

A Deep Learning Approach for Multi-Class Histopathological Classification of Colorectal Cancer Tissues

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ABSTRACT

Colorectal cancer (CRC) is the third most common cancer worldwide and the second leading cause of cancer-related deaths. Early diagnosis is critical for effective treatment and better patient outcomes, but the manual diagnosis process is time-consuming, inefficient, and prone to bias. This research proposes a deep learning-based automated system for the classification and diagnosis of CRC using histopathological images obtained from biopsy samples. The study utilizes advanced deep learning architectures, including EfficientNet-B4, to classify CRC tissues into eight categories: TUMOR, STROMA, COMPLEX, LYMPHO, DEBRIS, MUCOSA, ADIPOSE, and EMPTY. By focusing on biopsy images, which are crucial for accurate diagnosis but often underutilized compared to imaging modalities like CT scans and MRIs, the study aims to address gaps in the accuracy and efficiency of existing methods. Our approach demonstrates superior classification accuracy, particularly in differentiating challenging tissue classes such as STROMA and COMPLEX. The results show that the deep learning model not only automates the diagnosis process but also reduces the potential for human error, offering a promising tool for pathologists in diagnosing colorectal cancer at an early stage. This study contributes to advancing the application of AI in cancer diagnosis by enhancing the accuracy and efficiency of tissue classification from histopathological images.

Keywords: Colorectal cancer, Deep learning, Histopathological images, Automated diagnosis, Tissue classification, EfficientNet-B4.

INTRODUCTION

According to research by the World Health Organization (W.H.O.), colorectal cancer (CRC) is the third most common type of cancer globally and the second leading cause of cancer-related deaths [1]. Colorectal cancer, also known as bowel cancer, colon cancer, or rectal cancer, originates from the colon or rectum (parts of the large intestine) [6]. CRC affects the colon (large intestine) or rectum. The colon absorbs water and salt from the remaining food matter after it passes through the small intestine. The waste material left after passing through the colon enters the rectum, the final 6 inches (15 cm) of the digestive system, where it is stored until it passes through the anus. Ring-shaped muscles (sphincters) around the anus keep stool from coming out until they relax during a bowel movement [2].

This type of cancer can cause severe damage or death [27]. The symptoms of CRC include diarrhea, constipation, blood in the stool, abdominal pain, unexplained weight loss, fatigue, and low iron levels [7]. People over the age of 50 are at high risk for CRC. Risk factors include diet, obesity, smoking, and lack of physical activity (American Cancer Society) [2]. Dietary factors that increase the risk include red meat, processed meat, and alcohol [8]. According to W.H.O., in 2020, more than 1.9 million new cases of CRC and more than 930,000 deaths were recorded worldwide [1]. Variations in registered cases and death rates are found according to geographical areas. The incidence rates were highest in Europe, Australia, and New Zealand, while the mortality rates were highest in Eastern Europe. According to W.H.O. estimates, by 2040, CRC will increase to 3.2 million new cases per year (a 63% increase) and 1.6 million deaths per year (a 73% increase).

According to the American Cancer Society (ACS), most cases of CRC begin in the inner lining of the colon or rectum. These growths are called polyps. Polyps are quite common, especially as people age. Most polyps are benign, or noncancerous. Some types of polyps can become cancerous over time (usually over many years). The likelihood of a polyp turning into cancer depends on its type. According to the authors of [8] & [24] men are more commonly affected by this type of cancer than women.

Artificial Intelligence (AI) and computer vision techniques have been widely used in the medical industry, showing promising results, particularly in cancer diagnosis, for a long time [28]. Deep learning techniques have been widely used in healthcare since early on because previous research has developed robust automated solutions that help doctors, urologists, and pathologists provide more accurate disease diagnoses and treatment plans in complex scenarios [3]&[31]. The AI model learns patterns from medical data to diagnose and predict outcomes based on unseen or new data [29]. Deep learning uses artificial neural networks to replicate the human brain's method of learning [30]. This research study aims to provide an automated, deep-learning-based solution to classify and diagnose CRC using histopathological images. Histopathology is the examination of tissues from different organs, obtained through biopsy or surgical removal. Along with biopsy (the extraction of tissue for lab evaluation), histopathology remains the gold standard for diagnosing many solid-tumor cancers [18].

Histopathology can differentiate benign tumors from cancerous ones and also help determine the stage of cancer. It is also used for classifying different types of tissues in any organ. In our research, we will classify CRC histological whole-slide images, obtained through biopsy, into eight different classes: TUMOR, STROMA, COMPLEX, LYMPHO, DEBRIS, MUCOSA, ADIPOSE, and EMPTY. The first class (TUMOR) will contain tumor epithelium; the second class (STROMA) will contain simple stroma (homogeneous composition, including tumor stroma, extra-tumoral stroma, and smooth muscle); the third class (COMPLEX) will contain complex stroma (containing single tumor cells and/or few immune cells); the fourth class (LYMPHO) will contain immune cells (including immune-cell conglomerates and submucosal lymphoid follicles); the fifth class (DEBRIS) will include necrosis, hemorrhage, and mucus; the sixth class (MUCOSA) will contain normal mucosal glands; the seventh class (ADIPOSE) will include adipose tissue; and the eighth class (EMPTY) will contain background (no tissue).

Most existing colorectal cancer diagnosis studies focus on imaging modalities such as CT scans and MRIs, but very few researchers have focused on biopsy images, which are considered the most crucial source of data for accurate diagnosis [32]. The existing studies also lack accuracy, efficiency, and especially the accurate classification of tissue classes, particularly between class 2 (STROMA) and class 3 (COMPLEX), since the tissue structures are so similar and difficult to differentiate.

Doctors and pathologists find it difficult to make a diagnosis of colorectal cancer using manual diagnosis. In the vast majority of cases, they cannot diagnose the disease accordingly since CRC does not present itself at the beginning stages, and polyps are not always cancerous (benign). Diagnosis done through manual means is time-consuming, inefficient and biased. The paper is dedicated to the possibility to use Artificial Intelligence and deep learning to automate the diagnosis of colorectal cancer with the help of diagnostic biopsy or images of a H&E-stained microscope. The research study is innovative in the input data, accuracy, and efficiency as compared to the current studies. The study focuses on the training and comparison of the various deep learning algorithms with the help of the histopathology image data to effectively predict the presence of colorectal cancer and the classification of tissues.

LITERATURE REVIEW

Colorectal cancer (CRC) is becoming a major concern in Europe, Australia and New Zealand, and its diagnosis still emerged as a major challenge. Due to the progress in artificial intelligence (AI) and computing technology, scientists have devised automated systems to help physicians to monitor, plan, and treat cancer accurately. There has been literature on the various methodologies of diagnosis of CRC using CT scans, MRIs and biopsy images. The presented literature review includes general information about diagnostic techniques of CRC, models, findings, and essential characteristics studied by previous scientists.

As it is stated in [4], CRC is the third most frequently occurring cancer in terms of incidence and second most frequently occurring in terms of mortality. According to the research by [5], current pattern of CRC is anticipated to rise by up to 60 percent in the year 2030. CRC is regarded as one of the most malignant tumors of the digestive system that kills around half a million patients annually [8]. Whole-slide image (WSI)

analysis is characterized by several challenges such as extremely large image size ($>10,000 \times 10,000$ pixels), differences in size, shape, texture and staining of nuclei that complicate and take time in making a diagnosis [14]. According to [9], proper diagnosis of cancer demands skilled pathologists, which are scarce as the cases of CRC are on the increase. In order to solve this, computer-aided detection (CAD) systems have come up as sophisticated technologies to help in diagnosis. CAD systems are available with automatic object detection functions and have been found useful in the clinical decision-making process.

Deep learning (DL) is a sub-field of artificial intelligence (AI), and a promising method of classification and prediction, especially in the analysis of images and biomedical. The initial attempts at applying an architecture of DL to the processing of WSI were by [18].

It was observed in [12] that convolutional neural networks (CNNs) have been widely applied in the analysis of whole-slide images (WSIs) of several types of cancer, such as lung, breast, prostate, and skin cancer. CNN models have been shown to be very accurate in the diagnosis of CRC, but with small sample sizes, the CNN models do not necessarily represent the complete histologic spectrum, including tubular, mucinous, and signet ring cell types. A CNN model was used in the study by [19] to detect polyps with an accuracy of 96.4. This study relied on the significance of the adenoma detection rate (ADR) in colonoscopy, where the ADR outcome is a measure of the effectiveness of colorectal cancer prevention since it represents the prevalence rate of adenoma, which is estimated to be above 50 percent in the screening age groups. In different research, [20] applied deep learning to histopathological diagnosis of colonic adenocarcinoma using digitized pathology images. The authors used three variants of CNN and got an accuracy of 93.04.

An example of a computer-aided diagnosis (CAD) system [21] utilized CNNs to identify squamous cell carcinomas, adenocarcinomas of the lung and colon adenocarcinomas using digital pathology images. The maximum accuracy of the diagnosis was over 97 percent regarding the lung cancers and 96 percent regarding the colon cancers. A technique of identifying colon cancer through the use of biopsy images of variable magnification was suggested in [22]. In preprocessing, the study converted RGB into the HSV color space but saturation component was used in further processing. During the feature extraction, dual-tree and double-density 2-D wavelet transforms were utilized and a random forest classifier was employed, providing an accuracy of 85.3% in combined magnification images. In [24], the author used a random forest architecture on colored histograms of colorectal cancer tissues and had an accuracy of 93.53%. Lastly, the author of [25] applied the InceptionV3 model to the same dataset (Colorectal Histology-MINIST) and achieved an accuracy of 89.8% by classifying colorectal cancer tissues into eight classes.

Table 1 provides an overview of the literature review, showing how other authors used histopathology images and deep learning models in their studies to achieve their goals.

Table 1. Comparative analysis of existing research on colorectal cancer.

Ref. No.	Author	Year	Type of Cancer	Type of Images	Model/Classifier	Accuracy %
[19]	G.Urban et.al	2018	Colorectal cancer	Colonoscopy frames	CNN	96.4
[20]	S.U.K. Bukhari et.al	2020	Colorectal cancer	Histopathology images	RESNET-18,34 and 50	93.91
[21]	S.Mangal et.al	2020	Colorectal + Lungs cancer	Histopathology images	CNN	96.61
[22]	T.Babu et.al	2018	Colorectal cancer	Histopathological images	RF	85.3
[24]	S. K. Wildah et.al	2022	Colorectal cancer	Histopathological images (coloredvhistogram)	Random forest	93.53
[25]	S. Gupta et.al	2022	Colorectal cancer	Histopathological images	InceptionV3	89.8

METHODOLOGY

Deep learning-based automated diagnosis systems showed promising results and achieved breakthroughs in the medical industry. In this work, we used CNN architecture with pre-trained weights for the classification of CRS. Supervised learning proved helpful in training the dataset, even without exact labeling at the object level for small cancer cells. To achieve our objectives, we trained histopathological image data of colorectal cancer on neural network architectures such as ResNets, DenseNets, and efficient Xception, among others, which performed better. The system performed multiclassification between benign cancer (class 1) and the other 7 classes.

Protocol for Data Collection

The publicly available dataset from the Kaggle Respiratory collection was used to train and test the deep learning models. The colorectal cancer class assessment dataset, also known as the Colorectal_Histology_MNIST dataset, was utilized in this research. The training set was based on a well-known digital pathology dataset, which included around 5000 whole-slide images of digitized H&E-stained biopsies from patients across different hospitals. The dataset was divided into sets representing various textures found in CRC histology. This extensive dataset allowed for a thorough evaluation and classification of CRC tissue classes, ranging from benign to malignant. The dataset was publicly available on Kaggle and could be accessed via a provided link. (<https://www.kaggle.com/kmader/colorectal-histology-mnist>).

Table 2. Colorectal_Histology_MNIST dataset description

Features	Description
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Dataset Name	Colorectal_Histology_MNIST
Source	Kaggle
Data Type	Histopathological/Biopsy images
Samples	5000 whole-slide pictures of digitized H&E-stained biopsies with image size 150x150 px
Cancer Types	class 1, class 2, class 3, class 4, class 5, class 6, class 7, class 8
Availability	Publicly available dataset

Method for Analysis and Visualization

The architectures of the six deep learning models applied in this research work (INCEPTION V3, VGG 16, VGG 19, RESTNET 152 V2, RESTNET 50, and EFFICIENTNETB4) are based on the architecture of pretrained CNN models. The models were chosen because they have been successfully used in image recognition tasks, which are critical in the identification of the stages of colorectal cancer through the use of biopsy images in an accurate manner. The proposed solution by RestNet solved the vanishing gradient problem by introducing residual connections, and it is effective in mining deep features of histopathological images. Inception architecture is effective in capturing the spatial and channel-wise feature and is, therefore, appropriate in the classification of images with high detail, such as the diagnosis of the colorectal cancer.

Two distinct tasks were used to test the models: multi-class classification (classification of cancer based on tissue classes) and binary classification (benign vs. malignant). This dual approach aimed to precisely determine the class of tissue while also detecting its presence, which is crucial for treatment planning.

The code was implemented in Python, a widely used programming language for developing machine learning and deep learning models. A high-level overview of how the system classifies colorectal cancer through tissue classification is provided in

Figure 1.

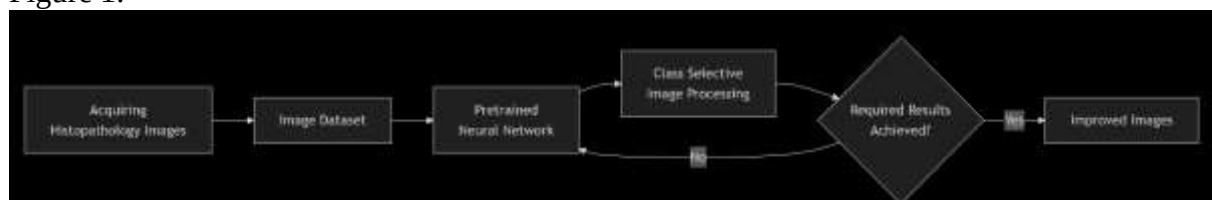


Figure 1. proposed model for transfer learning and class selective image processing.

The balanced dataset is used in the model's performance evaluation process in order to ensure the validity and reliability of the results.

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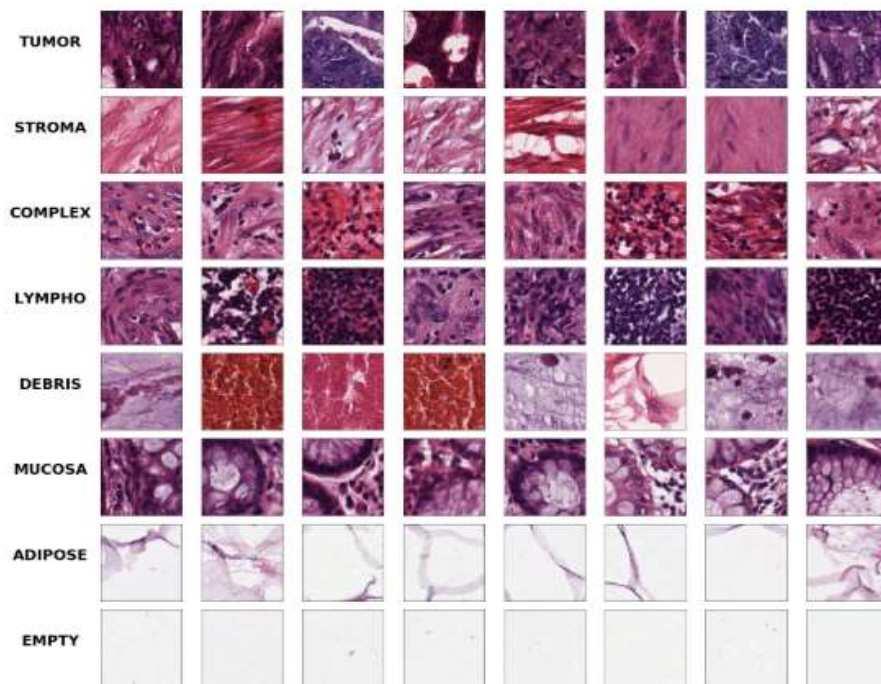


Figure 2. Sample images of eight classes from dataset being used.

Model Training

For model training we used histopathology-minist data set which contained 5000 whole slide images. The images belong to eight different classes of tissues; each class has 625 images. We split the data into training, testing and validation part with ratio 70%, 15% and 15% respectively.

Image Preprocessing

Image preprocessing was made according to the demand of model being used. Preprocessing steps were varied model to model. following technique were used during this step.

Image enhancement

Image resizing

Smoothing

Denoising

Color normalization

Data augmentation

Model Development

CNN architecture-based models (INCEPTION V3, VGG16, VGG19, RESTNET152V2, RESTNET50 and EFFICIENTNETB4) were used for this study purpose. Adam optimizer and ReLU activations were used for training. The model was trained for 50 epochs to evaluate the accuracy.

Model Testing

Model testing was the last step for the final classification of tissues. 15% reserved

histology images data was used by pre-trained CNN models to achieve our results. The proposed block diagram of this research study which is deep learning based automated colorectal cancer diagnosis using histopathologic ally classified images is provided in this section below.

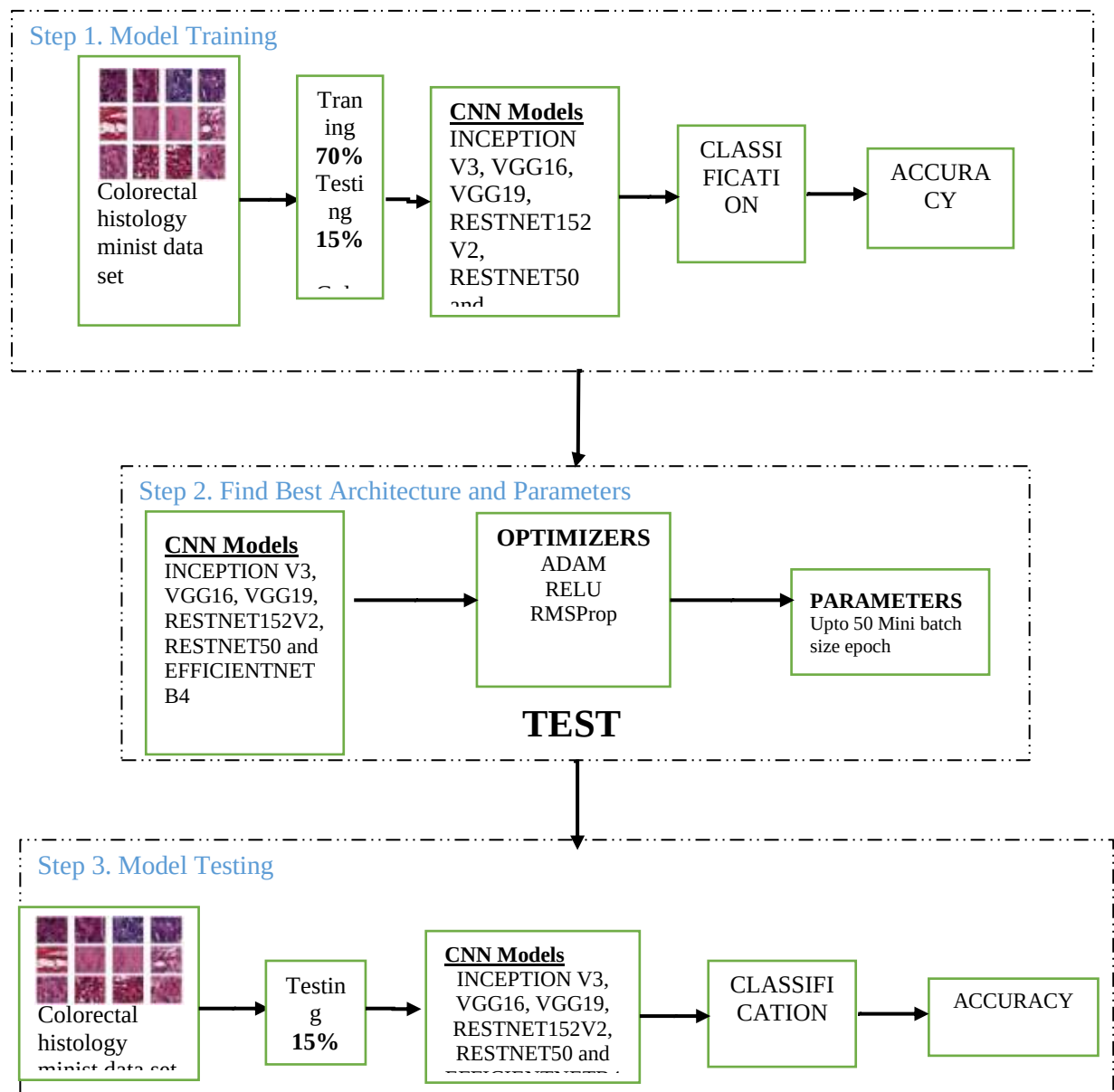


Figure 3: Methodology Flow diagram [25]

RESULTS

Results and comparative analysis are presented here for the different models used in this study, which aim to diagnose and classify colorectal cancer using histopathology images. To achieve the study's objectives, we utilized deep learning architectures such as INCEPTION V3, VGG16, VGG19, RESNET152V2, RESNET50, and EFFICIENTNETB4. The performance of these models was evaluated using metrics

such as accuracy, precision, recall, F1 score, and confusion matrices. The primary criterion for evaluating the binary classification of colorectal cancer as benign or malignant is accuracy. Confusion matrices provide a more comprehensive analysis of the models' performance in classifying tissues. This analysis will also help the automated system identify areas where the model can be further improved. The architectural details of models INCEPTION V3, VGG16, VGG19, RESTNET152V2, RESTNET50 and EFFICIENTNETB4 are given below in table 3.

Model	Input Shape	No. of Epochs	Optimizer
VGG-16	244x244	50	SGD,ADAM,RMSProp
VGG-19	244x244	50	ADAM
RESTNET50	144x144	50	SGD,ADAM
RESTNET152V2	144x144	50	SGD,ADAM
INCEPTION V3	299x299	50	RMSProp, ReLU
EFFICIENT NETB4	150x150	40	ADAM

Table 3. Architectural details of pretrained models

EfficientNet B4

The EfficientNet B4 model, with transfer learning capabilities, is used for multi-class classification in the automatic diagnosis of colorectal cancer. This model delivers the best results in terms of accuracy compared to all other models. The detail architecture of model (EfficientNet B4) is plotted in Figure 4.

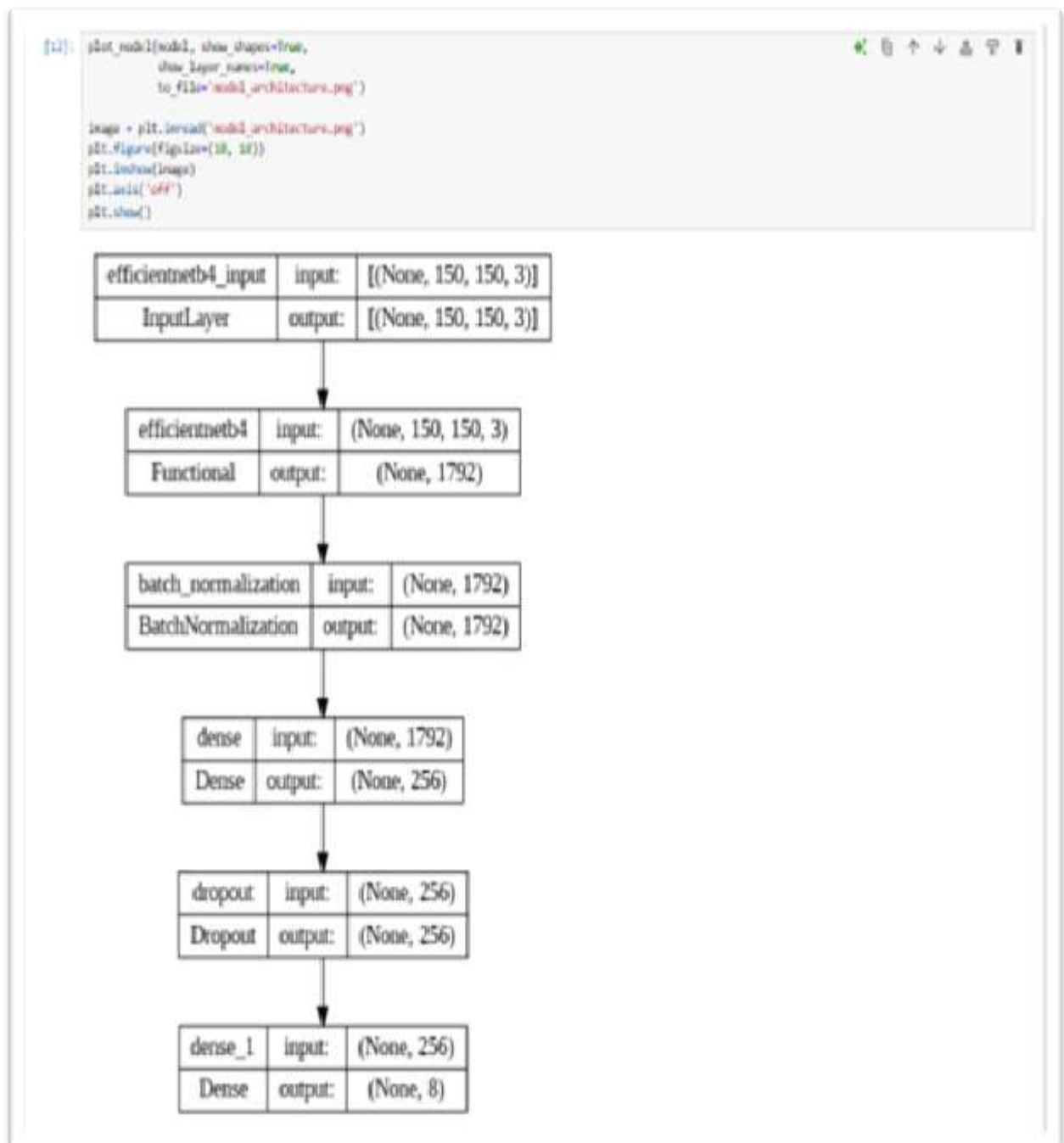


Figure 4: Architecture Diagram of Model EFFICIENTNETB4

As a pre-trained model, it has already been trained on similar tasks, offering the advantage of saving time and computational resources. In Figure 5, the model's training/validation accuracy and loss graphs are presented, allowing for an easy assessment of its performance. model training loss is 0.1689 and training accuracy is 1.0000, validation loss and validation accuracy are 0.3140 and 0.9525 respectively, while test loss and test accuracy are 0.2995 and 0.9547 respectively. The class-wise

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overall performance matrix where precision, recall, F1 score and support are shown in Table 4.

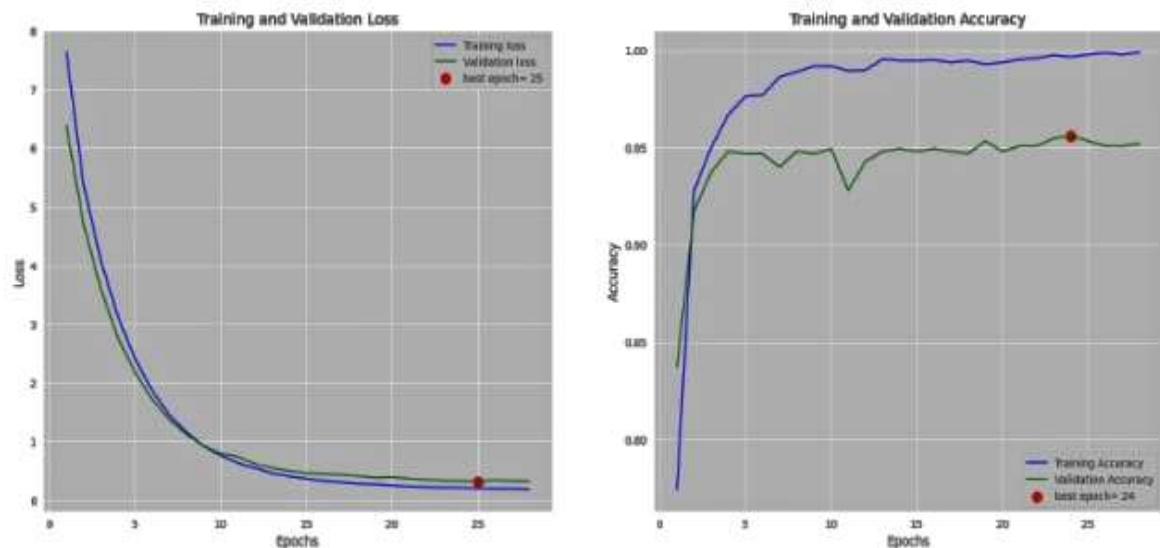


Figure 5: Model Training/Validation Accuracy and Loss graph of EFFICIENTNETB4

Table 4. Overall performance matrix of EFFICIENTNETB4

Type	Precision	Recall	F1-Score	Support
01_TUMOR	0.98	0.98	0.98	93
02_STROMA	0.89	0.90	0.90	94
03_COMPLEX	0.91	0.84	0.87	94
04_LYMPHO	0.95	0.97	0.96	94
05_DEBRIS	0.93	0.97	0.95	94
06_MUCOSA	1.0	1.0	1.0	94
07_ADIPOSE	0.98	0.98	0.98	94
08_EMPTY	1.0	1.0	1.0	93
ACCURACY	0.95	0.95	0.95	750
Macro avg	0.95	0.95	0.95	750
Weighted avg	0.95	0.95	0.95	750

Confusion matrix is one of the important matrices to evaluate the performance of model. In figure 7, confusion matrices visualize the performance of the model for

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each class of colorectal cancer. The rows and columns provide the comparison between predicted and actual results. The overall confusion matrix of the model demonstrates a promising breakthrough in terms of accuracy, precision, recall, specificity, and F1 score. The model achieved an overall accuracy of 0.95, which is relatively high compared to the other implemented models and even the previous research discussed in the literature review. Classifying between class 2 (STROMA) and class 3 (COMPLEX STROMA) proves to be a challenging task for the classifiers due to the similarity in tissue patterns. However, due to the model's ability to perform well with fewer data and a smaller number of parameters, it delivered some of the best classification results when compared to other approaches.

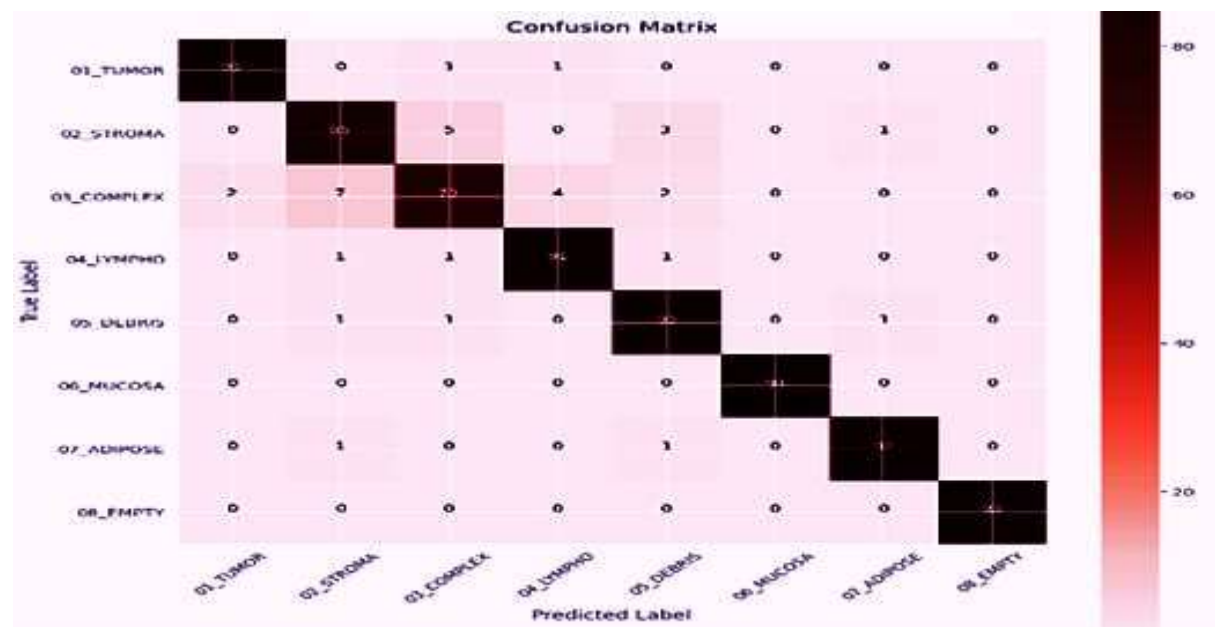


Figure 6: Confusion Matrix for EfficientNetB4

Comparative Analysis of Results

This research is carried out by implementing different deep learning models for accurate diagnosis of colorectal cancer. Deep learning models e.g., INCEPTION V3, VGG16, VGG19, RESTNET152V2, RESTNET50 and EFFICIENTNETB4 are implemented and provided some breakthrough results. However, EfficientNetB4 outclassed the other deep learning models in term of accuracy and other performance matrices. The EfficientNetB4 model provided the best result which demonstrate that the multiclass classification between different tissues of colorectal cancer is accurate. This research obtained the best results among previous work done by researchers on this dataset specially in term of accurate classification between all classes as well as classification between the complex tissue patterns such as class 2 and class 3.

The table 5 provides the comparative analysis of the deep learning models trained on the Colorectal_Histology_MNIST dataset for automatic diagnostic of colorectal cancer and classification of different tissues patterns.

Table 5. The overall comparative analysis of models on the basis of Accuracy.

MODEL	ACCURACY (%)
VGG-16	51.17
VGG-19	59.86
RESTNET50	78.94
RESTNET152V2	76.8
INCEPTION V3	85.73
EFFICIENT NETB4	95

The study is incomplete without the class wise classifications details. Class wise comparative analysis proved that our purposed model not only give best results for the two complex classes but also increase overall accuracy of all the eight classes. Table 6 illustrate the class wise comparative performance of all models.

Table 6. Class wise comparative analysis of models on the basis of Accuracy.

Tissue Classes	Tumor	Stroma	Complex	Lympho	Debris	Mucosa	Adipose	Empty
VGG-16	76	61	64	0	21	100	95	98
VGG-1	68	55	56	0	24	84	95	98
RESTNET50	65	68	74	92	55	95	99	99
RESTNET152-V2	71	65	60	83	54	87	95	95
INCEPTION V3	89.77	70.73	76.84	74.47	89.0	89.50	95.88	96.94
EFFICIENT NETB4	98	89	91	95	93	100	98	100

This research was carried out with the multiple deep learning models such as INCEPTION V3, VGG16, VGG19, RESTNET152V2, RESTNET50 and EFFICIENTNETB4. The highest accuracy and performance are achieved by using the EfficientNet B4 model. The highest accuracy is 95% which provided the better results and performance matrices as compared to base paper on same data set Colorectal Histology-MINIST with accuracy of 89.8% [25]. This is one of the main contributions of this research work in term of accurate diagnosis of CRC with tissues classification on histopathology images. This research also achieved the comparatively best results in order to accurate classification of the most complex classes STROMA and COMPLEX STROMA tissue patterns which was the challenging task for the researchers. The comparatively analysis of this research work with the other researchers are provided below in the table 7

Table 7. The comparative analysis of purposed model with related work.

Related work	Classification technique	No of classes classified	Accuracy
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Jakob Nikolas Kather et.al	Histogram-lower, LBP, histogram-higher, GLCM and Perceptual features	8	87.4
S. Gupta et.al	InceptionV3	8	89.8
Purposed method	EfficientNetB4	8	95

CONCLUSION

Colorectal cancer is third most common type of cancer and on second no in case of mortality found across the globe. This study of research provides deep learning-based solution to diagnose prostate cancer as well as classification of tissues into eight different classes. To achieve the goal colorectal histology-MINIST data set is being used. The training set is based on a well-known publicly available data set having 5000 whole slides image of H&E-stained biopsies. The study is carried out using different transfer learning and deep learning-based image classification models such as INCEPTION V3, VGG16, VGG19, RESTNET152V2, RESTNET50 and EFFICIENTNETB4 to train over one of the largest datasets freely available whole-slide picture collections for CRC diagnosis and classification. It concluded the several data processing techniques such as image resizing, image enhancement, pixels normalization etc. The region splitting technique for image segmentation and rotating, flip and other data augmentations techniques are used to improve the overall performance of the model and deal with class imbalanced and overfitting related problems. This study has obtained some of the breakthrough results to diagnose the CRC and classification of tissues, the EFFICIENTNETB4 model learned the complex tissue patterns well and provided one of the best results so far and achieve the highest overall accuracy of 95%. While the two most challenging classes STROMA and COMPLEX STROMA achieve accuracy of 89% and 91% respectively. The findings of this study have significance to the medical imaging as well as other domains of automatic cancer detection. Understanding the related features and patterns that predict the correct diagnosis of CRC enable analysis for developing the more reliable diagnostic models. Some of the limitations of this research includes that the data which is publicly accessible is insufficient to train deep learning models to achieve the best and optimized results which usually require the large amount of data. However, there was also a drawback that all data images are not well segmented and due to this, there is difficulty in pointing out the areas of interest in the histopathological biopsy images.

REFERENCES

- [1] World Health Organization, "Colorectal cancer," World Health Organization, [Online]. Available: <https://www.who.int/news-room/fact-sheets/detail/colorectal-cancer>. [Accessed: Feb. 7, 2025].
- [2] American Cancer Society, "What is colorectal cancer," American Cancer Society, [Online]. Available: <https://www.cancer.org/cancer/types/colorectal-cancer/about/what-is-colorectal-cancer.html>. [Accessed: Feb. 7, 2025].

Online ISSN

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Print ISSN

3007-3189

<http://amresearchreview.com/index.php/Journal/about>

- [3] I. Bhattacharya, Y. S. Khandwala, S. Vesal, W. Shao, Q. Yang, S. J. Soerensen, R. E. Fan, P. Ghanouni, C. A. Kunder, J. D. Brooks, and Y. Hu, "A review of artificial intelligence in prostate cancer detection on imaging," *Therapeutic Advances in Urology*, vol. 14, p. 17562872221128791, 2022, doi: 10.1177/17562872221128791.
- [4] F. Bray, J. Ferlay, I. Soerjomataram, R. L. Siegel, L. A. Torre, and A. Jemal, "Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries," *CA Cancer J. Clin.*, vol. 68, no. 6, pp. 394–424, 2018, doi: 10.3322/caac.21492.
- [5] M. Arnold, M. S. Sierra, M. Laversanne, I. Soerjomataram, A. Jemal, and F. Bray, "Global patterns and trends in colorectal cancer incidence and mortality," *Gut*, vol. 66, no. 4, pp. 683–691, 2017, doi: 10.1136/gutjnl-2015-310912.
- [6] U. F. Qureshi, M. N. Aslam, M. N. Ansari, and M. Khan, "Role of aspirin as prophylaxis against colorectal cancer," *Pakistan Postgraduate Medical Journal*, vol. 29, no. 1, pp. 16–19, 2018.
- [7] F. T. Bosman, "Chapter 5.5: Colorectal Cancer," in B. W. Stewart and C. P. Wild, Eds., *World Cancer Report*, International Agency for Research on Cancer, World Health Organization, 2014, pp. 392–402.
- [8] T. Tarver, *Cancer facts & figures 2012*, American Cancer Society, 2012.
- [9] Y. Huang, S. Huang, H. Wang, M. Wei, J. Wang, H. Zhang, ... and Z. Yi, "A prior-based method for colorectal lymph node region classification via deep neural network," in *2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, 2021, pp. 1741–1748, doi: 10.1109/BIBM52602.2021.9673739.
- [10] . K.-L. Hua, C.-H. Hsu, S. C. Hidayati, W.-H. Cheng, and Y.-J. Chen, "Computer-aided classification of lung nodules on computed tomography images via deep learning technique," *OncoTargets and Therapy*, vol. 8, pp. 2015–2022, 2015, doi: 10.2147/OTT.S89099.
- [11] M. Veta, P. J. van Diest, S. M. Willems, H. Wang, A. Madabhushi, A. Cruz-Roa, F. Gonzalez, A. B. Larsen, J. S. Vestergaard, A. B. Dahl, et al., "Assessment of algorithms for mitosis detection in breast cancer histopathology images," *Med. Image Anal.*, vol. 20, no. 1, pp. 237–248, 2015, doi: 10.1016/j.media.2015.05.004.
- [12] B. Ehteshami Bejnordi, M. Veta, P. J. van Diest, B. van Ginneken, N. Karssemeijer, G. Litjens, J. van der Laak, M. Hermsen, Q. F. Manson, et al., "Diagnostic assessment of deep learning algorithms for detection of lymph node metastases in women with breast cancer," *JAMA*, vol. 318, no. 22, pp. 2199–2210, 2017, doi: 10.1001/jama.2017.17709.
- [13] D. C. Cireşan, A. Giusti, L. M. Gambardella, and J. Schmidhuber, "Mitosis detection in breast cancer histology images with deep neural networks," in *Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, vol. 16, Springer, 2013, pp. 411–418, doi: 10.1007/978-3-642-40763-5_51.
- [14] D. Komura and S. Ishikawa, "Machine learning methods for histopathological image analysis," *Comput. Struct. Biotechnol. J.*, vol. 16, pp. 34–42, 2018, doi: 10.1016/j.csbj.2018.01.003.

- [15] M. Fleming, S. Ravula, S. F. Tatishchev, and H. L. Wang, "Colorectal carcinoma: Pathologic aspects," *J. Gastrointest. Oncol.*, vol. 3, no. 3, pp. 153, 2012, doi: 10.3978/j.issn.2078-6891.2012.028.
- [16] J. N. Kather, C. A. Weis, F. Bianconi, S. M. Melchers, L. R. Schad, T. Gaiser, A. Marx, and F. Zollner, "Multi-class texture analysis in colorectal cancer histology," *Scientific Reports*, 2016, doi: 10.1038/srep2471.
- [17] H. Choi, H. Kim, W. Hong, J. Park, E. J. Hwang, C. M. Park, Y. T. Kim, and J. M. Goo, "Prediction of visceral pleural invasion in lung cancer on CT: Deep learning model achieves radiologist-level performance with adaptive sensitivity and specificity to clinical needs," *Eur. Radiol.*, vol. 31, pp. 2866–2876, 2021, doi: 10.1007/s00330-020-07219-0.
- [18] D. C. Ciresan, A. Giusti, L. M. Gambardella, and J. Schmidhuber, "Mitosis detection in breast cancer histology images with deep neural networks," in *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2013: 16th International Conference, Nagoya, Japan, 2013*, pp. 411–418.
- [19] G. Urban, P. Tripathi, T. Alkayali, M. Mittal, F. Jalali, W. Karnes, and P. Baldi, "Deep learning localizes and identifies polyps in real time with 96% accuracy in screening colonoscopy," *Gastroenterology*, vol. 155, no. 4, pp. 1069–1078.e8, 2018, doi: 10.1053/j.gastro.2018.06.037.
- [20] S. U. K. Bukhari, A. Syed, S. K. A. Bokhari, S. S. Hussain, S. U. Armaghan, and S. S. H. Shah, "The histological diagnosis of colonic adenocarcinoma by applying partial self-supervised learning," *MedRxiv*, 2020, [Online]. Available: <https://doi.org/10.1101/2020.08.23.20180944>.
- [21] S. Mangal, A. Chaurasia, and A. Khajanchi, "Convolutional neural networks for diagnosing colon and lung cancer histopathological images," *arXiv preprint arXiv:2009.03878*, 2020.
- [22] T. Babu, D. Gupta, T. Singh, and S. Hameed, "Colon cancer prediction on different magnified colon biopsy images," in *2018 Tenth International Conference on Advanced Computing (ICoAC)*, 2018, pp. 277–280, doi: 10.1109/ICoAC.2018.8748403.
- [23] M. S. N. Raju and B. S. Rao, "Classification of colon cancer through analysis of histopathology images using transfer learning," in *2022 IEEE 2nd International Symposium on Sustainable Energy, Signal Processing and Cyber Security (iSSSC)*, 2022, pp. 1–6, doi: 10.1109/iSSSC55876.2022.9991089.
- [24] S. K. Wildah, S. Agustiani, A. Latif, R. Pebrianto, F. N. Hasan, and F. Indriyani, "Classification of colorectal cancer based on histological image using a combination of color histogram,
- [25] S. Gupta, A. Gupta, A. Kumar, S. Gupta, and A. Singh, "Multi-class classification of colorectal cancer tissues using pre-trained CNN models," in *TENCON 2022 - 2022 IEEE Region 10 Conference (TENCON)*, 2022, pp. 1–6, doi: 10.1109/TENCON55691.2022.9977516.
- [26] S. Mehmood, T. M. Ghazal, M. A. Khan, M. T. Zubair, M. T. Naseem, T. Faiz, and M. Ahmad, "Malignancy detection in lung and colon histopathology images using transfer learning with class-selective image processing," *IEEE Access*, vol. 10, pp. 25657–25668, 2022, doi:

Online ISSN

3007-3197

Print ISSN

3007-3189

<http://amresearchreview.com/index.php/Journal/about>

- 10.1109/ACCESS.2022.3177125.
- [27] M. Toseef, A. Khan, K. Ullah, S. Ahmad, I. Hussain, and S. K. Shah, "Enhancing breast cancer diagnosis through virtual biopsy and machine learning," *Dialogue Social Science Review*, vol. 3, no. 2, pp. 103–116, 2025.
- [28] T. Ullah, et al., "Machine learning-based cardiovascular disease detection using optimal feature selection," *IEEE Access*, 2024, doi: 10.1109/ACCESS.2024.3257493.
- [29] B. Saeed, et al., "Deep learning-based detection of one and two-column textual blocks in camera-captured Pashto document images," *IEEE Access*, 2025, doi: 10.1109/ACCESS.2025.3531713.
- [30] N. Khan, et al., "Robust Arabic and Pashto text detection in camera-captured documents using deep learning techniques," *IEEE Access*, vol. 11, pp. 135788–135796, 2023, doi: 10.1109/ACCESS.2023.3285614.
- [31] M. Ayaz, et al., "Automatic early diagnosis of dome galls in *Cordia dichotoma* G. Forst. using deep transfer learning," *IEEE Access*, vol. 11, pp. 59511–59523, 2023, doi: 10.1109/ACCESS.2023.3356357.
- [32] S. K. Wildah, S. Agustiani, A. Latif, R. Pebrianto, F. N. Hasan and F. Indriyani, "Classification of Colorectal Cancer Based on Histological Image Using a Combination of Color Histogram, Haralick and k-NN," 2022 International Conference on Information Technology Research and Innovation (ICITRI), Jakarta, Indonesia, 2022, pp. 179-183, doi: 10.1109/ICITRI56423.2022.9970214..