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Automated System for Colon Cancer Detection and Segmentation Based on Deep Learning Techniques

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ABSTRACT

Colon cancer is one of the world's three most deadly and severe cancers. As with any cancer, the key priority is early detection. Deep learning (DL) applications have recently gained popularity in medical image analysis due to the success they have achieved in the early detection and screening of cancerous tissues or organs. This paper aims to explore the potential of deep learning techniques for colon cancer classification. This research will aid in the early prediction of colon cancer in order to provide effective treatment in the most timely manner. In this exploratory study, many deep learning optimizers were investigated, including stochastic gradient descent (SGD), Adamax, AdaDelta, root mean square prop (RMSprop), adaptive moment estimation (Adam), and the Nesterov and Adam optimizer (Nadam). According to the empirical results, the CNN-Adam technique produced the highest accuracy with an average score of 82% when compared to other models for four colon cancer datasets. Similarly, Dataset_1 produced better results, with CNN-Adam, CNN-RMSprop, and CNN-Adadelta achieving accuracy scores of 0.95, 0.76, and 0.96, respectively.

KEYWORDS

Artificial Intelligence, Colon Cancer, Computer-Aided Diagnosis, Deep Learning, Optimization Algorithm

1. INTRODUCTION

Cancer is one of the most dangerous health threats to human life. It is ranked as the second most common cause of death after atherosclerosis and heart disease. Therefore, cancer is a serious challenge to most stakeholders. According to the National Cancer Institute (NIH), approximately 606,520 people

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were expected to die, and 1,806,950 million new cases of cancer were diagnosed in the United States in 2020. Among the cancer diseases, Gastrointestinal (GI) cancer affects the digestive tract starting from the esophagus to the anus, which is classified as upper malignancy (i.e., esophagus and stomach) and lower malignancy (i.e. include colon and rectal cancer), representing the third most dangerous GI cancer (Bray et al., 2018). Gastrointestinal cancers (GI) are responsible for one cancer case among four cases and one death case among three cases, as per WHO statistics. The statistics show more than 3.5 million GI cancer cases are officially registered in 2018 worldwide. In particular, colon cancer, also known as colorectal cancer, is a serious cancer that has a high incidence and mortality rate in developed countries. Colorectal cancer (CRC) is the third most common cancer in both men and women in the United States (Vijeta et al., 2020). In addition, CRC is the most diagnosed cancer in males and the third most diagnosed disease in females in Saudi society, representing 13% of diagnosed cancers (Alyabsi et al., 2021). Therefore, the early diagnosis of CRC is highly recommended to detect the polyps in the body before cancer develops and spreads to other normal cells. As known medically, cancer grows slowly with no significant symptoms. Thus, early diagnosis helps greatly to optimize treatment (Liu et al., 2016a). There are different biomarkers that may help physicians to detect cancer at the early stages such as radiographic, physiologic, molecular, and histologic applications (Liu et al., 2016b). For instance, endoscopy is widely used to diagnose cancer. However, the diagnosis results are not always accurate and it may be an uncomfortable procedure for patients (Lan et al., 2019). Alternatively, the Wireless Capsule Endoscopy (WCE) is swallowed by the patient to capture a high-resolution video with high frame rates for the whole gastrointestinal tract from the esophagus to the anus. However, such diagnostic videos must be processed and analyzed manually by physicians. This may be erroneous and time-consuming as the tumor might not be obvious in most of the frames. This problem has been overcome through the use of Computer Aided Diagnostic (CAD) systems. CAD systems play a crucial role in the early detection of cancer (Inbarani et al., 2020; Owais et al., 2019; Jothi et al., 2019, 2013; Banu et al., 2017; Abd El-Salam et al., 2014; Anter et al., 2013, 2014). The evolution of CAD systems for CRC can be traced from traditional models that require complex a priori mathematical knowledge (Tamai et al., 2017) to advanced machine learning (ML)-based systems (Min et al., 2019; Wang et al., 2019; Nadimi et al., 2020; Ozawa et al., 2020; Zeng et al., 2020; Qadir et al., 2020; Fati et al., 2022; Hassanien et al., 2014; Aziz et al., 2013) that can outperform human levels of accuracy. For example, in (Min et al., 2019), by analysing the colours of the lesions, the authors created a computer-aided diagnostic (CAD) system based on linked colour imaging (LCI) pictures to predict the histology outcomes of polyps. Wang et al. (2019) presented a revolutionary anchor-free polyp detector in this research. It is quicker than the anchor-based approach while providing superior performance. In addition to better performance, the authors eliminate the time-consuming process of manually fine-tuning anchor-related hyper-parameters. Nadimi et al. (2020) designed a convolutional neural network (CNN) for the autonomous identification of colorectal polyps in pictures taken during wireless colon capsule endoscopy, with the risk of malignant progression to colorectal cancer. The suggested CNN is an enhanced version of ZF-Net that employs transfer learning, pre-processing, and data augmentation. The authors then used CNN as the foundation for a Faster R-CNN to locate colorectal polyps in the images. In (Ozawa et al., 2020), a Single Shot MultiBox Detector deep convolutional neural network (CNN) architecture is used. The trained CNN recognised colorectal polyps (CP) with astonishing accuracy and speed, especially when the CP were tiny, which may help decrease missed CP if used during colonoscopy. To capture structural patterns in human colon optical coherence tomography (OCT) pictures, Zeng et al. (2020) created a convolutional neural network. The trained network correctly identified patterns that distinguish between normal and cancerous colorectal tissue. The experimental diagnoses indicated by the PR-OCT method were statistically analysed and compared to known histologic findings. Qadir et al. (2020) introduced a novel polyp identification framework that may be used in conjunction with any object detection algorithm to incorporate temporal information and improve overall polyp detection performance in colonoscopy movies. In its current condition, the suggested technique combines individual frame analysis with

temporal video analysis to reach the ultimate conclusion. Fati et al. (2022) described a collection of multi-method methods for early diagnosis of endoscopic pictures from a lower GI dataset. All of the suggested algorithms produced extremely accurate diagnosis findings in diagnosing endoscopic pictures of lower gastrointestinal illness datasets.

Deep learning methods can assist physicians by providing secondary ideas and highlighting image-related areas. Moreover, among medical methods, a single deep learning model has been shown to be effective in diagnosis. Although cancer diagnosis with deep learning (DL) has been a topic of much interest in the medical imaging community, comprehensive literature reviews covering various aspects of CRC diagnosis and prognosis using cutting-edge DL schemes remain scarce. Therefore, an enhanced and optimized DL model is proposed for this purpose, one which will segment the CRC at the very first stage and further classify it (Chouhan et al. 2019a,b,c).

Except for a few studies, all studies of colon cancer analysis are CNN-based without optimization algorithms, so data labeling takes a long time and requires expert knowledge. To reduce bias, these data must also be properly explained and verified by multiple experts. Histopathology public datasets are becoming more prevalent than colonoscopy datasets and are suitable for deep learning. However, datasets, particularly those based on colonoscopies, are scarce, insufficient, and of poor quality. There are no publicly available datasets for other imaging techniques. As a result, public datasets for colon cancer analysis are inadequate, resulting in poor performance.

In this paper, different optimizers such as Stochastic Gradient Descent (SGD), Adamax, AdaDelta, Root Mean Square Prop (RMSprop), Adaptive Moment Estimation (Adam), and the Nesterov and Adam optimizer (Nadam) can be used to update the network's weights and biases during training. While this research may not always involve the introduction of new innovations, it can still make an important contribution to the field by identifying best practices, improving existing methods, and establishing performance benchmarks. Researchers can identify the best practices and techniques for the specific task or problem being studied by comparing and evaluating existing methods and prior work. Researchers can potentially create new, more effective methods by combining the best aspects of each approach by identifying the strengths and weaknesses of each. This research can also be used to establish performance benchmarks for specific tasks or problems. This can assist researchers and practitioners in assessing the efficacy of new methods or techniques in comparison to existing methods, as well as informing decision-making for real-world applications. Therefore, this study aims to improve the detection and classification of colon cancer by employing an optimized deep-learning approach. Furthermore, real colonoscopy datasets will be collected and made available as open-source repositories. The following objectives can help achieve this aim.

- To explore the potential of deep learning techniques for colon cancer classification.
- An exploratory study that looks into different deep learning optimizers like Stochastic Gradient Descent (SGD), Adamax, AdaDelta, Root Mean Square Prop (RMSprop), Adaptive Moment Estimation (Adam), and the Nesterov and Adam optimizer (Nadam).
- The goal of this research is to find the most effective deep learning optimizer for accurately classifying various types of abnormal lesions and tissues associated with colon cancer in order to facilitate the proposed technique for timely cancer prediction.
- To statistically test the accuracy of the proposed model with and without an optimizer.

The rest of the paper is structured as follows: Section 2 covers related works for colon cancer detection and classification using various deep-learning techniques. The proposed methods and materials are explained in Section 3. Then, the results are detailed in Section 4. Section 5 shows the discussion of the results. Section 7 concludes the remarks and future work.

2. RELATED WORK

According to global cancer reports, colorectal cancer or colon cancer (CRC) is the third cause of cancer death after lung and breast cancer worldwide (Arnold et al., 2017). Early detection of cancer can alleviate the risks of mortality and increase patients' survival chances. Since the 1960s, machine learning algorithms and computer-aided detection/diagnosis (CAD) have been utilized to analyze medical images for cancer detection, classification and interpretation. Conventional machine learning methods such as Support Vector Machine (SVM), K-nearest Neighbor, and Random Forest rely heavily on image processing techniques for handcrafted feature extraction. Extracted features are subsequently inputted into a machine learning algorithm for classification tasks. The availability of data and computational capabilities has facilitated a steady conversion toward deep learning approaches. Recent years have witnessed the growth of deep learning methods in CRC detection, counting on their innate ability to directly extract features from raw images (Kermany et al., 2018). Different image techniques have been investigated in the detection of CRC such as histopathology, endoscopy, and colonoscopy images. Several important clinical medical imaging techniques, such as MRI, CT, and PET, can also be used to classify colon cancer. Emerging technologies such as molecular imaging and multi-parametric imaging, in addition to existing imaging approaches, are being developed for the classification of colon cancer. In order to improve diagnosis and treatment planning, CRC approaches seek to provide more detailed and comprehensive information about the tumor, such as its molecular profile and functional properties. This study made use of several colon cancer datasets, including Colon, Colonoscopy, Warwick-QU, and CRC-VAL-HE-7K. To collect image samples for early CRC studies, invasive endoscopy and colonoscopy procedures were used extensively. Researchers have turned to less invasive approaches with histopathology images, which have proven to examine and classify the underlying cancerous tissues distinctly (Tamang & Kim, 2021). A pathologist traditionally examines the shapes and textures in histopathology whole slide images (WSI). The development and increased use of less invasive approaches in histopathology imaging has been aided by advances in computational resources. Pathologists used microscopes to analyze histopathology images in the past, which required extensive training and expertise.. The development of digital imaging and computational resources in histopathology imaging has resulted in numerous advantages over traditional methods. Faster analysis times, improved accuracy and consistency, and the ability to extract more detailed information from images are among the advantages. Furthermore, computational resources have enabled the development of artificial intelligence (AI) algorithms capable of accurately and quickly analyzing histopathology images. Overall, advances in computational resources have transformed the field of histopathology imaging, allowing for less invasive approaches and improving analysis accuracy and speed. Deep learning algorithms have recently been widely used to assist pathologists in accurately detecting cancerous tissues (Khan et al., 2022; Rehman et al., 2021a,b; Saba et al., 2019). This section examines recent advances in machine learning and deep learning in the detection of colon cancer.

Machine learning techniques are increasingly being used in disease identification and medical diagnosis (Emary et al., 2014a,b; Azar et al., 2013, 2012; Elshazly et al., 2013a,b,c). Zhang et al. (2023) used targeted transcriptome and artificial intelligence to identify hematologic and solid tumors. For their investigation, they used the Geometric mean Näive Bayesian classifier. The authors used Computed Tomography (CT) radionics features with Random Forest and Support Vector Machine (SVM) in (Shang et al., 2023) and evaluated their output with Area Under the Receiver Curve (AUC). The term 'AUC' here refers to the area under the Receiver Operating Characteristic (ROC) curve. The AUC is calculated as the area under the ROC curve, which is a graphical representation of the performance of a deep learning classification model at various classification thresholds. The output shows excellent colorectal, breast, and renal carcinoma discrimination. Taghavi et al. (2023) investigated the feasibility of an existing machine-learning model for predicting the reappearance of Colorectal Liver Metastases (CRLM) after thermal ablation. They discovered that all existing models

performed poorly for the reappearance of CRLM, especially after 24 months of thermal ablation. In (Han et al., 2022), relevance prediction models based on the presence of gut microbiome in human feces have been investigated for the diagnosis of Colorectal cancer and Advanced Adenoma (AA). They demonstrated that in the given conditions, SNP outperforms Random Forest for identifying CRC based on gut microbiome. The gut microbiome plays a crucial role in the development of colorectal cancer (CRC) and advanced adenoma (AA). Identifying microbial targets that can distinguish between CRC and AA can aid in the early detection and treatment of CRC. This study used metagenomic sequencing data to analyze the differences in microbial abundance and single nucleotide polymorphism (SNP) characteristics between AA and CRC patients. The study found that using microbial SNP was the best method to identify CRC with an accuracy of 92.31%, which was superior to using the gut microbiome. This method could provide new targets for CRC screening. A comparative study was conducted in (Harold et al., 2022) on the detection and monitoring of gastrointestinal aberrations such as inflammation, fibrosis, and cancer, particularly in cases of colorectal cancer, colorectal stricture, gastric cancer, intestinal cancers, ulcerative colitis, Crohn's disease, and so on, using machine learning techniques. According to Hartwig et al. (2022), a clinically applicable AI system that can detect cancerous invasions in large sessile colorectal polyps has been developed. It aids in determining the likely depth of cancerous polyps in colorectal cancers so that treatment can be determined. Hartwig et al. (2022) used lymph node metastasis attributes of EGC patients and various machine learning predictive models, including a linear support vector classifier (Linear SVC), logistic regression model, extreme gradient boosting model (XGBoost), light gradient boosting machine model (LightGBM), and Gaussian process classification model, to predict the early detection of lymph node metastasis in the early stages of Colorectal Cancer. A Least Absolute Shrinkage and Selection Operator (LASSO) Logistic regression model is used in (Wang et al., 2022) for early prediction of colorectal cancer from four Danish health databases on patients diagnosed with colorectal cancer. The Danish health databases primarily consist of electronic health records (EHRs), which contain information such as patient demographics, medical history, diagnostic codes, medication use, and laboratory results. The databases also contain administrative data, such as hospital admissions and discharges, outpatient visits, and procedures performed. In addition to EHRs, the Danish health databases may also contain some imaging data and histological samples, but these are typically limited in scope and may not be readily accessible for research purposes. Evaluation of outcomes through Area under the receiver operating characteristic curve (AUROC) and Area under the precision and recall curve (AUPRC) showed Machine learning predictions outperformed present LASSO Logistic regression technique in use (Wang et al., 2022).

Deep learning tools have been widely used and successfully applied in a variety of related research areas (Ganesan et al., 2022; Boulmaiz et al., 2022; Yu et al., 2021; Amin et al., 2021, 2020a,b,c, 2019; Musallam et al., 2021; Altaheri et al., 2021; Ibrahim et al., 2020; Mohamed et al., 2020; Sayed et al., 2020; Elkholy et al., 2020a,b). Various deep learning algorithms have been used for cancer diagnosis and detection, as well as tumor segmentation. These potent algorithms can extract high-level features from medical images (Kermany et al., 2018). Convolutional neural networks (CNNs), which are widely used deep learning algorithms, have played an important role in the processing of medical images, yielding excellent results (Litjens et al., 2017).This article reviews the use of deep learning algorithms, specifically convolutional networks, in medical image analysis. It covers over 300 studies from the past year on the use of deep learning for various tasks, including image classification, object detection, segmentation, and classification. The studies are grouped by application area, such as neuro, retinal, pulmonary, digital pathology, and breast, cardiac, abdominal, and musculoskeletal.

Many recent studies have used deep learning to accurately classify Colorectal Cancer (CRC) regions. A study published by Ponzio et al. (2018) used a CNN-based model to distinguish CRC tumors from healthy tissues and benign lesions. A multi-layer CNN model was used to classify preprocessed images as adenocarcinoma, tubulovillous adenoma, or healthy tissue. The aim of this study was to classify Colorectal Cancer (CRC) tumors from healthy tissues and benign lesions using

images. The researchers utilized images of CRC to achieve this goal. Using a transfer learning strategy, they achieved 96% classification accuracy. In another study (Bychkov et al., 2018), the VGG16 framework, which is also a popular pre-trained CNN-based model, is used to analyze CRC images and classify them into several types of tumors using LSTM models. They achieved high accuracy by using SVM as a classifier. Another study (Yue et al., 2019) used a modified VGG16 framework and SVM classifier on the WSI slides. This study received an F1-score of 70% and a phenomenal accuracy of 100%. Many of these studies, in general, used data augmentation techniques to increase the number of data samples, as deep learning models require a large number of samples for good training and feature extraction. The more samples there are, the better the deep learning network's generalization. Many studies used pre-trained CNN models to investigate the effects of hyper-parameter tuning on accuracy. The authors of one such study, (Kather et al., 2019), used such models for the classification of human cancer tissues WSI slides. For feature extraction, they compared five models: AlexNet, VGG19, GoogLeNet, ResNet-50, and SqueezeNet. The authors in (Song et al., 2020) used segmentation and background filtering to detect and label tumors. They compared the performance of the ResNet-34 model to pathologists' results. According to the study, both results were comparable for detecting CRC adenoma, with an accuracy of more than 90%. The authors in (Choi et al., 2020) tested the Inception-v3 and DenseNet-161 models on endoscopic image samples to detect tumor tissues. Using transfer learning, they achieved a top accuracy of over 92%. These studies show that the best of deep learning models have been successfully applied for CRC diagnosis and detection. With the ever-increasing availability of datasets, deep learning is set to produce more phenomenal results in this field.

3. THE PROPOSED METHODS AND MATERIALS

Deep learning is a subfield of machine learning that is used to perform difficult tasks such as image recognition, speech recognition, image segmentation, voice recognition, text classification, and so on. Many deep learning algorithms have recently been developed to efficiently perform the tasks mentioned above. A deep learning algorithm is a system that is designed to function similarly to a human brain, with an activation function, input layer, output layer, hidden layers, loss function, and other parameters. Image data is fed into neurons as input. The input data is sent to the next layer with the appropriate weights and biases. The output is the estimated final value of the artificial neuron. The optimization method in a deep learning model discovers the value of the parameters that reduce error when mapping inputs to outputs. An optimizer is a function that modifies neural network parameters such as weights and learning rate. It will aid in improving model accuracy and lowering overall loss. Due to the numerous parameters in deep learning models, selecting the best optimizer is difficult. State-of-the-art deep learning optimizer strategies for colon cancer classification were investigated in this study. Different types of optimizers were investigated in the empirical analysis, including Stochastic Gradient Descent (SGD), Adamax, AdaDelta, Root mean square prop (RMSprop), Adaptive moment estimation (Adam), Nesterov and Adam optimizer (Nadam).

3.1 Convolutional Neural Networks (CNN)

A convolutional neural network (CNN) is a deep learning approach that can take an input image, train the model with learning weights and biases, and then classify the untrained image (Dudekula et al., 2023; Ramadan et al., 2022; Aslam et al., 2021). The architecture of a CNN model is made up of several layers, including an input layer, a convolution layer, a pooling layer, and a fully connected layer. To prepare the data for deep learning models, the input images must be preprocessed by resizing, normalization, and augmentation. The resized images are then saved in the input layer at 224 x 224 x 3. Typically, the dimensions 224x224x3 represent an image with 224 pixels in height and 224 pixels in width and a color depth of 3. The color depth of 3 in this case indicates that the image is an RGB (Red Green Blue) image, with each pixel containing values for the intensity of the red, green, and

blue color channels. A series of kernels/filters in the convolution layer help extract high-level features from input images, such as edges, color, and orientation. Depending on the needs, we can add more convolution layers. The Pooling layer is in charge of shrinking the Convolved Feature's dimensions. It also results in a reduction in computing time and dimensionality. In the CNN architecture, the dropout layer is used to avoid overfitting. Some neurons are removed from the network model during the training phase, resulting in a smaller model. The fully connected layer is the final layer of the CNN architecture, and it is used to compute the predicted score by using activation functions such as Softmax, Rectified Linear Unit (ReLU), and others. The expected outcomes are obtained from the output layer. Figure 1 depicts the CNN architecture for colon cancer classification.

3.2 Types of Optimizer

State-of-the-art optimizer algorithms such as SGD, Adadelta, RMSprop, Adam, Adamax, and Nadam were used in this study to determine the best optimizer for colon cancer classification.

3.2.1 Stochastic Gradient Descent (SGD) Optimizer

SGD, or Stochastic Gradient Descent, is a popular optimization technique for determining the gradient of the network loss function with respect to each specific weight in the network. It is a Gradient Descent (GD) optimization method extension. To compute the loss function, GD uses the entire dataset of n points at a time, which takes a long time to compute. SGD, on the other hand, uses equation 1 to deduce one point at a time:

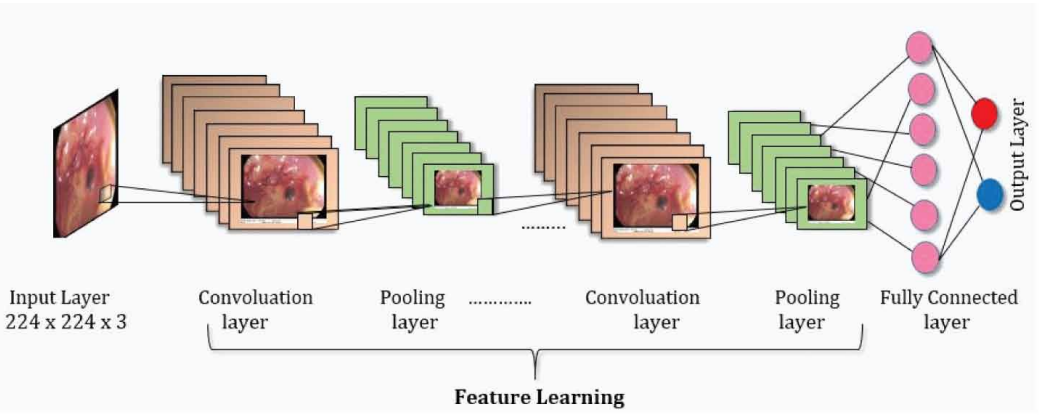
$$\theta = \theta - \alpha" _{\theta} J\left(\theta; x^{(i)}, y^{(i)}\right) \tag{1}$$

where $x^{(i)}$ and $y^{(i)}$ are training data and $J\left(\theta\right)$ is the objective function of the parameters. The newly revised weights are better in each iteration than in the prior iteration.

3.2.2 Adadelta Optimizer

The Adadelta optimization approach is an Adagrad extension that uses motion techniques to address the problem of monotonically decreasing learning rate (Zeiler, et al., 2020). The limitation of the Adagrad algorithm is its slow convergence due to its low learning rate. The initial learning rate hyperparameter is divided by the square root of the total of the squared partial derivatives in the

Figure 1. The CNN architecture for colon cancer classification



Adadelta optimization approach. The custom learning rate (LR) for one parameter in AdaGrad is calculated as follows:

$$LR\left(t+1\right) = LR \,/\, \left(1e-8+sqrt\left(s\left(t\right)\right)\right) \tag{2}$$

where $LR\left(t+1\right)$ is the estimated learning rate for an input variable at a given point in the search, LR is the initial step value, $sqrt()$ is the quadratic formula operation, and $s\left(t\right)$ is the sum of the squared partial derivatives of the input variable.

3.2.3 Root Mean Square Propagation (RMSprop) Optimizer

Geoff Hinton developed the RMSprop optimizer, which Adagrad improved (Hinton et al., 2018). It uses a mini-batch learning method, which means that the learning rate is further divided by an exponential function mean of all squared gradients (Dogo et al., 2018). This method compares the signs of two gradients; if both have the same sign, the application proceeds in the right direction and the learning rate improves slightly. Otherwise, the rate of learning will be slowed. To update the rule, use the following equation:

$$E\left[g^2\right]_t = \left[g^2\right]_{t-1} + \left(1-\beta\right)\left(\frac{\delta C}{\delta w}\right)^2 \tag{3}$$

$$w_t = w_t - 1 - \frac{\eta}{\sqrt{E[g^2]_t}}\frac{\delta C}{\delta w} \tag{4}$$

$E\left[g\right]$ denotes the linear trend of gradient descent. $\frac{\delta C}{\delta w}$ is the weight's cost function angle. n represents the learning rate. Beta is an average parameter with a suitable default value of 0.9.

3.2.4 Adam Optimizer

Similar to Adadelta and RMSprop, Adaptive Moment Estimation (Adam) stores an exponential decay average of prior squared residuals. The Adam optimizer combines RMSProp and motion Gradient. Good features (Zhang et al., 2018). The mean and variance of the gradient are calculated using the formula in this method:

$$\begin{aligned} m_t &= \beta_1 m_t - 1 + \left(1+\beta_1\right) g_t \\ v_t &= \beta_2 v_t - 1 + \left(1-\beta_2\right) g_t^2 \end{aligned} \tag{5}$$

The gradient's mean and variance are given by mt and vt, respectively. The decaying rates β_1 and β_2 regulate the relative contribution of the previous history versus the current gradient. Adam's rule is updated using the following equation:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{v_t}+\epsilon} m_t \tag{6}$$

3.2.5 AdaMax Optimizer

The AdaMax update rule:

$$\theta_{t+1} = \theta_t - \frac{\eta}{u_t} m_t \tag{7}$$

Note that as u_t relies on the max operation, it is not as suggestible to bias towards zero as m_t and v_t in Adam (Zhang et al., 2018).

3.2.6 Nadam Optimizer

The Nesterov-accelerated Adaptive Moment Estimation (Nadam) technique improves on the Adam optimization algorithm, which is an improved form of motion (Ruder, 2016). Movement adds an exponentially decreasing moving average (initial moment) of the gradient to the gradient descent process. Nadam aids in the smoothing of noisy objective functions while increasing convergence. (alpha) represents the initial learning rate, (sqrt()) represents the square root function, and (epsilon) represents a small number. Initial moment hyperparameters can improve performance. Finally, we can use the equation to calculate the parameter value for this iteration:

$$x\left(t\right) = x\left(t-1\right) - \alpha \,/\, \left(\sqrt{nhat} + \epsilon\right) * mhat \tag{8}$$

The update rule is of the form:

$$\theta_{t-1} = \theta - \frac{\eta}{\sqrt{v_t} + \epsilon} \left(\beta_1 m_t + \frac{\left(1-\beta_t\right) g_t}{1-\beta_1^t} \right) \tag{9}$$

4. DATASETS

The following datasets were used in this study: Colon, Colonoscopy, Warwick-QU, and CRC-VAL-HE-7K. The dataset is divided into three sections: training, validation, and testing (80% of the images are used for training, 10% for validation, and 10% for testing). Each colon dataset is described in detail in Table 0.

4.1 Colon Dataset (DS_1)

The colon dataset contains 500 images of colon tissue, 250 of which are benign and 250 of which are adenocarcinomas. The image size is 768 x 768 pixels in jpeg format (Borkowski et al., 2019).

4.2 Colonoscopy Dataset (DS_2)

A video of colon cancer is included in the Colonoscopy dataset, which includes 15 serrated adenomas, 21 hyperplastic lesions, and 40 adenomas. The video lasts less than 30 seconds, and image frames are generated from it (Mesejo et al., 2016). The image is 768 x 576 pixels in size.

4.3 The Warwick-QU Dataset (DS_3)

The Warwick-QU Dataset (DS 3) consists of a total of 165 images, out of which 74 are categorized as benign and 91 as malignant. The information came from the University Hospitals Coventry and Warwickshire NHS Trust in Coventry, England (Sirinukunwattana et al., 2017). The image data was generated by scanning 16 H E stained histological WSIs at 0.465m/pixel with a Zeiss MIRAX MIDI Slide Scanner. The image is 520 x 775 pixels in size.

4.4 CRC-VAL-HE-7K Dataset (DS_4)

The Colorectal Cancer Validation Histology 7K (CRC-VAL-HE-7K) dataset comprises 7180 images from 50 patients (Kather et al., 2019). The CRC-VAL-HE-7K Dataset contains high-quality histopathological images of colorectal cancer tissues with detailed annotations of various tissue structures, including glandular structures, stroma, and necrosis. The dataset includes both benign and malignant tissue samples, providing a diverse range of abnormalities for analysis. Dataset 4 comprises nine different classes, each containing varying numbers of images. The classes include adipose (ADI), which has 1338 images, back_ground (BACK), which has 847 images, debris (DEB), which has 339 images, lymphocytes (LYM), which has 634 images, mucus (MUC), which has 1035 images, smooth_muscle (MUS), has 592 images, normal_colon_mucosa (NORM), has 741 images, cancer_associated_stroma (STR), has 421 images, and colorectal_adenocarcinoma_epithelium (TUM), has 1233 images. The images have a resolution of 224 x 224 pixels and are stained with Hematoxylin and Eosin (H E), a common staining technique used in histopathology. Table 1 displays the sample images for each dataset.

5. IMAGE AUGMENTATION

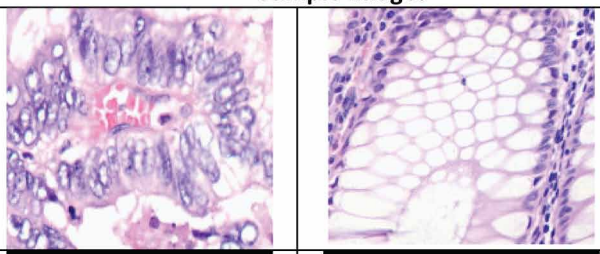
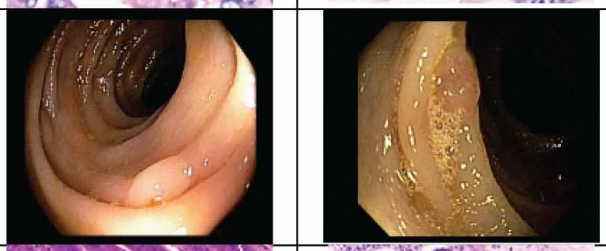
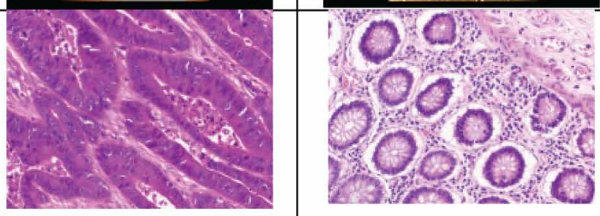
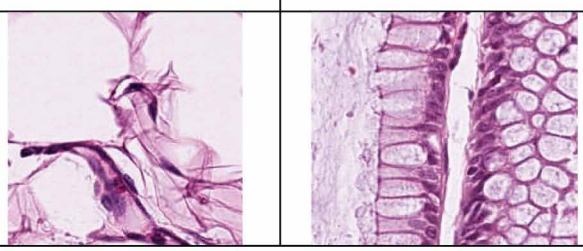
Image augmentation is a technique for artificially expanding the image data set. The small training data reduces the deep learning model's efficiency. The empirical analysis used image augmentation techniques to increase the training data to achieve good performance (Shorten et al., 2019). Figure 1 demonstrates the number of original and augmented images. To apply image augmentation to a colon image dataset, a generator is used to produce new images by applying different types of transformations such as rotation, scaling, flipping, and cropping to the original images. This can result in a significant increase in the number of images available for training, which can help improve the performance of deep learning models. In DS_1, DS_2, and DS_3, there are relatively low numbers of original images, with only 500, 279, and 165 respectively. This may lead to overfitting, lack of diversity, reduced accuracy, and instability in the deep learning model.

It is crucial to have a sufficient number of input images to ensure the model can accurately learn and generalize the underlying patterns in the data. Therefore, these three datasets are augmented in more different ways, for example, DS_1 is augmented in 10 different ways, resulting in 5000 images, and DS_3 is augmented in 16 different ways, resulting in 2527 images. However, DS_4 has a large set of original images, resulting in a smaller number of augmented images being generated. DS_1,

Table 1. Colon dataset description

Dataset	No. of Images	Augmented Images	Image Dimension
DS_1	500	5000	768 x 768
DS_2	279	1550	768 × 576
DS_2	165	2527	520 × 775
DS_4	7180	9513	224 x 224

Table 2. Sample images: Colon data set

Dataset	Sample Images
DS_1	
DS_2	
DS_3	
DS_4	

DS_2, and DS_3 generate augmented images of 10% to 18% from the original images. This helps to improve the classification performance.

Multiple augmentation properties were used in this study. The image augmentation generator generates images with a rotation of 30 degrees, a width shift range of 0.2, a height shift range of 0.2, a shear range of 0.2, a zoom range of 0.2, horizontal flip set to True, fill mode set to nearest, and vertical flip set to True. Figure 2, 3, 4, and 5 show the visualization of the image augmentation of each dataset.

6. RESULTS AND DISCUSSION

6.1 Environmental Setup

Python was used in the experimental analysis to build a deep neural network model with a Keras and TensorFlow backend. The implementation happened in the cloud, specifically in Google Colab, an online Jupyter notebook for training deep learning models on GPUs. The RAM on the Google virtual machine is 0.90GB/12.68GB, and the storage space is 22.93GB/107.72GB.

Figure 2. Original vs. augmented images

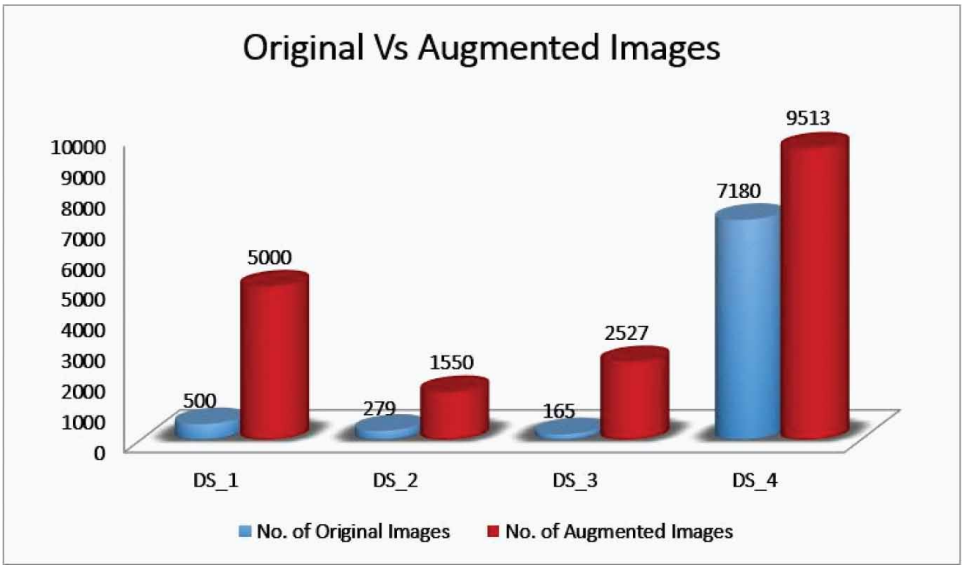
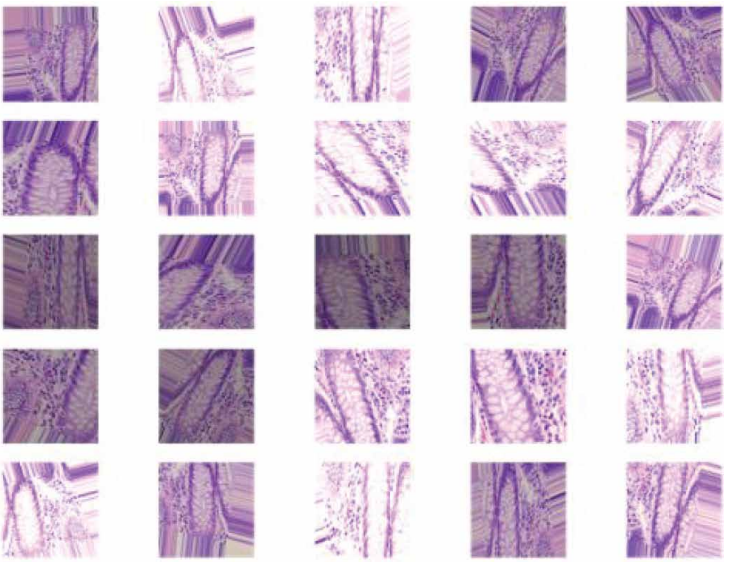


Figure 3. Augmented images for DS_1



6.2 Performance Evaluation

Convolutional neural network (CNN), a popular deep learning technique, is used to classify a colon cancer image. Empirical research was conducted on the CNN model and various optimizers such as Adam, RMSprop, Adadelta, Adamax, Nadam, and SGD. To evaluate the performance of the aforementioned deep learning models, various classification metrics such as precision, recall, F1 measure, and accuracy were used. These measures are commonly used to evaluate the performance of multi-class classification models. It also provides information on how well the model is able to

Figure 4. Augmented images for DS_2

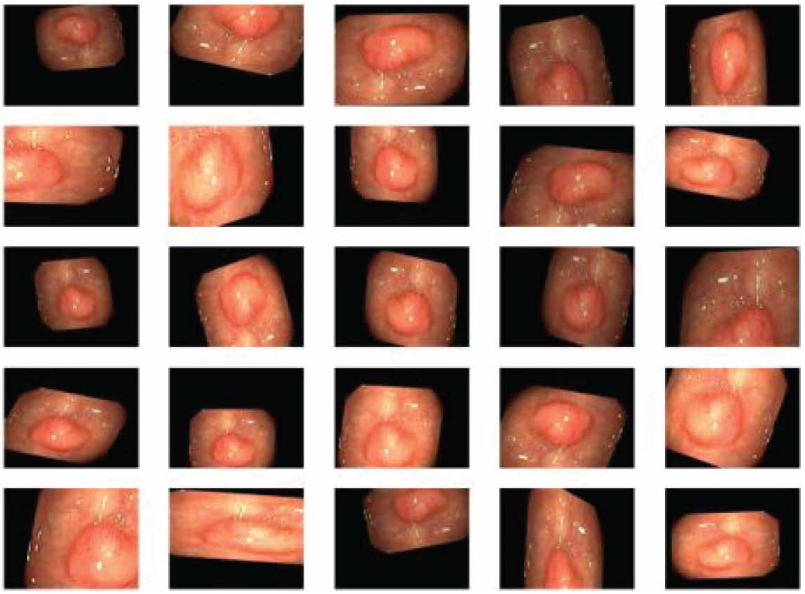
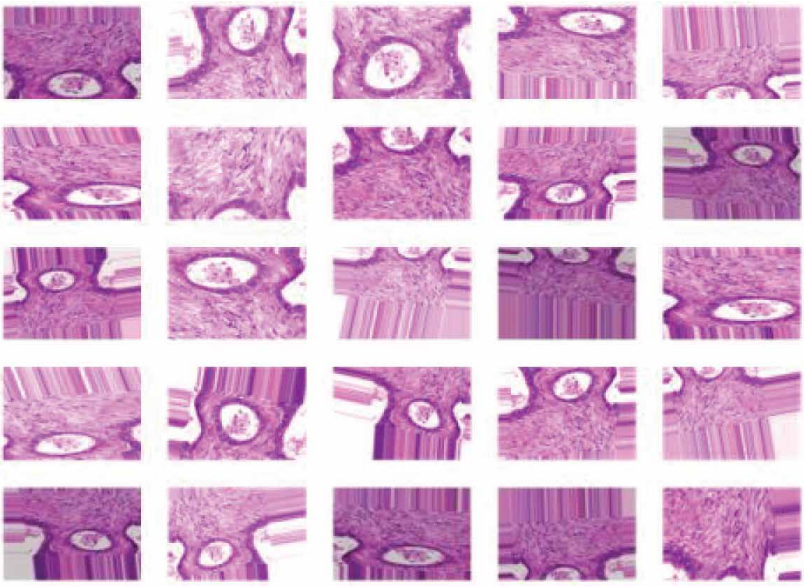
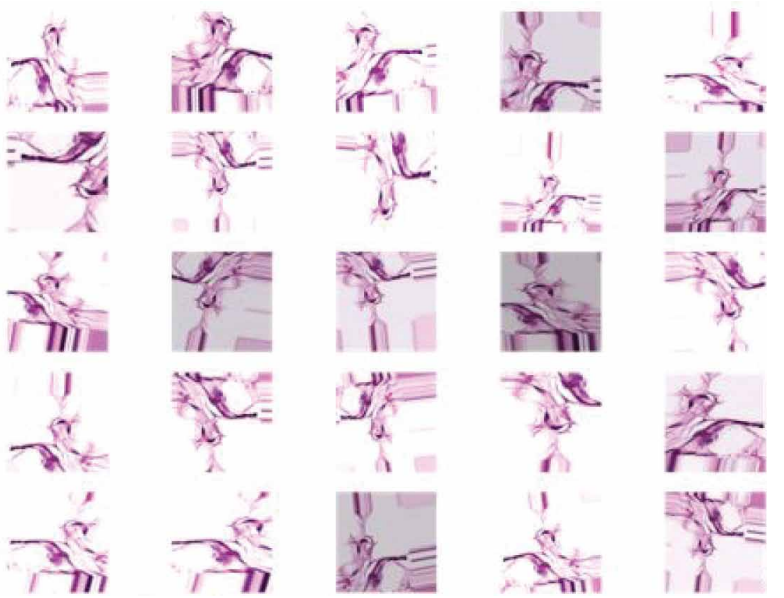


Figure 5. Augmented images for DS_3



correctly classify instances across all classes and can help identify areas for improvement in the model. Table 3 describes the performance evaluation of various deep learning models for the Colon Dataset (DS_1). True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) are the four key terms used to compute the classification measures (FN). In the case of colon cancer prediction, True Positive means that the deep learning model correctly identified the cancerous colon tissue. False Positive indicates that the deep learning algorithm incorrectly classified cancerous

Figure 6. Augmented images for DS_4



colon tissue. True Negative means the deep learning model correctly identified non-cancerous colon tissue. False Negative indicates that the deep learning algorithm incorrectly classified non-cancerous colon tissue.The performance evaluation of a multi-class classification model is crucial in identifying its effectiveness in solving a problem. Among the most common metrics used for this purpose are accuracy, precision, recall, and F1_Score (Jothi et al., 2022; Lavanya et al., 2022; Inbarani et al., 2022). These measures help to assess the model's overall performance and can identify specific areas that require improvement. The formulas associated with the most common evaluation metrics, such as precision, recall, F1 measure, and accuracy, are described and explained briefly below:

$$Accuracy = \frac{correctly\,classified\,the\left(cancerous\,tissue + noncancerous\,tissue\right)}{TotalNo.ofSamples} \tag{10}$$

$$Precision = \frac{correctly\,classified\,cancerous\,tissue}{correctly\,classified\,cancerous\,tissue + Incorrectly\,classified\,cancerous\,tissue} \tag{11}$$

$$Recall = \frac{correctly\,classified\,the\,cancerous\,tissue}{correctly\,classified\,the\,cancerous\,tissue + Incorrectly\,classified\,noncancerous\,tissue} \tag{12}$$

$$F1Measure = 2x\frac{\left(Precision \times Recall\right)}{\left(Precision + Recall\right)} \tag{13}$$

Dataset 4 consists of nine distinct classes, each representing a different type of abnormal lesion or tissue group in colon cancer classification. The classes include adipose, background, debris, lymphocytes, mucus, smooth muscle, normal colon mucosa, cancer_associated stroma, and colorectal adenocarcinoma epithelium.

As a result, the dataset represents a diverse set of abnormalities that require separate classification rather than the use of a single abnormal lesion and tissue group in a single classification task for colon cancer classification. It is not an average of different sets of algorithm performance measures from different classification tasks for different abnormal lesion and tissue types. Instead, it provides a

collection of labeled images representing various types of abnormalities in colon cancer classification, which can be used to train and evaluate machine learning models for each individual classification task. Each class in the data set corresponds to a distinct classification task, and performance measures can be calculated separately for each task based on machine learning models.

Table 3 shows that the CNN - Adadelta method performs better on the Colon cancer dataset (DS_1), with a precision value of 0.97, a recall value of 0.94, an F1 measure of 0.96, and an overall accuracy of 0.96. Similarly, with an accuracy of 0.95, the CNN-Adam method produces better results. The accuracy of the CNN-RMSprop and CNN-Nadam methods is greater than 75%. It is also noted that the CNN - SGD and CNN - Adamax methods produce less performance with precision values of 0.68 and 0.52, recall values of 0.68 and 0.50, an F1 measure of 0.69 and 0.52, and accuracy values of 0.67 and 0.68.

Table 4 shows the evaluation of deep learning models for the Colonoscopy Dataset (DS_2). According to Table 4, CNN - Nadam technique produces better results, with a precision of 0.76, recall of 0.79, F1 measure of 0.76, and accuracy of 0.79. The remaining methods, on the other hand, produce less than 70% overall accuracy.

The assessment of various deep learning methods for The Warwick-QU Dataset (DS_3) is shown in Table 5. The CNN - Adadelta methods perform worse, with a precision of 0.58, recall of 0.59, and accuracy of 0.59, respectively. It is observed that CNN- Adam produces the highest F1 measure value of 0.72 and an accuracy of 0.76. CNN-SGD has the highest recall of 0.78 and accuracy of 0.76, while CNN- Adamax has the highest precision of 0.77. These empirical findings indicate that no single method is more effective. Each deep learning model excels at a distinct metric.

Table 6 illustrates the DS_4 performance of several CNN models. The CNN - Adam algorithm outperforms the others, with a precision of 0.89, recall of 0.87, F1 of 0.87, and accuracy of 0.90. The CNN-Adamax and CNN-Nadam algorithms also produce better results, with precision and recall of 0.86 and 0.87, F1 measures of 0.83 and 0.86, and accuracy of 0.87, respectively. The remaining

Table 3. DL algorithm performance: Colon dataset (DS_1)

Deep Learning Algorithms	Precision	Recall	F1 Measure	Accuracy
CNN - adam	0.91	0.95	0.95	0.95
CNN - RMSprop	0.75	0.77	0.76	0.76
CNN- Adadelta	0.97	0.94	0.96	0.96
CNN- Adamax	0.52	0.50	0.52	0.68
CNN – Nadam	0.79	0.73	0.78	0.79
CNN – SGD	0.68	0.68	0.69	0.67

Table 4. DL algorithm performance: Colonoscopy dataset (DS_2)

Deep Learning Algorithms	Precision	Recall	F1 Measure	Accuracy
CNN - adam	0.62	0.68	0.60	0.68
CNN - RMSprop	0.69	0.63	0.61	0.63
CNN- Adadelta	0.53	0.53	0.69	0.69
CNN- Adamax	0.71	0.60	0.60	0.68
CNN – Nadam	0.76	0.79	0.76	0.79
CNN – SGD	0.62	0.63	0.63	0.63

Table 5. DL algorithm performance: The Warwick-QU dataset (DS_3)

Deep Learning Algorithms	Precision	Recall	F1 Measure	Accuracy
CNN - adam	0.66	0.60	0.72	0.76
CNN - RMSprop	0.67	0.70	0.67	0.74
CNN- Adadelta	0.58	0.59	0.51	0.59
CNN- Adamax	0.77	0.59	0.68	0.64
CNN – Nadam	0.56	0.61	0.58	0.64
CNN - SGD	0.58	0.78	0.67	0.76

algorithms, such as CNN-Adadelta, CNN-RMSprop, and CNN-SGD, produce less accurate results when the accuracy is less than 0.75.

Figure 7 depicts the overall accuracy of deep learning algorithms for four different colon datasets. Based on Figure 3, it is believed that CNN - Adam outperforms the other deep learning models. The DS_4 produces better results, with accuracy values of 0.87, 0.87, and 0.73 for CNN-Adamax, CNN-Nadam, and CNN-SGD, respectively. Similarly, Dataset 1 produces better results, with accuracy values of 0.95, 0.76, and 0.96, for CNN-adam, CNN-RMSprop, and CNN-Adadelta respectively. The DS_3 dataset exhibits lower accuracy values of 0.76, 0.59, 0.64, and 0.64 for the CNN-adam, CNN-Adadelta, CNN-Adamax, and CNN-Nadam models, respectively. This may be due to the fact that DS_3 contains a large number of augmented images that do not have significant features compared to the original images.

The findings also indicate that having a large number of augmented images may result in low performance for the deep learning model.

In this paper, cutting-edge CNN optimizer techniques are tested on a variety of colon cancer datasets. Model learning curves are a popular machine learning assessment procedure for algorithms that learn incrementally from a training dataset. The training and validation loss curves reveal how learning performance changes over time (epochs) and identify models that are underfit or overfit. The CNN model was trained over 100 epochs. The training and validation loss charts, as well as the accuracy charts, of various deep learning methods for the Colon Dataset (DS_1), are shown in Figure 8. The CNN - Adam technique outperforms the other models. CNN-Adamax, CNN-Adamdelta, Nandam, and SGD provide a smooth curve for training and validation loss values in each epoch while CNN-RMPros generate up and down scores for accuracy and loss

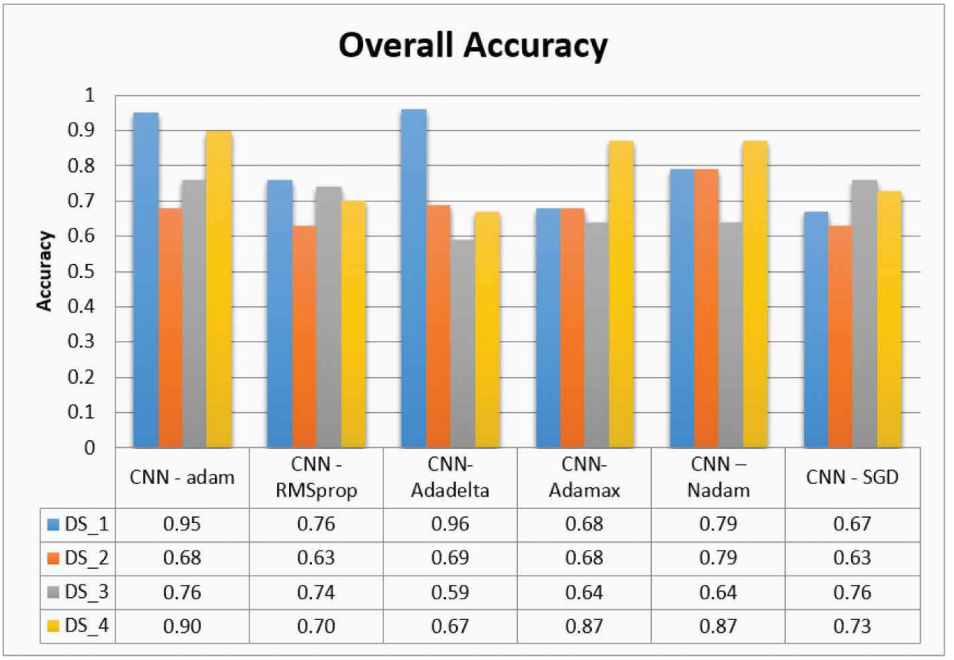
6.3 Training and Validation Curves Analysis

In this paper, cutting-edge CNN optimizer techniques are tested on a variety of colon cancer datasets. Model learning curves are a popular machine learning assessment procedure for algorithms that learn

Table 6. DL algorithm performance: CRC-VAL-HE-7K dataset (DS_4)

Deep Learning Algorithms	Precision	Recall	F1 Measure	Accuracy
CNN - adam	0.89	0.87	0.87	0.90
CNN - RMSprop	0.70	0.64	0.63	0.70
CNN- Adadelta	0.66	0.65	0.66	0.67
CNN- Adamax	0.86	0.84	0.83	0.87
CNN – Nadam	0.87	0.86	0.86	0.87
CNN - SGD	0.73	0.72	0.72	0.73

Figure 7. Original vs. augmented images



	CNN - adam	CNN - RMSprop	CNN- Adadelta	CNN- Adamax	CNN – Nadam	CNN - SGD
DS_1	0.95	0.76	0.96	0.68	0.79	0.67
DS_2	0.68	0.63	0.69	0.68	0.79	0.63
DS_3	0.76	0.74	0.59	0.64	0.64	0.76
DS_4	0.90	0.70	0.67	0.87	0.87	0.73

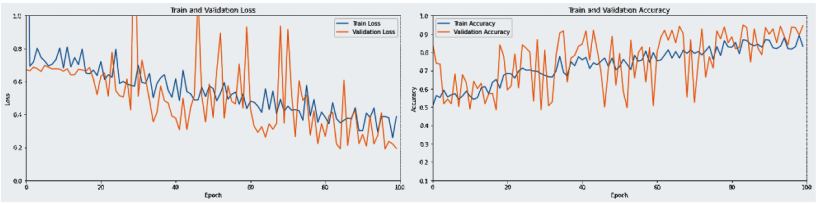
incrementally from a training dataset (Hoiem et al., 2021). The training and validation loss curves reveal how learning performance changes over time (epochs) and identify models that are underfit or overfit. The CNN model was trained over 100 epochs. The training and validation loss charts, as well as the accuracy charts, of various deep learning methods for the Colon Dataset (DS_1), are shown in Figure 8. The CNN - Adam technique outperforms the other models. In each epoch, CNN-Adamax, CNN Adamdelta, Nandam, and SGD provide a smooth curve for training and validation loss values while CNN - RMPros that generate up and down scores for accuracy and loss.

The training and validation loss charts, as well as the accuracy chart, of several deep learning methods for the Colonoscopy Dataset (DS_2) are shown in Figure 9, CNN - Adamdelta generates a smooth curve for both accuracy and loss values during training and validation. In terms of performance, CNN - Nandam outperforms the other deep learning models significantly. CNN-Adamax and CNN-SGD gradually lower the loss values during the training and validation processes.

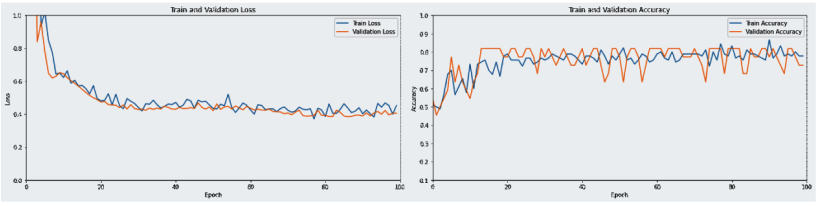
Figure 10 depicts the training and validation loss charts and the accuracy charts of different deep learning algorithms for the Warwick-QU Dataset (DS_3). CNN - Adamax produces the best training model accuracy scores. However, in both training and validation, it executes the lowest loss values. CNN-RMPros, CNN-Nandam, CNN-Adam, and CNN-SGD all have relatively high loss values (higher than 0.65). At each epoch, CNN - Adamdelta generates smooth curves for loss values.

Finally, Figure 11 shows the learning curves of different deep learning models for CRC-VAL-HE-7K Dataset (DS_4). The CNN-Adam and Nandam optimizers produce a minimum loss score of 0.3 and a maximum accuracy of 0.90. CNN - Adamdelta has the worst performance, increasing loss values while decreasing accuracy values. This optimizer is insufficient for colon DS 4. It's also worth noting that CNN-RMPros and CNN-SGD produce the best accuracy curves for training and validation, with values greater than 0.87.

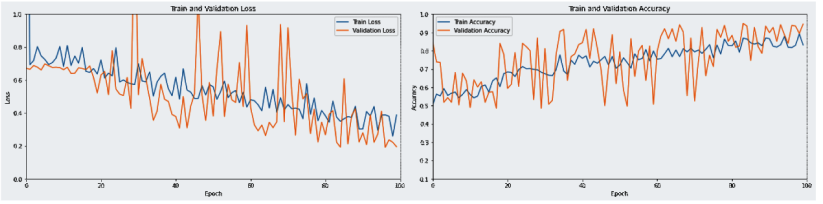
Figure 8. Learning curves for the colon dataset (DS_1)



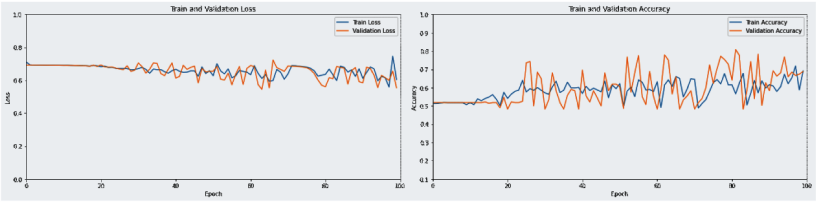
(a) CNN-Adam- DS_1



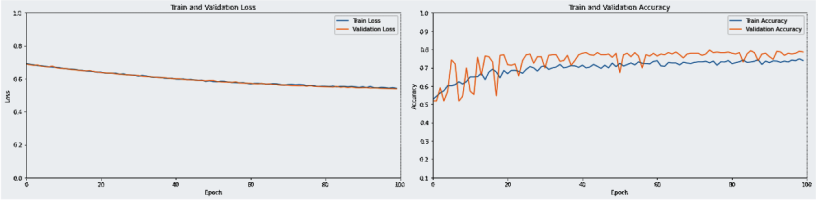
(b) CNN-Adammax- DS_1



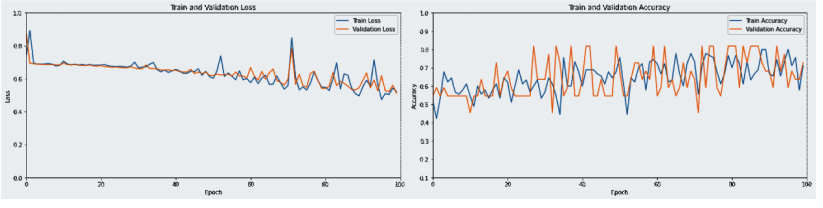
(c) CNN-Adamdelta- DS_1



(d) CNN-RMPros- DS_1

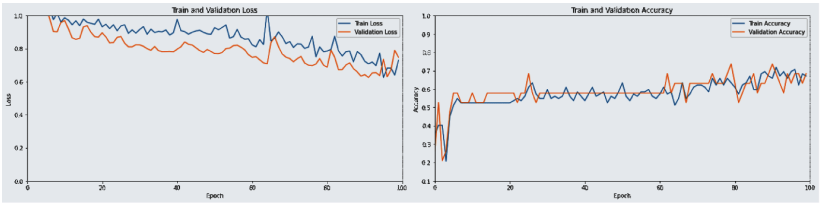


(e) CNN-Nandam- DS_1

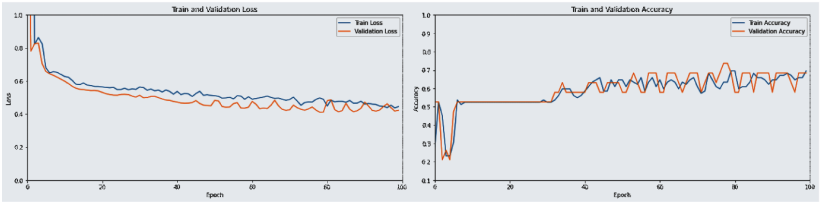


(f) CNN-SGD- DS_1

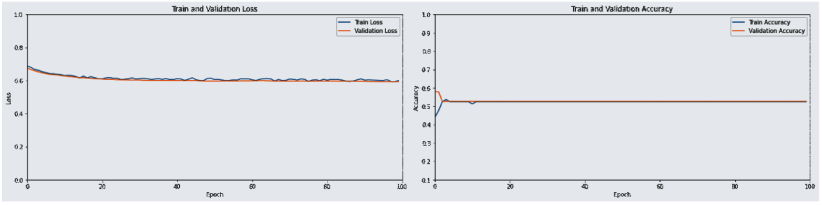
Figure 9. Learning curves for the colonoscopy dataset (DS_2)



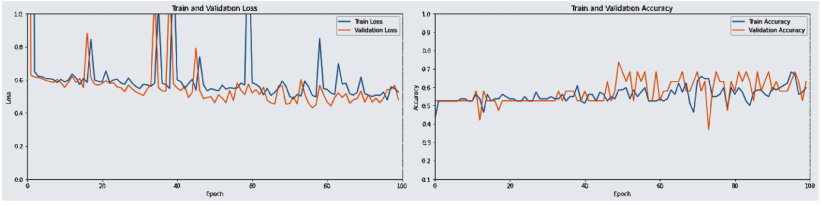
(a) CNN-Adam-DS_2



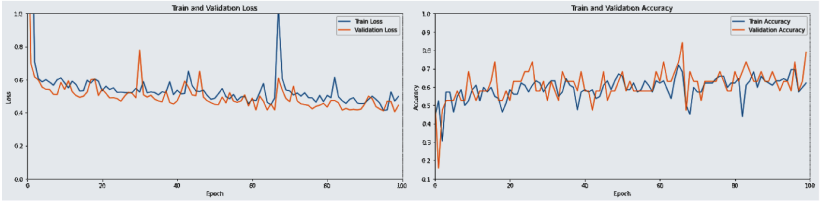
(b) CNN-Adammax- DS_2



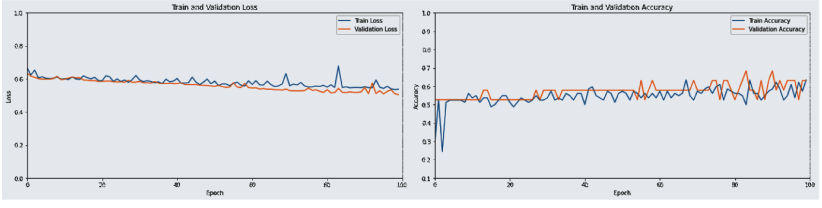
(c)CNN-Adamdelta- DS_2



(d) CNN-RMPros- DS_2

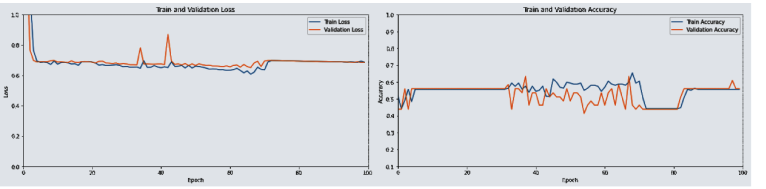


(e) CNN-Nandam- DS_2

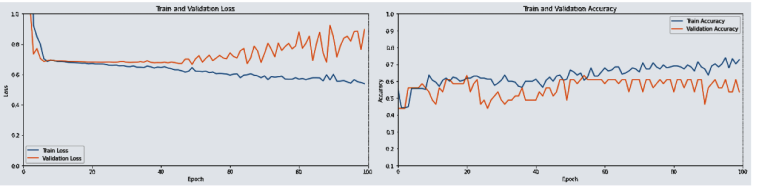


(f) CNN-SGD- DS_2

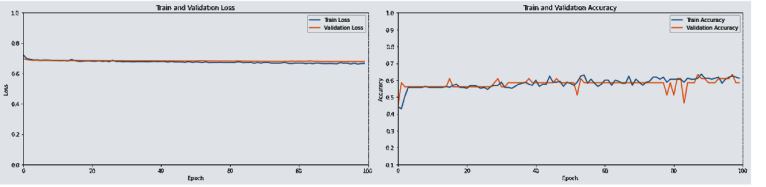
Figure 10. Learning curves for the Warwick-QU dataset (DS_3)



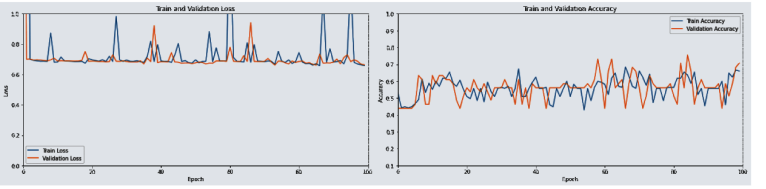
(a) CNN-Adam - DS_3



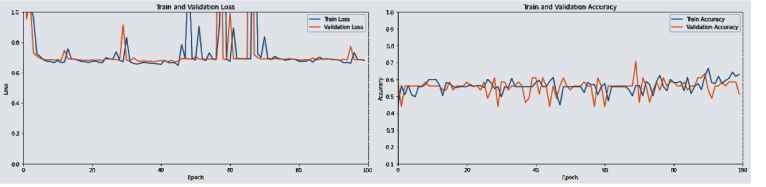
(b) CNN-Adammax - DS_3



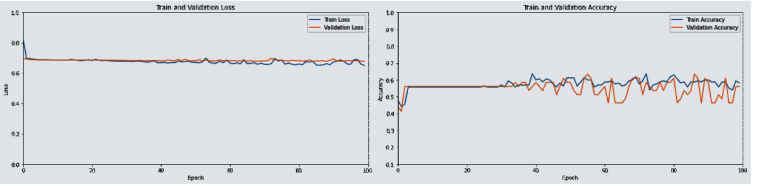
(c) CNN-Adamdelta - DS_3



(d) CNN-RMPros - DS_3

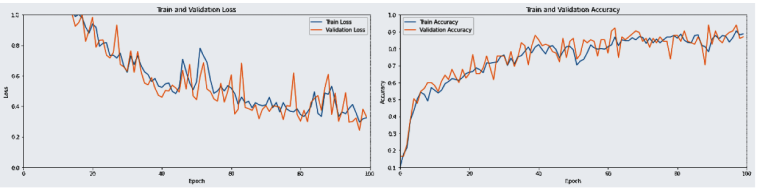


(e) CNN-Nandam - DS_3

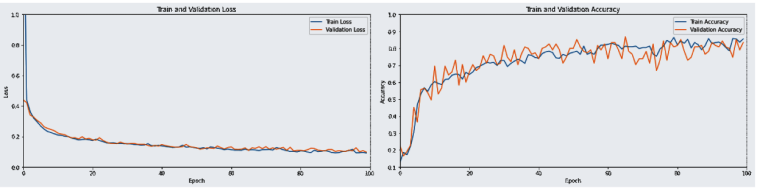


(f) CNN-SGD - DS_3

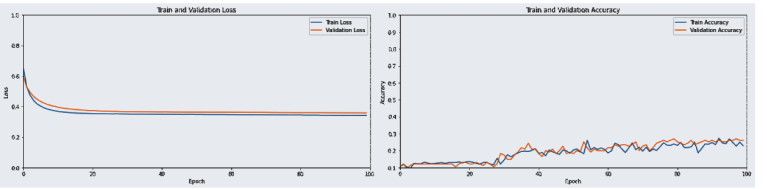
Figure 11. Learning curves for the CRC-VAL-HE-7K dataset (DS_4)



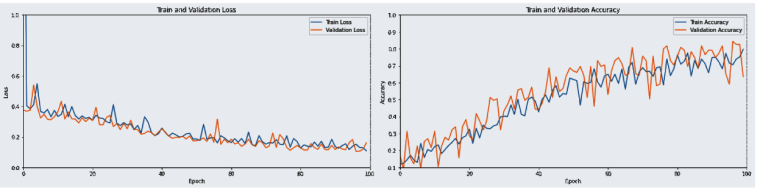
(a) CNN-Adam - DS_4



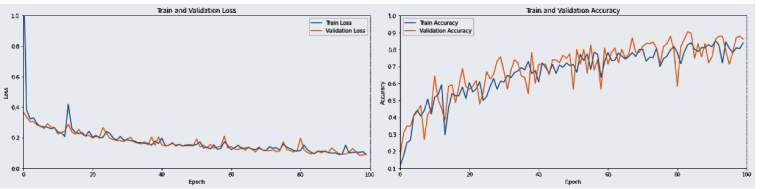
(b) CNN-Adammax - DS_4



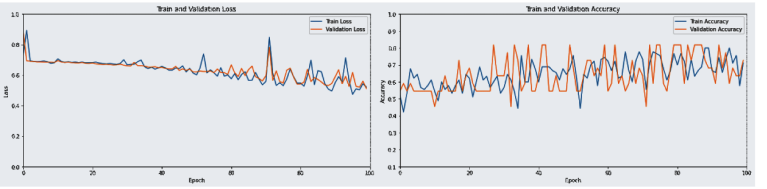
(c) CNN-Adamdelta - DS_4



(d) CNN-RMPros - DS_4



(e) CNN-Nandam - DS_4



(f) CNN-SGD - DS_4

7. CONCLUSION AND FUTURE DIRECTIONS

We presented and analyzed improved DL models for colon cancer detection and segmentation for the colon cancer detection automated system in this research. The classification task and performance measures used in this study are not intended to be used to directly diagnose cancer. The study is more likely to focus on training and evaluating deep learning models to accurately classify various types of abnormal lesions and tissues associated with colorectal cancer. Metrics such as accuracy, precision, recall, and F1 score, which are commonly used to evaluate the performance of deep learning models for classification tasks, may be used as performance measures. These measures, however, do not provide a direct diagnosis of cancer in patients, and additional clinical evaluation would be required to confirm any suspected diagnoses based on the study's findings.

The proposed method ensures early detection of colon cancer. We introduced and studied new deep learning optimizers such as Stochastic Gradient Descent (SGD), Root Mean Square Prop (RMSprop), Adamax, AdaDelta, Adaptive Moment Estimation (Adam), Nesterov, and Adam (Nadam). The models were also tested on 18590 augmented images, and the CNN-Adam technique outperformed all other DL optimizers with an average accuracy of 82% for four colon cancer datasets. Simultaneously, for Dataset 1, we achieved 95%, 77%, and 96% for CNN-adam, CNN-RMSprop, and CNN-Adadelta, respectively. Preliminary results show that the CNN-ADAM model outperformed the existing optimizer's model for detecting colon cancer. The proposed system with DL optimizers may be ideal for screening cases in order to select the best regions for pathologists to focus on when making cancer diagnoses. More colon cancer datasets and external validations with oncologists are needed to establish the diagnostic accuracy of DL models in clinical practice and overcome limitations.

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