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Original Paper

ADVANCING COLON CANCER DIAGNOSIS: A NOVEL APPROACH TO CLASSIFICATION THROUGH EXPLAINABLE AI METHODOLOGIES

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Abstract

Deep learning algorithms are implemented to accurately find and diagnose colon cancer, specifically focusing on adenocarcinomas and benign colonic tissues. The EfficientNet model is a part of the convolutional neural networks (CNNs) with high accuracy. The priority is interpretability by integrating Explainable AI (XAI) and an XAI model that uses Grad-CAM to highlight and focus the regions implanted in the images used, enabling better comprehension of the diagnostic process. Healthcare can benefit a lot with the help of deep learning models and transparent AI approaches. The proposed technique provides doctors with insights into the model's decision-making, which creates the ability to accelerate clinical decision-making, improve diagnostic accuracy, and ultimately improve their outcomes.

KEYWORDS

Grad-CAM, histopathology, EfficientNet, Colon cancer, Explainable AI.

1. INTRODUCTION

The disease in which a collection of abnormal cells grow out of control is termed as Cancer. Among these, colon or colorectal cancer, involving cancers of the colon and rectum, is one of the most occurring and lethal malignancies globally [1]. It is the third most prevalent cancer in the world. Its insidious nature often leads to late-stage diagnoses, significantly reducing the chances of successful treatment.

Colonoscopy is the most effective and common screening test. Fecal DNA tests, fecal occult blood tests, barium enema, flexible sigmoidoscopy, and CT colonography are other screening procedures (virtual colonoscopy). Your risk components, especially a congenital linkage of colorectal and rectal cancers, will govern when and at what age such screening tests should start [7].

Convolutional Neural Networks (CNNs), a classification of deep learning models specifically tailored for analysis and study of images, have exhibited noteworthy performance in numerous medical imaging tasks, including detection of cancer and image classification [3]. Colon Cancer is categorized into two types: Adenocarcinoma and Benign Tumours.

Cancer encompasses a diverse range of diseases distinguished by the growth of abnormal cells and their proliferation. Among the myriad types, adenocarcinoma stands out as one of the most prevalent forms, affecting various organs and tissues throughout the body. Adenocarcinoma arises from glandular cells, which are responsible for secreting fluids or mucus, and can develop in organs such as the lungs, prostate, breast, pancreas and colon [4]. Adenocarcinomas exhibit distinctive histological features, including glandular or ductal structures, under microscopic examination.

In contrast to malignant tumor like adenocarcinoma, benign tumor is an abnormal but non-cancerous collection of cells that do not invade adjacent tissues or metastasize to other parts of the body. While benign tumor may grow locally and exert pressure on surrounding structures, they do not possess the capacity to spread aggressively. Benign tumours can arise from various cell types and can occur in virtually any organ or tissue, including the brain, skin, breast, and uterus [5].

The choice of CNNs for colon cancer detection is motivated by their noteworthy ability to learn discriminative features from raw input dataset automatically, thereby obviating the requirement for handcrafted features or domain-specific knowledge [6]. Moreover, CNNs inherently capture hierarchical representations of images, allowing them to discern subtle patterns indicative of pathological conditions, such as cancerous lesions, with remarkably high accuracy and efficiency.

The proposed EfficientNet model is a Convolutional Neural Network (CNN) architecture which uses a compound scaling method to evenly measure depth, width, and resolution, providing high accuracy with computational efficiency. It is integrated with Explainable AI using gradient-weighted class activation mapping (Grad-CAM) which is a visualization approach.

As we know the importance of early and precise detection of colon cancer, Convolutional Neural Networks (CNNs) have come out as powerful tools in the medical imaging industry, particularly for analysing the complex histopathological patterns. This has the potential to revolutionize diagnostic methods, yet challenges remain that must be addressed for clinical adoption. The following section will explore the significant contributions of recent studies in advancing CNN-based approaches for colon cancer detection.

2. Related Work

Convolutional neural networks (CNNs) play a huge role in colon cancer detection research, there are various studies that highlight their proficiency in the process of extracting intricate features from colonoscopy and histopathology images, thereby bringing significant advancement in the field.

Byrne et al. introduced a pioneering deep learning framework based on CNNs for automated polyp detection in colonoscopy images, showcasing high sensitivity and specificity. Wang et al. proposed a multi-scale hierarchical network for polyp detection [8], incorporating local and global features to enhance accuracy [9]. Kather et al. designed a CNN-based system for tumour classification in colorectal histology slides, achieving performance comparable to expert pathologists [10]. Similarly, Cruz-Roa et al. utilized CNNs to differentiate between benign and malignant colorectal tissues, underscoring the efficacy of deep learning in analysis of histopathological images [11].

Masud et al. built a classification model which used CNN and DIP algorithms and attained an accuracy of 96.33% [16]. Z Tasnim et al. used this dataset but only the colon cell images and achieved 97.49% accuracy with CNN algorithm and 99.67% accuracy with MobileNetV2 model [15]. A.H. Chehade et al. used the same dataset and worked with five different models [14]. In those, the best one was XGBoost with 99.3% for colon cancer detection and 99% for both lung and colon cancer classification. Bukhari et al. used the same dataset for training and validation but used CRAG dataset for training and testing. In their models, ResNet-50 had 93.91% accuracy [18].

The InceptionV3 transfer learning model, InceptionResNetV2 Network and Convolutional Neural Network (CNN) [19] were used for classification of cells into whether they had cancer or not. InceptionV3 produced 99.3% training accuracy along with 99.9% validation accuracy. InceptionResNetV2 achieved 99.7% training accuracy along with 99.78 percent of validation accuracy. CNNs have demonstrated promising results in colon cancer detection, several challenges persist, including interpretability, generalization to diverse patient populations, and robustness to image artifacts. Addressing these challenges will be paramount for the translation of CNN-based models into clinical practice, ultimately enhancing the efficiency and accuracy of colon cancer diagnosis and treatment.

Building on the various insights which we have gained from previous studies, our research also leverages the LC25000 dataset to make colon cancer detection techniques more interpretable. The following section gives a detailed overview of the dataset and preprocessing methodologies that play a major role in our study, which helps us in laying the groundwork for the accurate classification of colorectal cancer subtypes.

3. Dataset Information

In medical research the significance of datasets cannot be overstated. A high-quality dataset provides a strong foundation for development and validation of predictive models, diagnostic algorithms, and

prognostic tools. In our study, we leverage the LC25000 dataset as a foundational resource for investigating colon cancer at a histopathological level. With its vast collection of 25,000 color images spanning multiple tissue types, including both lung and colon tissues, the dataset offers an invaluable opportunity to explore the intricate cellular architecture and pathological features associated with colon cancer. By focusing specifically on the subset of images related to colon tissue, we aim to delineate the distinct morphological characteristics of colon adenocarcinomas, the primary histological subtype of colon cancer, from benign colonic tissues. This focused approach allows us to hone in on the specific cellular alterations and aberrations that underlie the development and progression of colon cancer, shedding light on potential diagnostic markers and therapeutic targets for this devastating disease. To isolate the cellular components relevant to colon cancer, we exclusively utilize the images contained within the "colon_image_sets" subfolder of the LC25000 dataset. Within this subfolder, focus is on analysis of two distinct classes: colon adenocarcinomas and benign colonic tissues. Each class comprises 5,000 images, with pixel size of 768 x 768 available in JPEG format. By meticulously curating this subset of the dataset, ensuring that our analysis is tailored specifically to the histopathological features and cellular morphology characteristic of colon cancer cells, thereby minimizing confounding factors and maximizing the relevance and specificity of our findings. Through this targeted approach, the aim is to elucidate the intricate cellular signatures and pathological hallmarks associated with colon cancer, ultimately advancing our understanding of the disease and paving the way for improved diagnostic and therapeutic strategies.

Table 1. Colorectal cancer classes with class categories and size.

Types of Cancer cells	Class label	Number
Adenocarcinoma Cells	adeno	5000
Benign Cells	benign	5000

In Table 1, the cancer cells are divided into adenocarcinoma and benign. The images which were 1024x768 pixels were brought to the size of 768x768 pixels. By doing this we were able to improve accuracy. These images then underwent augmentation procedures. After the comprehensive analysis of the dataset, further getting to know more about the architecture of the proposed CNN-based model, which makes use of the advanced capabilities of EfficientNet. This model is known for its performance in image classification tasks.

4. PROPOSED CNN- BASED MODEL

EfficientNet is the modern model for image classification, which achieves advanced performance on ImageNet. The general architecture of the proposed model consists of stem and final layers (Figure 1).

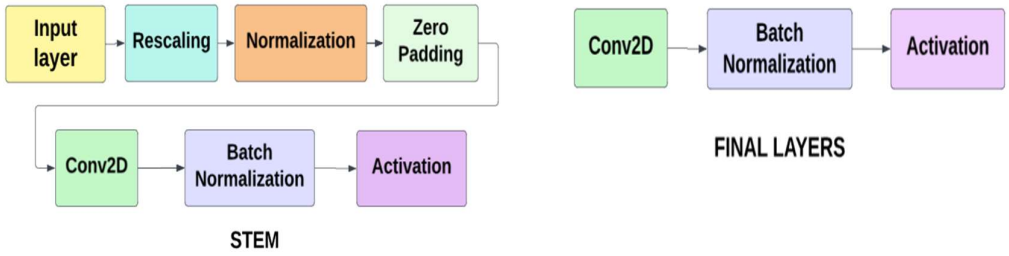

Fig. 1. Proposed model architecture.

The input layer of the EfficientNet architecture processes raw image pixels, which are subsequently rescaled to normalize pixel ranges, which are frequently between 0 and 1. Involving division of the standard deviation, subtraction of the mean, and optimization of the data scale for pattern identification. In order to maintain spatial dimensions during convolution processes, zero padding is applied to the input pictures. Convolutions are used by Conv2D layers to extract features, and activations are normalized by Batch Normalization to stabilize training. The EfficientNet architecture is structured into several functional modules as in Figure 2- Module I consist of a Depth-wise Conv2D layer, Batch Normalization, and an Activation layer, forming the basic structural unit for subsequent modules. Module II extends this setup by adding Zero Padding to manage input size adjustments. Module III introduces Global Average Pooling and Rescaling followed by two Conv2D layers, streamlining the transformation of feature maps. Module IV incorporates a Multiplication layer before the Conv2D and Batch Normalization, enhancing feature interaction. Lastly, Module V follows a similar structure to Module IV but includes a Dropout layer to mitigate overfitting by randomly omitting units during the training process. These modules collectively enhance feature extraction and processing efficiency within the network.

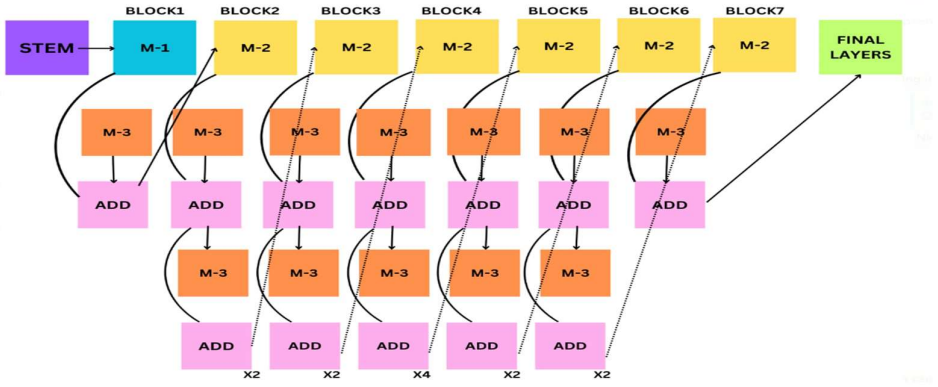

Fig. 2. EfficientNetB4 architecture.

4.1. Scaling a ConvNet

Expanding a Convolutional Neural Network (ConvNet) The process of expanding a Convnet remains a topic of ongoing exploration, with numerous methodologies available. Primarily, it involves tuning the network's dimensions and parameters to enhance its performance results. These dimensions are - Depth signifies the number of layers within a network, with deeper configurations generally correlating with improved performance. Width represents the quantity of channels in a convolutional layer, where wider networks excel at capturing intricate features and are often more trainable. Resolution denotes the dimensions of image inputs (width x height). As highlighted in sources like [1], larger image sizes typically contribute to enhanced accuracy, albeit at the cost of increased computational requirements, as indicated by the rise in FLOPS.

4.2. Compound Scaling

Rather than manipulating layer architectures to increase accuracy, it's better to go in a different direction. Consider a base network (N) with its length (L), having width (C), and its resolution (W, H) where W is for width, H is for height of input images. This changes the optimization task to finding the best values for the mentioned parameters width (w), depth (d), and resolution (r) to achieve the highest performance considering resource constraints like memory and flops [20]. max d,w,r Accuracy(N(d,w,r)),

$$\text{Memory}(N) <= \text{target\_memory}$$
$$\text{FLOPS}(N) <= \text{target\_flops}$$

depth: $d = \boldsymbol{\alpha}\Phi$, width: $w = \boldsymbol{\beta}\Phi$, resolution: $r = \boldsymbol{\gamma}\Phi$. Where Φ, is called the compound coefficient,that is specified accordingly to regulate resources that are accessible. Meanwhile, α, β, and γ allocate the available resources to the given network's parameters or dimensions. Additionally, it was observed that a standard convolution operation had FLOPS that were proportional to w^2, r^2 and d. Knowing that convolution operations are important to the computational price in ConvNets, FLOPS can be amplified by $(\alpha.\beta^2.\gamma^2)\ \Phi$ in a ConvNet using compound scaling. Thus, to increase the FLOPS by 2Φ the constraint $\alpha.\beta^2.\gamma^2 \approx 2$ is applied.

4.3. MBConv

To facilitate information flow within deep neural networks, residual blocks are commonly employed. These blocks establish connections between the start and end of a convolutional block through skip connections. Channel widths typically follow a pattern within a normal residual block: they begin wide, gradually narrow along the block's depth, and widen again towards the end due to the incorporation of additional information. A normal residual block in Figure 3, shows from wide to narrows back to wide considering the number of channels.

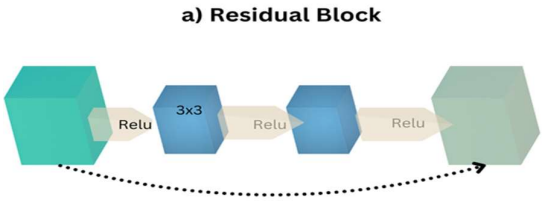

Fig. 3. Structure of residual black.

The inverted residual block, in Figure 4, deviates from the conventional residual block sequence by adopting a pattern that progresses from narrow to wide to narrow again, it goes from narrow to wide and then again narrow.

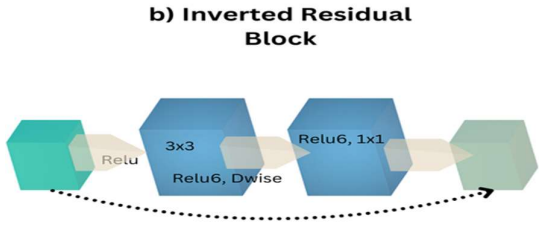

Fig. 4. Structure of inverted residual block.

To appreciate it, MBConv is used to improve the efficiency as well as adaptability of CNNs for mobile arenas. This can be done by using Depth-wise Separable Convolution [22]. In the beginning, channels are expanded by using a point-wise convolution (1x1). Next there is a 3x3 depthwise convolution which largely decreases the variable count. At last, a 1x1 convolution reduces the channel number, facilitating addition at starting of the block and also the end. It's noteworthy that prior to the addition operation, a linear function is applied to mitigate the risk of non-linearities excessively distorting information.

EfficientNetB4, being a larger variant compared to EfficientNetB0, typically has more layers and parameters, which lets it identify more complex patterns present in the input images. However, it maintains efficiency by carefully balancing model size and computational cost through scaling techniques.

The EfficientNet model used on ImageNet is the backbone network. The experiment is conducted in two stages. Initially, during the pre-training stage, the weights of all network layers except the classification layer are frozen. In the subsequent stage, training continues by fine-tuning and retraining only the fully connected layer of the lowest layer, which includes swapping out the 1000-dimensional softmax classification layer that EfficientNet has with an X-dimensional layer, adapted to the dimensions of the remote sensing image dataset.

5. Proposed XAI Model

The proposed model has been trained using the Grad-CAM XAI tool, which utilizes gradients from colon and rectal tissue images, which are streamed into the final convolutional layer of the model to

indicate critical areas for prediction (Figure 5). Additional fully-connected convolutional layers are attached to the heat map of Grad-CAM [23]. The gradient calculations capture the relative relevance of successive feature maps for the last convolutional layer [24]. Input images, sized 729 x 729, undergo forward propagation to the last selected CNN layer, saving feature maps before the process restarts. The selected CNN layer undergoes back-propagation along with the predicted image. Weighted gradients are determined for every CNN layer to assess the significance of every neuron regarding the input image, followed by global average pooling. The resulting heat map emphasizes regions relevant to the predicted image, such as colon cancer. Gradients typically concentrate in the corner or middle parts of the images, indicating colon cancer presence with precision [24]. The heatmap demonstrates the significance of each feature map which is extracted from CNN after classification (k). Suppose A represents the feature map, and Z indicates the total number of features in each A, then wc k = Z ∂Yc ∂Aki,j, where Yc represents the gradient of the score pertaining to class c.

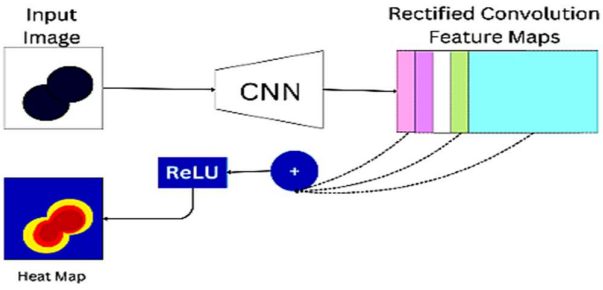

Fig. 5. Proposed XAI model.

Grad-CAM is applicable to various CNN model classes without architectural modifications or retraining. By integrating the heat maps of Grad-CAM, as shown in Figure 6, along with fine-grained detail and applicability for visualization, it's feasible to generate visualizations of high-resolution across various categories and implement them with pre-trained image classification models. The advantages include an in-depth understanding of the failure modes, robustness to conflicting images, superior localization compared to previous CNN explanation methods, fidelity to underlying model training results, and assistance in identifying dataset biases to achieve goals. For instance, in [25], a CNN-based artificial intelligence framework was employed to determine patients' races exclusively from clinical images. The research scrutinized both the classification accuracy and the underlying mechanisms behind these classifications, employing Grad-CAM. The outcomes highlighted the CNN-based models' capability to differentiate between races solely based on medical images, outperforming the diagnostic accuracy of a significant proportion of doctors. The investigation underscores Grad-CAM's potential to provide explanations for CNN-based model decisions that exceed human standards.

The primary objective of the proposed method is to analyse Grad-CAM's explanatory power in assessing whether and to what extent Grad-CAM can assist physicians in making accurate diagnoses or

preventing misdiagnosis. Clinicians can use the heatmap generated from Grad-CAM to visually examine the regions of interest within histopathological images. This allows them to re-evaluate the model's prediction with their knowledge and expertise, so they can check the AI's conclusion consistency with medical expectations. For instance, when the model highlights areas commonly associated with one type of cancer, say adenocarcinoma, the clinician can verify the presence of cancerous tissues, thereby improving their confidence in the diagnosis.

6. Result and Analysis

EfficientNetB4 received training on a dataset with split 8:1:1 where 8 is train, 1 is valid and 1 is test, which was done for 20 epochs. Techniques like early stopping are with patience set to 3 to avoid overfitting the model. The model has a Root Mean Square Error (RMSE) of 0.69. We used it to predict the cancer classes and it gave confidence of around 99% for both classes - benign and adenocarcinoma. GradCAM is integrated into the last CNN layer to produce a heatmap of the input image, highlighting regions containing cancerous polyps in the colon. It generates a heatmap with variant colors - areas in red, yellow, or orange indicate regions of focus for cancer detection, with red areas specifically pointing to cancerous tissues. Blue or green areas signify regions contributing less to the model's decision-making, as in Figure 6.

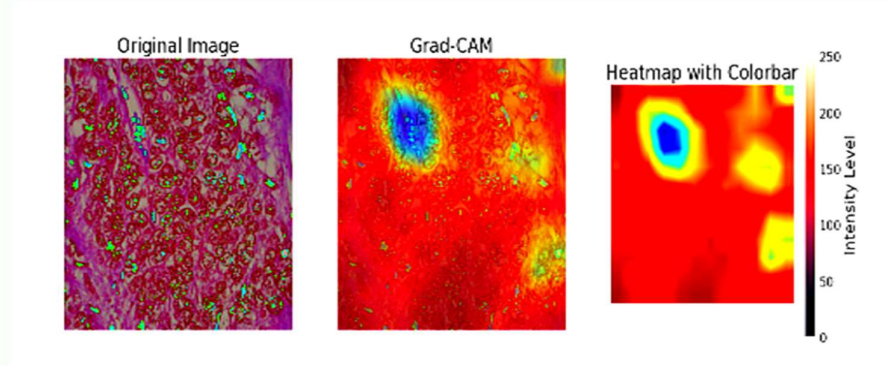

Fig. 6. Heatmap generated from Grad-CAM.

Table 2. Proposed Model comparison with other state of art models.

Model	Training Accuracy	Validation Accuracy
ResNet50	96.66	96.33
InceptionV3	96.5	98.7
EfficientNetB4	99.886	99.65

EfficientNetB4 showed better accuracy than other models as shown in Table 2. Early Stopping is used to check the model`s performance and stop the training early to avoid overfitting. The graph in Figure 7 shows how the training and validation accuracy change as training progresses.

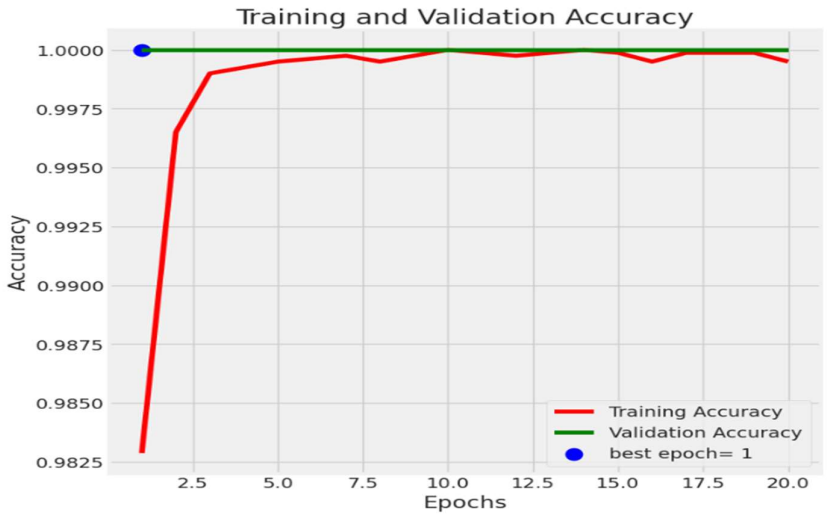

Fig. 7. Graph showing training and validation accuracy.

Along with accuracy, loss is also monitored. As training continues, the loss keeps decreasing at each epoch which is shown in Figure 8. This tells us how well the model learns.

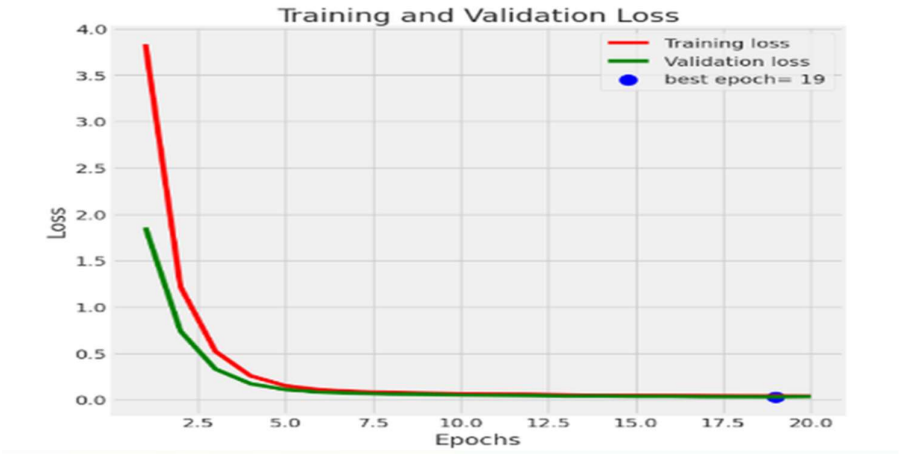

Fig. 8. Graph showing training & validation loss.

Incorporating 1000 images, the confusion matrix is generated for the EfficientNetB4 model for the test set and train-valid-test split of 8:1:1 with 500 images of colon adenocarcinoma with the label 1 and 500 images of colon benign with label 0. The model can predict 500 malignant images with an error rate of 0 and for colon benign, the model can predict 99.4% of the 500 images with an error rate of 3 images. The confusion matrix is shown in Figure 9.

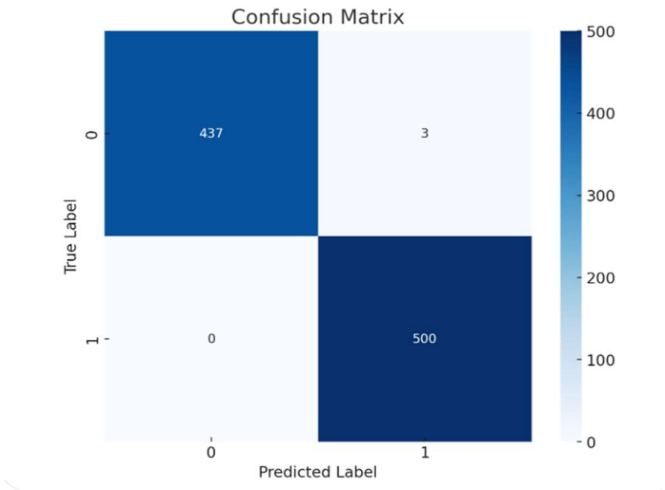

Fig. 9. Confusion matrix.

7. CONCLUSIONS

In this study, deep learning and explainable AI (XAI) techniques are applied to classify colon cancer, specifically focusing on adenocarcinomas and benign colonic tissues, using the EfficientNetB4 architecture and the LC25000 dataset. Achieving a high confidence level of around 99.8 percent, our model demonstrated the efficacy of advanced CNN architectures in medical image analysis. A significant feature of the proposed approach was the integration of Grad-CAM, which made it possible to visualize regions within histopathological images that highly influenced the model's decisions. The added layer of transparency is crucial for clinical applications, as the interpretability that Grad-CAM offers not only improves the speed and accuracy of the diagnostic process but also connects AI-driven models, essentially the AI world, with clinical practice, enabling healthcare professionals to make more accurate and confident decisions. The combination of high accuracy and interpretability in our approach can significantly enhance the diagnostic process, potentially leading to prior detection of colon cancer with higher accuracy and improving patient outcomes. Researchers in the future should be well focused on validating the proposed model across manifold and larger datasets to establish robustness and generalizability, and exploring other XAI techniques to further enhance transparency and utility in medical diagnostics. Overall, this study highlights the promising potential of deep learning and XAI in advancing the analysis of medical images and improving cancer diagnostics.

To ensure the robustness of the EfficientNetB4 model in real-world clinical settings, it is necessary to evaluate its performance across diverse patient populations and different imaging conditions. The future scope includes conducting cross-validation studies using datasets from multiple institutions, having data that is demographically diverse. This will help assess the model's ability to generalize effectively to new data, thereby enhancing its reliability and applicability in diverse clinical environments. The EfficientNet architecture is known for optimizing both accuracy and efficiency through compound scaling. Nevertheless, further analysis is needed to evaluate the model's performance on resource-

constrained hardware commonly found in clinical settings. We propose to investigate the model's inference time, memory usage, and scalability on various devices, including edge devices and cloud-based platforms. Additionally, optimization techniques such as model pruning, quantization, or using a smaller EfficientNet variant may be explored to ensure the model can be deployed efficiently without compromising accuracy.

Authors Contributions (Compulsory):

All authors are equally contributed for this work.

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