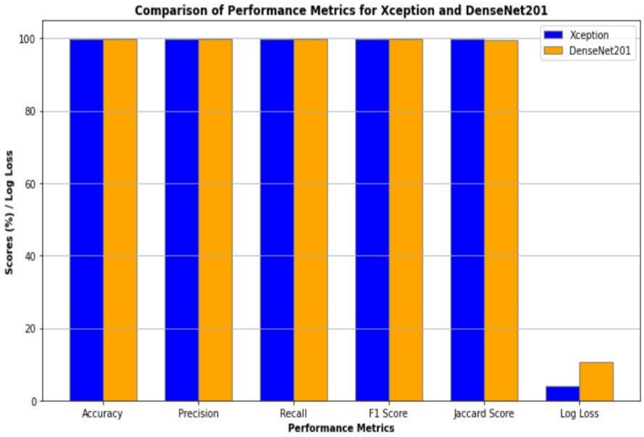


Fig. 3. Performance metrics of Xception and DenseNet201

Results show AI diagnostics helped to enhance trust and interpretability with the aid of XAI. More robust feature utilization was seen by the DenseNet201 in the classification task, whereas Xception slightly did better. Therefore, these findings validate the potential to use pre trained CNNs together with XAI methods to create accurate and interpretable cancer diagnostics in medical imaging.

6. Conclusion

Lung and colon cancers are among the world's main causes of death. Early and precise diagnosis of these cancers can produce huge improvements in both treatment results and survival rates. This study aimed for accurate and effective detection of lung and colon cancer. This study shows the vast application of merging high level deep learning structures such as Xception and DenseNet201 with explainable AI (XAI) techniques in cancer classification, specifically in lung and colon cancer. Classification accuracies of 99.89% and 99.71% using pre trained convolutional neural networks demonstrate their ability in accurately diagnosing cancer from histopathological images. XAI methods, including GradCAM, vanilla saliency maps, SHAP not only improve model interpretability but also builds trust in AI driven diagnostic systems. These techniques address the critical need for transparency of medical AI applications by providing visual insights into the decision making processes of the models.

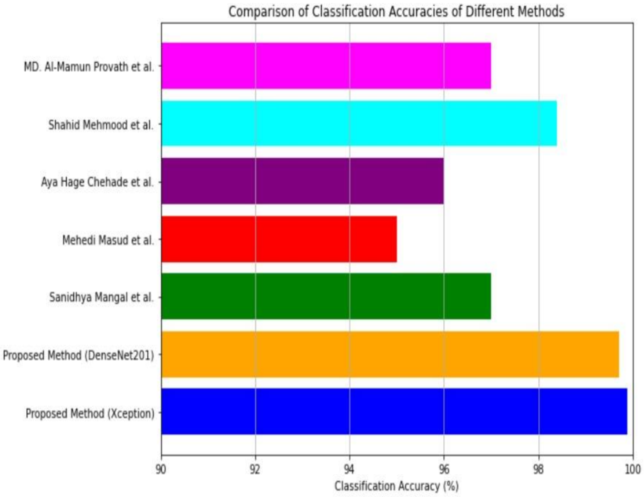


Fig. 4. Comparison graph of proposed methodology

Our results show that our method not only increases diagnostic accuracy, but also provides a robust framework for utilizing AI in clinical settings, thereby improving patient outcomes. As we move towards expanding the database diversity and investigating the actual capacity of these techniques in real world clinical settings, there should be future work aimed at a holistic advancement in cancer diagnostics.

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