2023 3rd International Conference on Intelligent Technologies (CONIT)
Karnataka, India. June 23-25, 2023

EfCNN-Net: Smart Detection of Colon and Lung Cancer using Histopathological Images

Nandini Kapoor
Department of Networking and Communications
SRM Institute of Science and Technology, Kattankulathur,
Chennai,Tamil Nadu,India
nk9994@srmist.edu.in

Ayush Gupta
Department of Networking and Communications
SRM Institute of Science and Technology, Kattankulathur,
Chennai,Tamil Nadu,India
ag6589@srmist.edu.in

Meenakshi K*
Department of Networking and Communications
SRM Institute of Science and Technology, Kattankulathur,
Chennai,Tamil Nadu,India
meenaksk@srmist.edu.in

2023 3rd International Conference on Intelligent Technologies (CONIT) | 979-8-3503-3860-7/23/$31.00 ©2023 IEEE | DOI: 10.1109/CONIT59222.2023.10205918

***Abstract*— In low- and middle-income nations where there is little access to health care and cancer screening, the death rate from lung cancer is highest. Contrarily, colon cancer is the subsequent most prevalent cancer worldwide and the third biggest illness overall, accounting for 935,000 fatalities in 2022. The death rate from colon cancer varies by region, with developed nations reporting the highest rates. The odds of survival for lung and colon cancer can be considerably increased with early detection and treatment. Therefore, it's critical to promote routine cancer screening and prompt treatment while raising awareness of the risk factors linked to these malignancies. Cancer can be found through histopathological image analysis, which makes it possible to spot morphological abnormalities in tissue samples. In this study, we suggest a unique method for using histopathological scans to identify lung and colon tumors. The recommended approach uses convolutional neural networks (CNNs) for feature extraction and categorization. The underlying technology of this method is deep learning. To assess the suggested method and show its efficacy in highly accurate lung and colon cancer detection, we used the LC25000 Lung and colon histopathology imaging collection. On the basis of the parameters and accuracy, we have also contrasted the various image analysis methods. Our findings imply that the EfficientNet algorithm has the potential to increase the precision of cancer detection and support the creation of more efficient therapeutic approaches.**

Keywords*— Convolutional Neural Network (CNN), Machine Learning, VGG 16, ResNet 50, EfficientNet B1, EfficientNet B3, Lung Cancer, Histopathological Image, colon cancer; deep learning;

I. Introduction

Almost of gut and rectum cancers are caused by a type of cancer which damage the large intestine (colon) and rectum membranes.Colorectal cancer often manifests as a dermoid cyst-like tumour on the outer most layer of the gut lining, or rectum.The rectum or colon may infiltrate neighbouring or nearby lymph nodes. Because blood runs from the bowel's wall and a significant piece of the testicles to the liver, colorectal cancer may progress to the liver after spreading to adjacent lymph nodes. The two most frequent kinds of cancer in Western nations, as well as the second largest cause of cancer mortality, are intestinal and rectal cancer. Colorectal cancer risk is increased by a family history of the disease as well as certain dietary factors (poor fibre and high fat). Typical symptoms include blood in the faeces, fatigue, and weakness. As a result, cancer in its early stages is more curable. We present a unique and effective technique for automated early diagnosis of colon cancer using histopathological image processing in this work.Lung cancer, which can afflict both men and women, accounts for over 25% of all cancer-related mortality. Smoking is to blame for almost 80% of lung cancer fatalities. Lung cancer can be caused by nonsmokers' contact with radon, secondary smoking, air pollution, and other causes such as occupational asbestos exposure, exhaust from engines being exposed, or various chemical exposures. Nonsmokers can acquire lung cancer as well. Spit cytology, which for blood samples, diagnostic imaging (x-ray, CT scan), also biopsies are only a few of the therapies used to check for malignant cells and rule any other probable ailments. Skilled pathologists must study the tiny histopathology pictures obtained following the biopsy to diagnose carcinoma of the lung and determine its numerous forms and subtypes. Pathologists and other medical specialists are having difficulty diagnosing the many types of lung cancer.

It has been demonstrated that pathologists mostly rely on image-based pattern recognition for making diagnoses. Using this approach, cellular and architectural traits match the known characteristics of a disease. It is possible for inter- and intra-observer variability to exist when accurate diagnoses or estimations of prognosis and predictive factors are subject to different interpretations. The continual effort to improve the accuracy of pathology diagnosis and the rapid delivery of all vital information for the best patient treatment can both benefit greatly from the new and revolutionary technology.

II. Literature Survey

Lin Xu et al [1]introduce using digitized H&E-stained histology slide data, a deep learning-based method for segmenting and diagnosing colorectal cancer. A CNN with a nine-class accuracy of >94% was trained using more than 100,000 H&E picture patches. 322 digitised slides pertaining to colorectal cancer from St. Paul's Hospital made up the dataset that was used. The entire slide was separated into several patches, each of which was called separately.

Md. Alamin Talukder et al stresses creating a resourceful and organised framework so that big histopathological imaging (HPI) datasets (LC25000) can be used, and various pre-processing techniques can be applied to the datasets. It is subjected to feature extraction and k-fold cross-validation. In our analysis, we assessed a number of performance metrics, including AUC score ,accuracy, the ROC Curve , RMSE, f1-score, MAE, confusion matrix, MSE, recall, and precision [2].

Wang et al. [3] recommended a novel, anchor-less technique for quick polyp diagnosis. By utilising a CenterNet-based design with a VGG16 foundation, they were able to enhance this scenario. To allow real-time detections, they eliminated the centre sharing from the Center Net topology, which led to a speedier detection. In order to prevent memory loss, they also acquired a more powerful polyp detecting detector and suggested a cosine earth projection technique. Next they employed the Etis-Larib database for both training and testing, together with the CVC-ClinicDB and EndoSceneStill datasets. The greatest outcomes for them came from the VGG16 backbone as compared to ResNet-50 and ResNet-101.

Ozawa et al. [4] used a confidential dataset, and their methodology showed that CNNs were effective at foretelling colorectal cancer.Single Shot MultiBox Detector (SSD) design for polyp detection and classification suggested using CNN.

Soberanis-Mukul et al. [5]provided a template for locating polyps based on RetinaNet. This concept was motivated by the idea of using the artefact information revealed in the polyp photos without forgetting the frame. This model was used to test the impact of artefact and the polyp detecting programme. In this study, artifacts were similarly exploited for the first time in polyp identification.

Qadir et al. [6] proposed a novel framework for polyp detection to combine temporary data and enhance polyp detection performance in colonoscopy recordings. Any object detector might be used with this frame. The proposed method combined temporal video analysis and individual frame analysis to reach a conclusion for the given situation. The suggested technique enhanced detection output and more effectively found missing polyps. With the Inception Resnet and MobileNet architecture, faster CNN was deployed.

Nadimi et al. [7] suggested a CNN advanced learning model for cordless colon endoscopy in capsules image-based end-to-end autonomous colonic polyp detection. They located specific areas of the colorectal polyp images using the Faster R-CNN technique. A vast dataset of capsule endoscopy images were gathered along with data augmentation for the training and testing phases.

Xiao Xiao et al [8] created a Convolutional Neural Network based algorithm for the colonoscopy-based in order to detect polyps. To validate measurements, they employed four separate, distinct datasets. The dataset was split in half and used for video and image analyses, respectively. Via real-time evaluation, their trials demonstrated that they were able to achieve excellent sensitivity and specificity.

T. Atsushi et al [9] suggested using cytological images, utilising DCNN to automatically detect and distinguish the type of lung cancer. Their dataset comprised pictures of adenocarcinomas, squamous cell carcinomas, and small cell carcinomas. We used the DCNN architecture, which has a dropout of 0.5, two completely linked layers, three convolution and pooling layers, and three layers of convolution. Overall accuracy for the created model was 71.1%, which is below average.

W. Rahane et al [10] proposed employing computed tomography (CT) images for lung cancer diagnosis with machine learning (Support Vector Machine).The photos were processed using grayscale conversion, noise reduction, and binarization. The support vector machine (SVM) model was given the region of interest region's area, perimeter, and eccentricity.

M. Šarić et al [11] Using whole-side histopathology images as input, suggested CNN architectures using VGG and ResNet were used to detect lung cancer. For VGG16 and ResNet50, patch level accuracy values of 0.75 and 0.72, both very poor, were obtained. Using a number of slides, the authors illustrated how the poor performance of the given models was attributable to the high pattern variance.

III. METHODOLOGY

Hierarchical data representations are learned via deep learning using neural networks with several layers. Because deep learning models can automatically learn properties from raw input data, they are more flexible and powerful than traditional machine learning algorithms. Many tasks, including audio and picture recognition, natural language processing, and autonomous driving, have been effectively tackled by deep learning. Deep learning models are able to identify intricate patterns and connections within the data in these applications, which allows them to anticipate outcomes accurately.

The application of neural networks, which are created after the anatomy and functioning of the human brain, is one of the primary elements of deep learning. Neurons, which are interconnected nodes that convey and process information, make up a neural network. Each layer of neurons in a deep neural network learns to separate increasingly abstract elements from the input data. The final layer's output can be used to categorise the input or generate predictions based on it

Large volumes of labelled data are sent to a deep learning model during training, and To lessen the disparity between the anticipated and actual results, the learning network's parameters are altered. Back propagation, a mechanism that helps models learn from their errors and become more accurate over time. Deep learning has significantly influenced many different areas of artificial intelligence and, among other things, led to major breakthroughs in language processing, machine vision, and recognition of speech. Deep learning will likely continue to push the limits of what machines are capable of as more data becomes available and processing power rises.

A. *Convolutional Neural Network:*

CNN has shown huge promise in the detection and diagnosis of cancer. They can analyze large amounts of medical image data and automatically learn to detect patterns and features that are indicative of cancer.

One application of CNNs in cancer detection is in the analysis of medical images, such as mammograms or CT scans. The images are first preprocessed to enhance the relevant features and reduce noise. The CNN is then taught to distinguish between healthy and malignant tissues using a sizable dataset of labelled images. The pretrained CNN can then be used to analyze new images and make a diagnosis [12-13]. A matrix plot called the confusion matrix is created to evaluate the effectiveness of the CNN model. There are some other things, including the f1-score, precision, metrics precision and recall also used.

$$\text{Accuracy} = \frac{(\text{TN} + \text{TP})}{(\text{TP} + \text{FN} + \text{TN} + \text{FP})} \quad (1)$$

$$\text{Precision} = \frac{\text{TP}}{(\text{FP} + \text{TP})} \quad (2)$$

$$\text{Recall} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \quad (3)$$

$$\text{F1} - \text{Score} = \frac{2 * (\text{Recall} * \text{Precision})}{(\text{Recall} + \text{Precision})} \quad (4)$$

B. *VGG 16*

The convolutional neural network's structure VGG16 was created for picture classification and recognition applications.. It is characterized by its deep structure, with 16 layers of trainable parameters, and its use of small 3x3 convolutional filters. The VGG-16 architecture includes a max-pooling layer, 3 fully connected layer, five sets of convolutional layer and five fully connected layer.

Fig. 1. VGG16 Model

Finally, a prediction relating the class of the input image is made using a completely connected layer. In order to diminish the difference between the predicted and actual result, it alters the weights of the network. The VGG16 architecture's consistency and simplicity are two of its distinguishing qualities. Small 3x3 filters and layer stacking enable it to extract more intricate and abstract elements from the input image. The VGG16 architecture has achieved cutting-edge performance on a range of picture identification and classification challenges, including the ImageNet Large Scale Visual Identification Challenge (ILSVRC).

C. *EfficientNet B1*

EfficientNet B1, a convolutional neural network design was created in order to achieve cutting-edge performance on image classification tasks with the least amount of computational effort and memory use.The foundation of the EfficientNet B1 design is a revolutionary scaling technique that consistently scales the network's depth, width, and resolution. As a result, the network may successfully strike a compromise between accuracy and computational expense.

The convolutional and pooling layers are distinguished in the EfficientNet B1 architecture by a number of fully linked layers. Layers that are fully connected are used to foresee the class of the input image, whereas convolutional layers are used to extract data from the image getting processed. The key innovation of the EfficientNet B1 architecture is the use of a compound scaling strategy, which increases the network's depth, width, and resolution all at once. This enables the network to perform better than earlier state-of-the-art architectures with fewer input parameters and less processing.

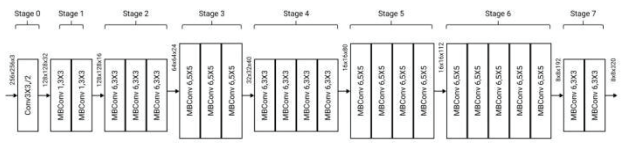

Fig. 2. EfficientNet Model

Modern performance was shown by the EfficientNet B1 architecture on the ImageNet dataset and other image classification benchmarks. Overall, the EfficientNet B1 algorithm is a powerful tool for image classification and computer vision tasks. Its efficient use of computational resources and superior performance make it a valuable addition to the field of deep learning.

D. *EfficientNet B3*

A convolutional neural network (CNN) architecture called EfficientNet B3 was created in order to efficiently utilise computational resources while achieving high accuracy on image recognition tasks. It is part of a family of EfficientNet models that are designed using a scaling method to balance model accuracy and computational efficiency.

The EfficientNet B3 architecture is characterized by its use of a compound scaling method that optimizes the model depth, width, and resolution based on a set of fixed scaling coefficients. This approach enables the model to be scaled up or down to achieve the desired level of accuracy and efficiency.

A stem, numerous convolutional layer building components, and a top convolutional layer with a fully linked layer make up the EfficientNet B3 architecture. Convolutional, squeeze-and-excitation, and depth-wise convolutional layers are all part of the blocks of convolutional layers. The depth-wise convolutional layers boost the efficiency of computation while the squeeze-and-excitation layers help the model focus on important features.

During training, the EfficientNet B3 architecture uses a combination of standard stochastic gradient descent and other techniques such as mixup and label smoothing to improve accuracy and reduce overfitting. The model is then fine-tuned on the target dataset to optimize its achievement.

EfficientNet B3 has attained high accuracy on a variety of image recognition benchmarks ILSVRC and COCO dataset. Its efficient use of computational resources makes it a useful tool for applications that require high accuracy on large image data-sets but have limited computational resources.

Overall, The EfficientNet B3 technique, which has made significant strides in the department of computer vision, exemplifies the value of finding a balance between accuracy and computing simplicity in deep learning models.

E. *ResNet 50*

ResNet 50 is a CNN architecture that was developed to address the problem of vanishing gradients in deep neural networks. Its use of remaining connections, which enable the training of extremely deep networks, defines it.

The batch normalization layer, the ReLU activation function, and the shortcut connection come after each block of convolutional layers in the ResNet 50 framework. The information can bypass a layer or several thanks to the shortcut link, which can aid in avoiding the issue of disintegrating gradients.

ResNet 50's residual connections enable the training of extremely complex networks with up to 50 layers. The depth of older CNN designs was constrained because to the issue with vanishing gradients.

Backpropagation is applied to train ResNet 50, which changes the network's weights in order to minimize the difference between what was hoped for vs what was really accomplished.It produced excellent results on a variety of picture identification and classification tasks, which included the Image Network Large Scale Visual identification Challenge (ILSVRC).

Thus, the ResNet 50 technique has served improve computer vision and has become an established standard for deep neural networks. It has increased the accuracy and efficiency of image identification and classification tasks by utilizing residual connections to train very deep networks.

IV. DATASET DESCRIPTION

A. Data Acquisition

The five classifications are benign colon tissue, squamous cell cancer, metastatic lung adenocarcinoma, benign tissue from the lungs, and benign lung tissue. Each class has 5000 images. Each image is a jpeg file with a size of 768 by 768 pixels. This dataset can be used for research in the areas of computer vision, deep learning and medical image analysis. The images are annotated with pathological labels which can facilitate tasks like object detection or semantic segmentation. Also, this dataset could be useful to train classifier models as well as generate meaningful features from these complex histopathological data.

B. Image augmentation

Every image is cropped to 768 by 768 pixels using Python from their initial 1024 x 768 pixels. Thereafter Augmentor software is used to enhance the photos. In order to be more useful, enable finer-grained supervision of augmentation, and provide augmentation techniques that are most advantageous in real-world circumstances, it aims to function as an independent library that is different from platforms and frameworks. It employs a stochastic method with modular building pieces that allow processes to be connected in a pipeline.We used Augmentor to add the following augmentations, bringing the total number of pictures in our dataset to 25,000: left and right spins (up to 25 degrees with 1.0 probability), as well as vertical and horizontal flips (0.5 probability).

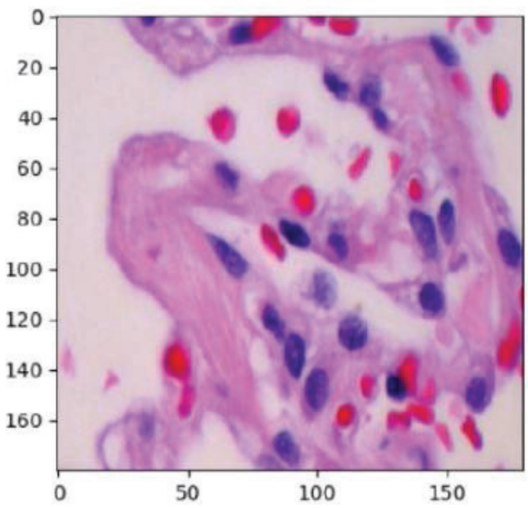

Fig. 3. (a): Histopathology Image

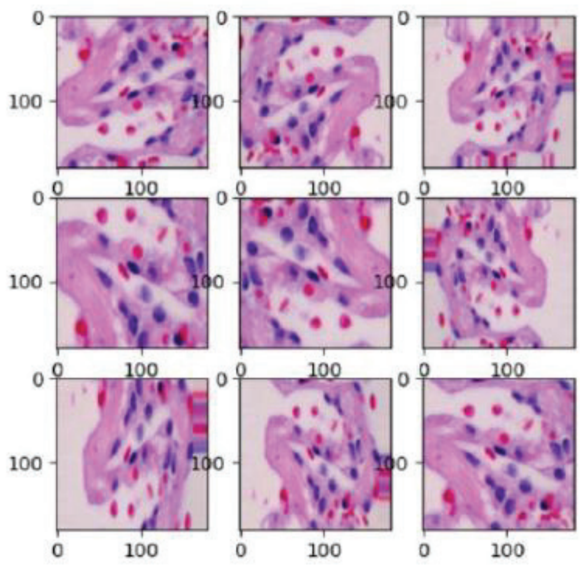

Fig. 3 (b): Corresponding Augmented Histopathology Images

V. RESULT

The widely used deep learning architectures VGG16, ResNet50, EfficientNet B1, and EfficientNet B3 can all be applied to cancer detection problems. The size of the dataset, the complexity of the job, and the processing resources available will all influence which architecture is optimal to use. Each of these architectural designs has benefits and drawbacks.

There are 16 layers total in the well-known convolutional neural network (CNN) architecture known as VGG16, comprising a number of convolutional and pooling layers. Although it has been demonstrated to perform well on picture classification tasks, more challenging tasks like object identification or segmentation may provide challenges. Fig 4(a) and Fig 4(b) shows the VGG 16's Accuracy and Loss chart, respectively.

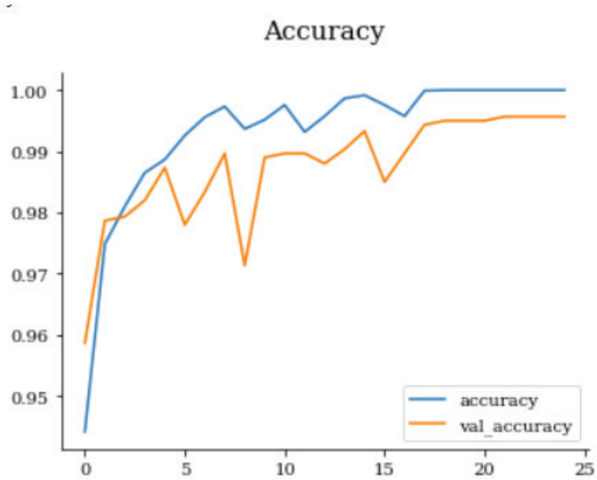

Fig. 4. (a): VGG 16 Accuracy

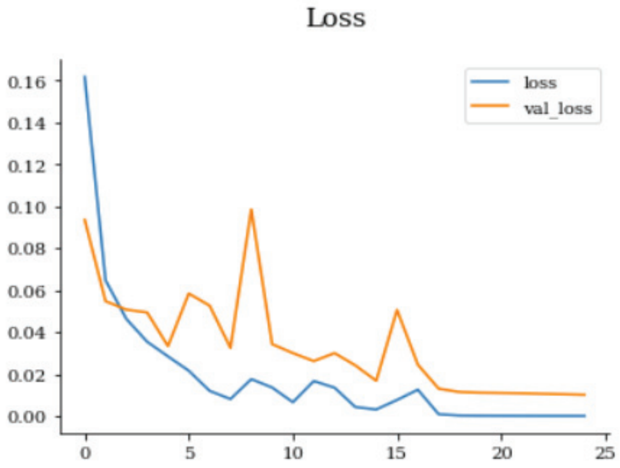

Fig. 4 (b): VGG 16 Loss Chart

ResNet50, a more advanced CNN design that includes residual connections across layers, allows the network to learn more complex features and reduces the vanishing gradient problem. It has been demonstrated to outperform VGG16 on a number of benchmarks for image classification, and it might be a suitable option for cancer detection tasks that call for more intricate feature extraction. Fig 5(a) and Fig 5(b) shows the ResNet 50's Accuracy and Loss chart, respectively.

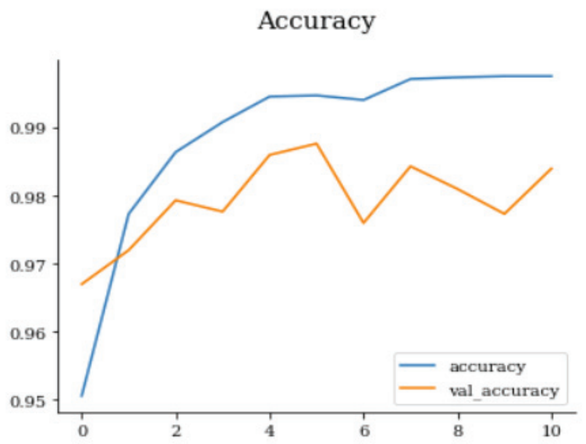

Fig. 5. (a): ResNet 50 Accuracy Chart

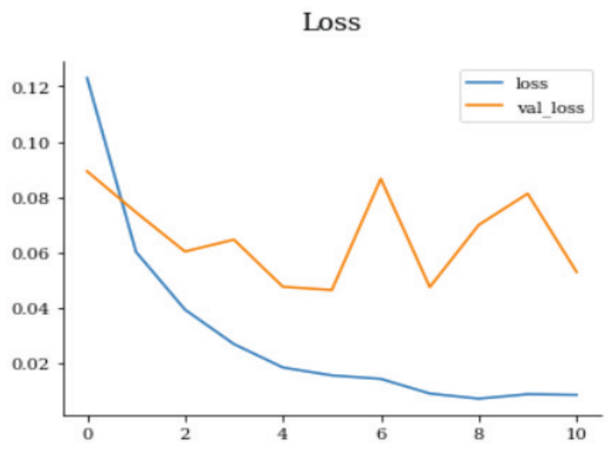

Fig. 5. (b): ResNet 50 Loss Chart

EfficientNet was created expressly to be more computationally effective while maintaining good performance. Two of the most common models are b1 and b3, with b3 being a more complicated model than b1. To improve speed while using less computer resources, these models combine depth, width, and resolution scaling. On a variety of benchmarks, including as object detection and picture classification, they have been demonstrated to outperform several alternative CNN architectures. Fig 5.5 and Fig 5.6 shows the EfficientNet B1's Accuracy and Loss chart, respectively.

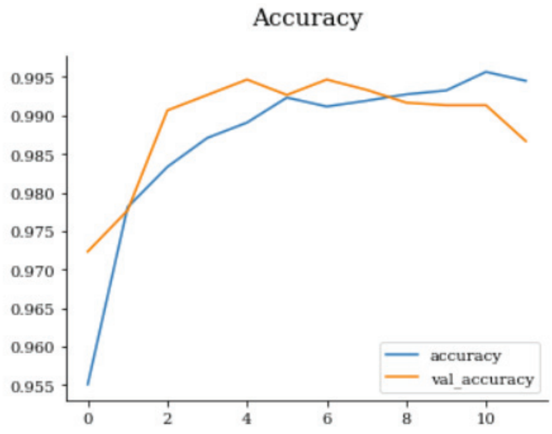

Fig. 6. (a): EfficientNet B1Accuracy Chart

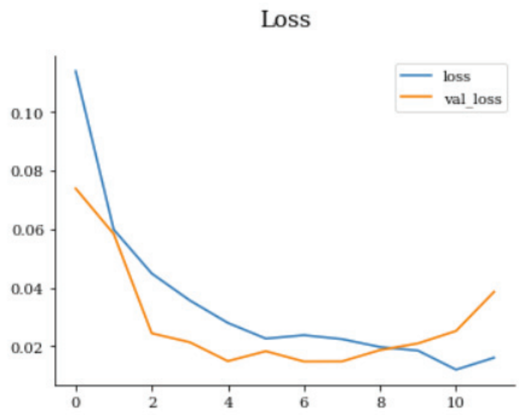

Fig. 6 (b): EfficientNet B1 Loss Chart

Table 1 shows the comparison of various state of art models with respect to accuracy.

TABLE I. RELATED WORK SUMMARY

Author/ Year	Accuracy
Hamida et al., 2021	99.12%
Bansal et al(2021)	93.73%
Hatuwal and Thapa(2020)	97.2%
Shandilya and Nayak	98.67%
Our approach	99.7%

Table 2 shows the accuracy of various pretrained medels and the same as represented in fig. 7.

TABLE II. COMPARISON OF MODELS

Model	Trainable Parameters	Accuracy
VGG16	14,780,739	100%
ResNet50	23,827,459	99.76
EfficientNet B1	6,739,594	99.45
EfficientNet B3	11,183,922	100%

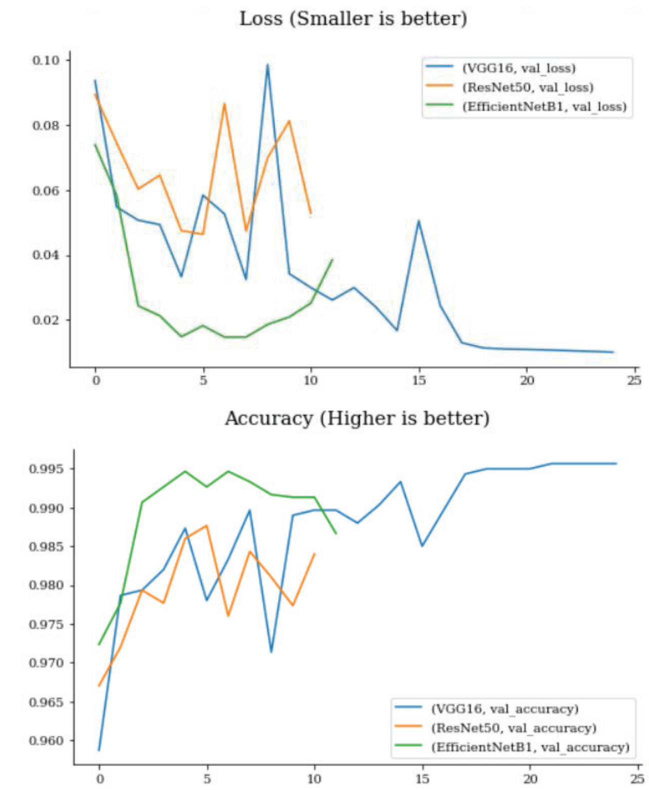

Fig. 7. Accuracy – performance of various models

VI. CONCLUSION

CNN has shown promising outcomes in the detection of lung and colon cancer. VGG16, ResNet50, EfficientNetB1, and EfficientNetB3 have been extensively used and demonstrated to be successful in identifying cancer among the numerous CNN models examined.

EfficientNet's distinctive architecture design, which combines a variety of methods to enhance the model's performance while minimising the amount of parameters and computing cost, is the primary factor explaining why it performs better than other models. In comparison to other commonly used CNN models, EfficientNet achieves state-of-the-art performance on a variety of image recognition benchmarks while using significantly less parameters and FLOPS (floating-point operations per second).

REFERENCES

[1] Atsushi Teramoto, Tetsuya Tsukamoto, Yuka Kiriyama , Hiroshi Fujita "Automated Classification of Lung Cancer Types from Cytological Images Using Deep Convolutional Neural Networks" Hindawi BioMed Research International, August 2017.

[2] Matko Saric, Mladen Russo, Maja Stella, Marjan Sikora ´ University of Split, "CNN-based Method for Lung Cancer Detection in Whole Slide Histopathology Images".

[3] Zhang Li, Zheyu Hu, Jiaolong Xu, Tao Tan, Hui Chen, Zhi Duan, Ping Liu, Jun Tang, Guoping Cai, Quchang Ouyang, et al. Computer-aided diagnosis of lung carcinoma using deep learning-a pilot study. 2018

[4] Xu L, Walker B, Liang PI, Tong Y, Xu C, Su YC, et al. Colorectal cancer detection based on deep learning. J Pathol Inform 2020;11:28

[5] Wang, P., Xiao, X., Glissen Brown, J.R. et al. Development and validation of a deep-learning algorithm for the detection of polyps during colonoscopy. Nat Biomed Eng 2, 741–748 (2018).

[6] Smits, L.J.H.; Vink-Börger, E.; Lijnschoten, G.; Focke-Snieders, I.; Post, R.S.; Tuynman, J.B.; Grieken, N.C.T.; Nagtegaal, I.D. Diagnostic Variability in the Histopathological Assessment of Advanced Colorectal Adenomas and Early Colorectal Cancer in a Screening Population. Histopathology 2022, 80, 790–798.

[7] Sawicki, T.; Ruszkowska, M.; Danielewicz, A.; Niedźwiedzka, E.; Arłukowicz, T.; Przybyłowicz, K.E. A Review of Colorectal Cancer in Terms of Epidemiology, Risk Factors, Development, Symptoms and Diagnosis. Cancers 2021

[8] A. Krizhevsky, I. Sutskever, and G. E. Hinton. (, 2012). "ImageNet Classification with Deep Convolutional Neural Networks. Neural Information Processing Systems."

[9] M. Šarić, M. Russo, M. Stella and M. Sikora, "CNN- based Method for Lung Cancer Detection in Whole Slide Histopathology Images," 2019 4th International Conference on Smart and Sustainable Technologies (SpliTech), Split, Croatia, 2019

[10] Masud, M.; Sikder, N.; Nahid, A.A.; Bairagi, A.K.; AlZain, M.A. A machine learning approach to diagnosing lung and colon cancer using a deep learning-based classification framework. Sensors 2021

[11] Hamida, A.B.; Devanne, M.; Weber, J.; Truntzer, C.; Derangère, V.; Ghiringhelli, F.; Forestier, G.; Wemmert, C. Deep learning for colon cancer histopathological images analysis. Comput. Biol. Med. 2021

[12] Meenakshi, K., and G. Maragatham. "An optimised defensive technique to recognize adversarial Iris images using Curvelet transform." Intelligent Automation & Soft Computing 35, no. 1 (2023): 627-643.

[13] G. Saranya, G. Geetha, C. K, M. K and S. Karpagaselvi, "Sentiment analysis of healthcare Tweets using SVM Classifier," 2020 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS), Chennai, India, 2020, pp. 1-3, doi: 10.1109/ICPECTS49113.2020.9336981.