Lung And Colon Cancer Classification Using Medical Imaging: With Best Image Pre-Processing Techniques Employing Transfer Learning Approach

BY

Name: Chaity Mondol ID: 232-25-048

This Report Presented in Partial Fulfillment of the Requirements for the Degree of M.sc. of Science in Computer Science and Engineering

Supervised By

Dr. Sheak Rashed Haider Noori
Professor & Head
Department of CSE
Daffodil International University

Co-Supervised By

Abdus Sattar
Assistant Professor & Coordinator M.Sc Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

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APPROVAL

This Project/Thesis titled **"Lung And Colon Cancer Classification Using Medical Imaging: With Best Image Pre-Processing Techniques Employing Transfer Learning"**, submitted by **Chaity Mondol,** ID No: **232-25-048** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of M.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **11-01-2025.**

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Data Scientist
Risk Management Division,
BRAC Bank Limited

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I hereby declare that, this project has been done by me under the supervision of **Dr. Sheak Rashed Haider Noori, Professor & Head,** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

Supervised by:

Dr. Sheak Rashed Haider Noori
Professor & Head
Department of CSE
Daffodil International University

Co-Supervised by:

Abdus Sattar
Assistant Professor & Coordinator M.Sc
Department of CSE
Daffodil International University

Submitted by:

Chaity Mondol
ID: 232-25-048
Department of CSE
Daffodil International University

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ABSTRACT

Early detection and treatment of lung and colon cancer can reduce death rates globally. The most popular, effective, and successful imaging method for detecting lung and colon cancer at the moment is transfer learning. The goal of this research is to determine which of the following 10 CNN architectures—VGG19, MobileNet, InceptionV3, ResNet50, ResNet50V2, ResNet101, MobileNetV2, DenseNet201, VGG16 and Xception—offers the most efficiency in terms of identifying lung and colon cancer while minimizing data loss and finishing time. A matrix for evaluation is used to compare completion time, performance, and data loss. When it comes to accuracy, MobileNet tops the list, followed by VGG19 in second place and VGG16 in third. There are 25,000 photos in the dataset. MobileNet's training accuracy, validation accuracy, and testing accuracy were the highest at 99.90%, 99.88%, and 99.58%, respectively. With 45 seconds each epoch, it has the shortest completion time, 0.332 percent data loss, and the best outcome in the shortest epoch. The suggested approach, which is based on image processing and transfer learning, produces best accuracy, quickest completion time, and the least amount of data loss.

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CHAPTER 1

Introduction

1.1 Introduction

Colorectal cancer is third among related to cancer causes of death for both men and women. Colorectal cancer (CRC) incidence has increased dramatically worldwide in recent years. Colorectal cancer was found in 614,000 women and 746,000 men in 2017 [1], making up 9.2% of all new cancer cases globally. In 2020, there will likely be 0.94 million colorectal cancer (CRC) deaths and 1.93 million new cases; these cases will account for 10% of the global cancer prevalence (or 19.29 million more cases) and 9.4% of all fatalities caused by cancer. An estimated 9.96 million people will die from CRC. The estimated death toll is 419,536 females and 515,637 males. Breast cancer affects 7.79 million people globally, whereas colorectal cancer affects more than 5.25 million people in the last five years [2]. It is estimated that 13 million people would lose their lives to cancer by 2030, a 60% rise over the next 15 years [1, 3]. CRC begins as flat dysplasia or adenomas and progresses to malignancy over time [4]. Stage 0 of colorectal cancer is the earliest stage, according to the American Cancer Society (ACS), and is followed by stages I (1) through IV (4). Early detection has often resulted in reduced spread of cancer. Patients with CRC in its latter stages sometimes have a higher postoperative death rate because the disease has progressed to stage IV or beyond [5]. Even after surgery, the patient fatality rate is significant in the advanced stages of colorectal cancer [6]. Twenty years have passed since the first testimony that colorectal cancer (CRC) screening can reduce mortality [1]. Significant differences exist in CRC survival rates even among wealthy nations. It has been proposed that the significant variation in survival rates across CRCs can be attributed to the fact that they are identified at varying stages of the disease [7]. Recent years have seen a rapid advancement in technology that has an impact on all facets of life, including surgery [8]. The main tools for detecting CRC are endoscopes with varying stiffness, localization capability, and magnification. In addition to increasing treatment options and improving our understanding of the pathophysiology of colorectal cancer, medical local excision, endoscopic resection, radiation therapy, chemotherapy, ablative therapies, and immunotherapy have everything improved the overall persistence of progressive colorectal cancer to three years [9]. Various biological signal types have been predicted using machine learning techniques. Machines can process high-dimensional data, such photos, movies, and multidimensional anatomical scans, thanks to deep learning algorithms. Deep Learning is a type of learning algorithm that is supported by the brain's composition and capacity [10]. Deep learning is part of machine learning and is used in medical image processing and computer vision. Over the previous six years, deep learning has garnered significant attention due to a number of new data sets, a combination of rising processing power and falling hardware costs. Through the ability to extract complex features directly from unprocessed images, deep learning techniques are able to identify and diagnose cancer as well as divide tumors. Using a deep learning technology, physicians may find connections between photos and offer supplementary suggestions. Moreover, it has been shown that a specific deep learning model is useful for both medical operations and CRC diagnosis [11]. ANNs have become well-known in medical image processing because of their ability to enhance pattern detection. There are now a lot of deep learning systems available, but not all of them have been evaluated for how well they can detect colon cancer. These algorithms extract important information from images without human interaction, enabling fully automatic detection and categorization. When the quantity of pictures required to train a Deep CNN system is inadequate, transfer learning can help to improve diagnosis performance. This is especially important when addressing the complex characteristics of colon cancer. In order to solve complex classification problems, systems that use pre-trained weights for transfer learning (TL) have recently attracted the attention of intellectuals.

1.2 Problem Statement

As previously said, time plays a critical role in saving lives regarding colon and lung cancer. The technology and human resources required to provide patients with timely colon cancer monitoring, diagnosis, and treatment services are lacking in many countries. Researchers have proposed many strategies and methods for diagnosis and detection, however these systems often provide false negative and false positive outcomes. This project intends to lessen radiologists' workload and misdiagnosis rates by improving image preprocessing methods and models for early detection and diagnosis of lung and colon cancer. In developing, emerging, and even industrialized nations, the creation of a rapid and affordable technique could save lives. It explains how to use the best image preparation methods and models to obtain a high degree of accuracy for colon cancer.

1.3 Research Objectives

a) The areas where the current deep learning based systems need improvement in order to accurately identify various lung and colon categories within their classes.

b) To improve their class separation accuracy, they should employ a straightforward deep learning-based technique.

1.4 Research Questions

a) How can we identify the limitations of current deep learning-based systems that are used for accurately classifying different types of colon and lung cancer?
b) How can we develop a deep learning-based approach to improve the accuracy of classifying various forms of colon and lung cancer?

1.4 Report Layout

Chapter 1 provides an overview of the study's introduction, objectives, and main research questions. Chapter 2 offers synopses of the related works in brief. Chapter 3 provides a detailed description of the suggested methodology. Chapter 4 describes and analyzes the paper's experimental results. The sustainability plan, societal and environmental effects, and ethical considerations are covered in chapter 5. The current study is concluded in chapter 6, which also lays forth a plan for further research.

CHAPTER 2
Literature Review

2.1 Related works

The algorithms for supervised learning that have been developed over the past three decades are quite capable of processing biology-related data. CNN models with average pooling layers, MobileNetV2, and maximum polling, the study sought to analyze colon cell imaging data for classification purposes and determine the learning rate of a classification accuracy of 99.68 percent for MobileNetV2 with 1.24 percent of data loss, and 97.49 percent and 95.48 percent for the layers of average pooling and maximum polling, respectively [12]. A simplified yet reliable annotation approach and cell identification models can be employed to recognize cells on slides stained with immunohistochemistry using deep learning based on artificial intelligence. This can serve as a basis for evaluating nuclear staining biomarkers. Cells on immunohistochemistrystained slides can be identified using deep learning based on artificial intelligence (AI) as a basis for evaluating nuclear staining biomarkers using cell identification models and a straightforward but reliable annotation method. [13]. Diagnostic images are evaluated by deep learning cell identification approaches using two CNN working series, such as a detection network and a classification network [14]. The analysis of histological images using deep learning and digital image processing techniques aims to identify cancer tissues from the framework with a maximum accuracy of 96.33 percent [15]. The data from Fourier Transform Infrared (FTIR) spectroscopy were used to categorize the verifiability of colon c cancer. Before using SVM and ANN to categorize the signals, they extracted several statistical characteristics or properties from the signals. ANN achieved a 95.71 percent accuracy of classification. Grayscale variance, Grayscale mean, and 16 texture features were among the 18 ordinary characteristics that were extracted using the GrayLevel Co-occurrence Matrix (GLCM) approach. This allowed for the determination of the SVM-based classifier's 96.67 percent accuracy, as well as its 83.33 percent and 89.51 percent F1-score and recall, respectively. Transfer learning architectures are employed to diagnosis and prognosticate colon cancer by utilizing high-level attributes collected from colon biopsy images. For the purpose of training a Bayesian optimum Support Vector Machine classifier, an already trained convolutional neural network (CNN) is used to segregate the picture properties. The pre-trained neural network frameworks Alexnet, VGG-16, and Inception-V3 had the highest accuracy in identifying colon cancer, with detection rates ranging from 96.5 to 99 percent according to the investigation. [16]. Deep learning algorithms are particularly reliable and reproducible for biological picture analysis. When comparing ResNet-18 and ResNet-50 to images of colon glandsIn terms of accuracy, sensitivity, and specificity, ResNet-50 is regularly proven to yield the best results [17]. Using conventional machine learning techniques, Random Forest (RF) and k-nearest neighbor (KNN), the texture feature (local binary pattern, or LBP) and the shape feature (histogram-oriented gradient) were retrieved for comparison. The trial showed that CNN surpassed RF (85%) and KNN (83%) in terms of accuracy for colon segmentation, and CNN's polyp identification accuracy (88%) is greater than Random Forest's (85%) and KNN's (80%), respectively [18]. In 2018, Selvanambi et al. proposed a prediction method for lung cancer based on glowworm swarm optimization (GSO) using photos from many sources [30]. The maximum accuracy they achieved was 98% using the Recurrent Neural Network (RNN) as their learning algorithm. Suresh and Mohan presented a method in 2020 that uses nodule areas of interest (ROI) to learn feature patterns. Generative Adversarial Networks (GANs) were utilized to create additional data from the CT scan databases of LIDC and IDRI in order to expand the study. CNN-based classification techniques had the highest classification accuracy of 93.9% [31]. The CNN model serves as the foundation for the lung cancer detection technique developed by Hatuwal et al. They achieve 96.11 percent training accuracy and 97.2 percent validation accuracy using the CNN model [32].

2.2 Scope of the Problem

As previously said, time is of the essence in preventing colon cancer and saving lives. For patients to receive timely monitoring, diagnostic, and treatment services for lung and colon cancer, many countries lack the human resources and technology required. Researchers have suggested a variety of strategies and methods for diagnosis and detection, but these systems often produce false positive and false negative records. In order to decrease radiologists' workload and misdiagnosis rates, this study intends to improve models and image preprocessing techniques for early lung and colon cancer diagnosis and detection. It is possible to save lives in developing, emerging, and even established nations by creating a rapid and affordable technique. How to use the best picture preprocessing methods and models to obtain a high degree of accuracy in detecting colon cancer is explained.

2.3 Challenges

These are some of the scientific challenges that are the focus of this study:

a) **Data Collection:** With regard to medical imaging, actual medical data is crucial, however gathering actual medical data for our investigation presents certain challenges. We used datasets from the open-source online platform Kaggle because of this. Thus, compiling the imaging data from the field of lung and colon cancer was quite laborious.

b) **Raw Image Processing**: This work concentrates on improving the model's accuracy through image processing approaches because the images in the lung and colon cancer datasets contain a lot of noise and artifacts. A deep-learning model is first trained on image processing since pictures are often crowded with noise and artifacts.

c) **Determine Deep Learning Approach**: Various deep learning methods are employed by several researchers to accomplish the objectives with ease. In order to accurately classify various types of lung and colon cancer, the best deep learning technique was used.

d) **Accuracy Improvement:** Enhancing the deep learning model's accuracy and choosing the best model are two more difficult problems.

CHAPTER 3

Materials and Methods

3.1 Working Process

To complete the challenge, there are four phases. These are as follows:

A. Original dataset
B. Image Pre-processing
C. Model selection
D. Result analysis

Figure 1 shows the complete process of working, from images collecting to analysis, which is explained in detail in the parts that follow.

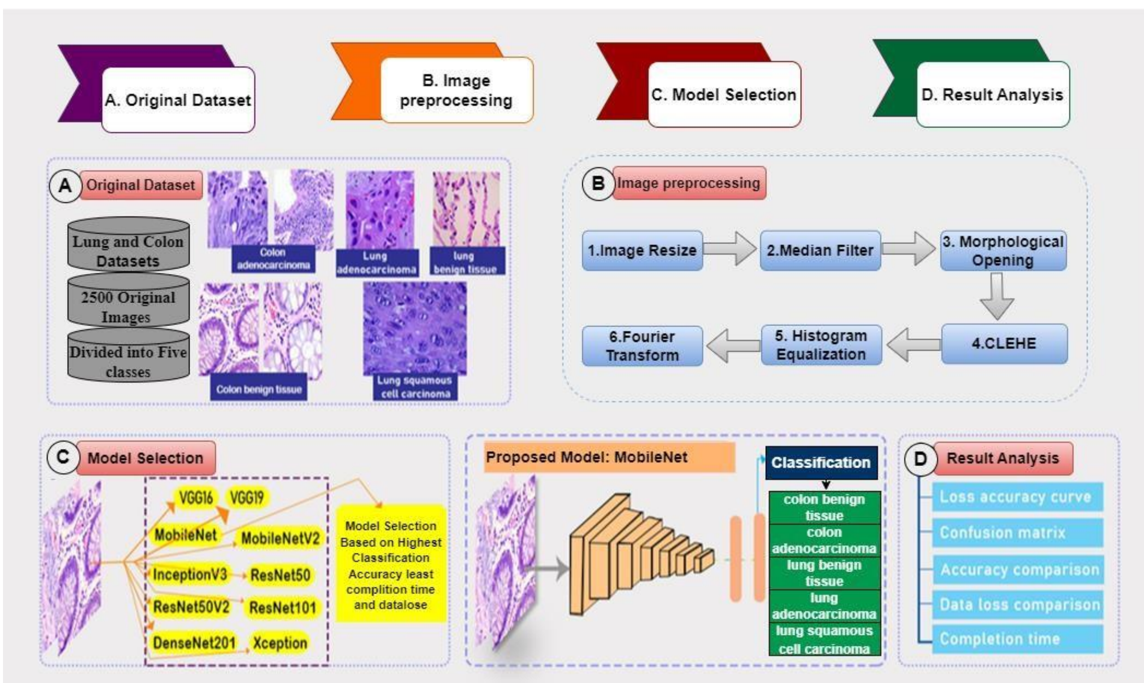

Figure 1. A summary of the complete classification procedure

3.2 Preparing the Dataset

This research analyzes 25,000 histopathological photos from the Kaggle dataset of lung and colon cancer histological images. This collection contains photos of five different categories:
colon_benign_tissue_(c_1), colon_adenocarcinoma_(c_2), lung_benign_tissue_(c_3), lung_adenocarcinoma_(c_4), and lung_squamous_cell_carcinoma_(c_5).
There are 5000 photos in each category [19]. The resolution of each image is 768 × 768 pixels. The most common type of lung and colon cancer is colon adenocarcinoma, which accounts for almost 95% of all cases. It develops when an adenoma, a type of polyp, grows inside the large intestine and eventually develops into cancer. Lung adenocarcinomas, which make up more than 60% of all cases of lung cancer, frequently start in the glandular cells in the lung's outer region before moving on to the alveoli. Lung squamous cell carcinoma, the second most common type of lung cancer, affects the bronchi or airways of the lungs and makes up around 30% of all cases. An overview of the dataset's synopsis is given in Table 1.

Table 1. The dataset's description

Name	Description
Total Number of images	25000
colon_benign_tissue_(c_1)	5000
colon_adenocarcinoma_(c_2)	5000
lung_benign_tissue_(c_3)	5000
lung_adenocarcinoma_(c_4)	5000
lung_squamous_cell_carcinoma_(c_5)	5000

Figure 2 displays some samples from the dataset's several classifications of colon cancer:

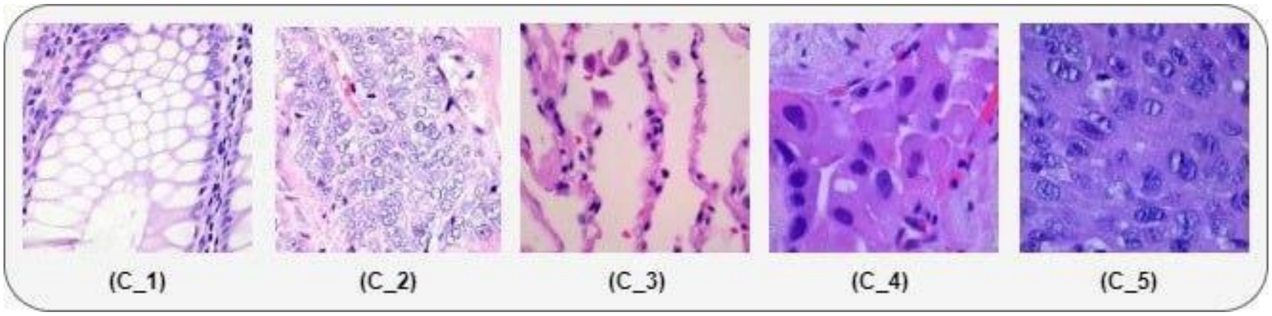

Figure 2. Sample images the datasets

3.3 Image Pre-processing

The goal of this research is to increase the model's accuracy through image processing approaches because the images in the lung and colon cancer datasets contain a lot of noise and artifacts. A deep-learning model is first trained on image processing since images are often crowded with noise and artifacts. The photos are first resized, after which noise is eliminated using a median filter, and artifacts are eliminated using a morphological opening. Following the application of CLAHE to improve image quality, we applied histogram equalization to the CLAHE images to modify their intensity. Finally, we utilize the Fourier transform.

3.3.1. Image resizing

We can decrease an image's size without sacrificing quality by shrinking it. Changing the dimensions of an image frequently causes the file size to grow and the quality to decrease [33]. Our models for transfer learning can train faster with fewer images. It will take longer for our network to learn from eight times as many pixels if the input image's dimension is doubled. Numerous huge and small merged photos can be found in our dataset. In order to achieve the ideal shape of the photos in our dataset, we downsized them from 768 x 768 pixels to 224 x 224 [34].

3.3.2. Median Filter

The edges of the images in our dataset were unclear due to noise. And misclassification may result from that. Thus, a median filter was used. Image and signal noise can be eliminated with a median filter. The median filter's demonstrated ability to preserve edges while lowering noise makes it essential in image processing. We apply a two-dimensional median filter to our dataset [35].

3.3.3. Morphological Opening

The two processes that make up an image's morphological opening—erosive and dilation—share a structuring factor [36]. Opening moves little objects—usually the bright pixels—out of the forefront and into the background of an image. After applying the median filter, we employed morphological opening on our dataset of images. "Opening" refers to the dilatation in mathematical morphology, when a structuring element B destroys a set A,

$$A \circ B = (A \ominus B) \oplus B \tag{1}$$

Where $\oplus$ and $\ominus$ represents erosion and dilatation, respectively.

3.3.4. CLAHE

In image processing, the adaptive histogram equalization method known as CLAHE (Contrast Limited Adaptive Histogram Equalization) is used to enhance image contrast. A sophisticated variation of the classic histogram equalization method, it applies histogram equalization to each individual tile after splitting an image into tiny, non-overlapping tiles. Ragab et al. [26] examined the two methods and explained why they chose CLAHE instead of AHE. In order to improve the quality of complex structures in medical imaging, CLAHE was developed [27].CLAHE's local contrast enhancement improves the readability of medical imaging [28]. This paper's author gives a concise explanation of mathematical equations and the CLAHE formula [29]. This is done to make an image appear more natural and to lessen the amount of noise in it. In terms of mathematics, CLAHE operates by converting the intensity value at a certain pixel location x, represented by I(x), as follows:

$$I'(s) = (I(s) - \min(I)) * (L-1)/(\max(I) - \min(I) + 0.5 \quad (2)$$

where the number of intensity levels is L, and the minimum and maximum values of the image's intensity values are denoted by min(I) accordingly. Through this alteration, the image's histogram is effectively stretched to encompass its whole dynamic range. In [29], the CLAHE algorithm is also described in detail.

3.3.5. Histogram Equalization

Histogram equalization is a method of altering image intensities to improve contrast. After applying CLAHE, we adjusted the photos' intensity by applying histogram equalization. An overview of the mathematical formulas and equations used in the CLAHE is provided below [37]. Let us consider an image that is represented as a by matrix and contains integer pixel intensities that range from 0 to L − 1. L, which is often 256, is the total number of possible intensity values. For every possible intensity, there is a bin. Let p be the normalized histogram of so,

$$p_n = \frac{Amount\ of\ pixel\ with\ intensity\ n}{total\ amount\ of\ pixels} \quad n = 0,1, \dots \dots, l-1 \quad (3)$$

In order to define this histogram-equalized image g,

$$g_{ij} = floor\ ((L-1) \sum_{n=0}^{f_{ij}} p_n \quad (4)$$

3.3.6. Fourier transform

In image processing, the Fourier transform is a potent technique for obtaining valuable information from an image. By contrasting an image in the spatial domain with one in the Fourier domain, Fourier domain images are produced [38, 39]. It is employed to examine an image's frequency content and can highlight characteristics that the human eye is unable to see. A mathematical expression for an image's Fourier transform is as follows:

$$F(u,v) = \int\int f(x,y)\, e^{2\pi i}\,(ux + vy)dxdy \quad (5)$$

Where F (u,v) is the Fourier transform of the image f(x,y) at the frequency (u,v). The image's spatial coordinates are indicated by the variables x and y, while its frequency coordinates are shown by the variables u and v. A complex number is the outcome of calculating the integral over the whole image. The strength of the frequency at that location in the image is indicated by the complex number's magnitude. Features like edges, lines, and forms can be extracted from a picture using the Fourier transform. Additionally, it can be applied to reduce noise, compress, and enhance contrast in images.

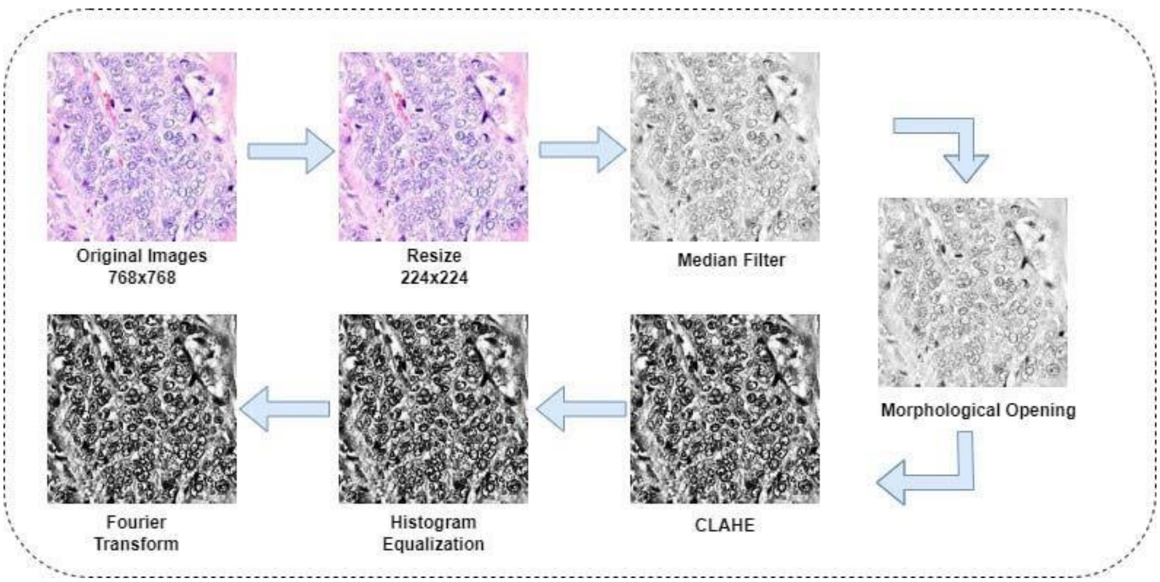

Figure 3. Image processing step by step

3.4 CNN Transfer Learning Development

Convolutional neural networks (CNNs), a subclass of neural networks that may be used to identify objects from images, have gained a lot of popularity recently due to their exceptional performance [20, 21]. The layers that make up a standard CNN design include convolution, pooling, normalizing, and fully connected layers. Convolution, pooling, and normalization layers are inserted one after the other to construct the network. High-level features are produced by combining convolution and pooling techniques, and these are subsequently used for classification. The classification is done at the fully linked layer of the CNN architecture. The CNN architecture has a large number of parameters that must be adjusted during training. CNN training usually use the conventional back propagation technique. Additional layers can be employed for models that get more complex. Examples of a typical CNN are shown in Figure 4 and [22] [40].

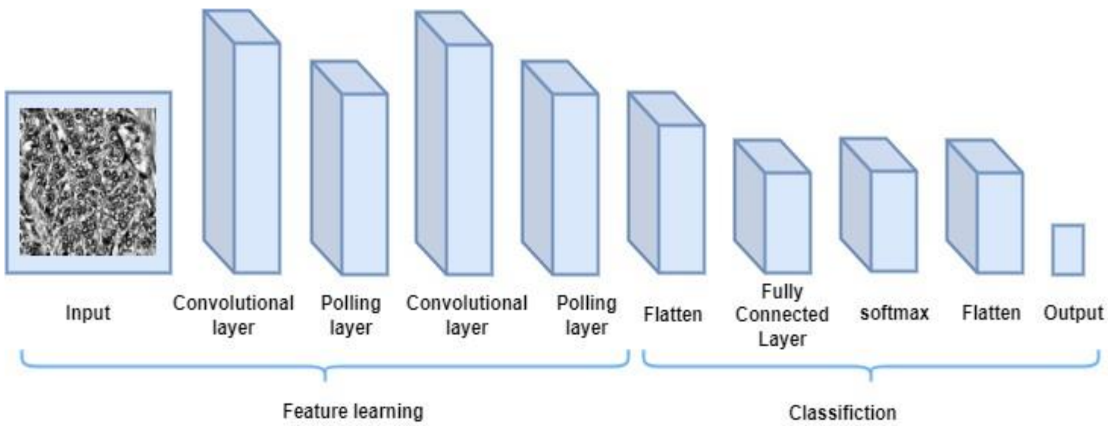

Figure 4. The typical CNN model structures

3.5 Transfer Learning Model Selection

The deep learning technique called "transfer learning" is used to create and train models for particular activities before applying them to another closely related task. It depicts a situation where optimization in one context is improved by using lessons learnt in another [23]. In situations when the new dataset is less than the original dataset used to train the pre-trained model, transfer learning is commonly utilized [24]. Ten transfer learning models are the focus of this study; mobilenet provides the best accuracy, while the other models provide standard accuracy.

3.5.1. VGG16

In their 2014 study "Very Deep Convolutional Networks for Large-Scale Image Recognition," K. Simonyan and A. Zisserman of the University of Oxford proposed the VGG16 convolutional neural network model. VGG16 is a deep convolutional neural network model that can both recognize and classify objects in an image. It is made up of 16 convolutional layers [41]. An input is an image, and an output that informs the model on the objects in the image is produced by a series of convolutional, pooling, and fully connected layers. Applications including automatic picture captioning, object identification and segmentation, and image classification have made extensive use of VGG16. Additionally, it has been utilized in transfer learning to initialize other neural networks' weights. Among the most accurate models for picture identification that are now on the market is VGG16. A common baseline model for new image recognition tasks, It received a 7.3% error rating in the top five for the ImageNet challenge.

3.5.2. VGG19

In 2014, Andrew Zisserman and Karen Simonyan created the convolutional neural network VGG19. It was the 19th network in the Visual Geometry Group (VGG) network family hierarchy. For image identification and classification applications, the 19-layer network VGG19 is widely utilized [42]. A powerful yet straightforward architecture, VGG19 may be used to a number of computer vision problems. VGG19 is made up of three fully linked layers and five convolutional blocks. Multiple convolutional layers with batch normalization, pooling, and non-linear activation functions make up the convolutional blocks. Max-pooling layer with stride of 2 comes after each convolutional block. There are 4096, 4096, and 1000 neurons in each of the three fully connected levels. A 1000dimensional vector that represents an image's projected class is the VGG19 network's output.

3.5.3. InceptionV3

A new InceptionV3 design modifies previous Inception designs to lower the required processing power. Regularizing, lowering the dimension, factoring convolutions, and parallelizing calculations can all help to lower the computational cost. InceptionV3 [43] has various notable improvements over previous Inception models, including factorized

7x7 convolutional layers and label smoothing, as well as the use of an auxiliary classifier to transport label information throughout the network.

3.5.4. Xception

An employee of Google named Francois Chollet introduced this network. With two convolutional blocks and ReLU activation in the convolutional layer, Xception is typically categorized as the "extreme" version of an Inception module. The deep convolutional neural network design Xception [44], which has 71 layers, only employs depthwise separable convolution layers.

3.5.5. ResNet50V2

ResNet50V2, an improved version of ResNet50 that outperforms ResNet50, introduced a change to the way the relationships between blocks are formulated for distribution [45]. Images can be classified into many item categories using ResNet50V2.

3.5.6 ResNet101

ResNet-101[46] has over 44.5 million trainable parameters and 101 layers. The pre-trained network detects objects in photos with efficiency. This has resulted in the architecture gaining extensive feature representations for numerous images. 224x224 photos are the only ones that the architecture can recognize.

3.5.7. ResNet50

Convolution filters of different sizes and shapes are combined in the ResNet50 architecture to solve the CNN models' degradation problem and reduce the training time brought on by deep structures. The ResNet50 [47] has 48 convolutional layers, an average pool layer, a maxpool layer, and about 23 million trainable parameters.

3.5.8. MobileNet

Convolutional neural networks (CNNs) of the mobilenet kind are made to function well on portable devices with constrained processing resources. It was created by Google and was the first mobile application to use it [48]. The primary objective of MobileNet is to minimize the network's size without sacrificing accuracy. This is accomplished through the use of depth wise separable convolutions, which basically lower the quantity of parameters and calculations that a network needs to perform. MobileNet can be applied to a number of tasks, including semantic segmentation, object detection, and image classification. It may also be used on a wide range of platforms, such as embedded devices and mobile phones, and is reasonably simple to teach.

3.5.9. MobileNetV2

In 2018, Google developed the architecture for convolutional neural networks known as MobileNetV2 [49]. Compared to its predecessor, MobileNetV1, it is a more accurate network that is lightweight and optimized for mobile devices. The 'inverted residual blocks' are a new class of residual blocks introduced by MobileNetV2 that are intended to facilitate computing on mobile devices. In order to decrease computation time and increase model correctness, these blocks combine depthwise and pointwise convolution strategies. Additionally, MobileNetV2 employs a depth multiplier to regulate the number of parameters in the model and batch normalization layers to lessen overfitting. The end product is an accurate and lightweight model that can be used for tasks like image categorization and object recognition.

3.5.10. DenseNet201

DenseNet201 consists of a sequence of transition layers and dense blocks. A transition layer connects each dense block, which has many convolutional layers. The output from the dense block has its spatial dimension reduced by the transition layer. Next, the dense block's output is sent to the next dense block. Complex traits and patterns can be captured by the model because to its architecture. Comparing DenseNet201 to other image recognition architectures like ResNet and InceptionNet, there are a number of benefits. It is easier to train and more efficient because to it’s substantially smaller number of parameters. Plus, it is less likely to overfit and has a faster inference time.

3.6 Developing MobileNet Model

In the present study, we develop a convolutional neural network (CNN) model based on MobileNet for autonomous identification of malignancy in histopathology (HP) photos of breast tissues.

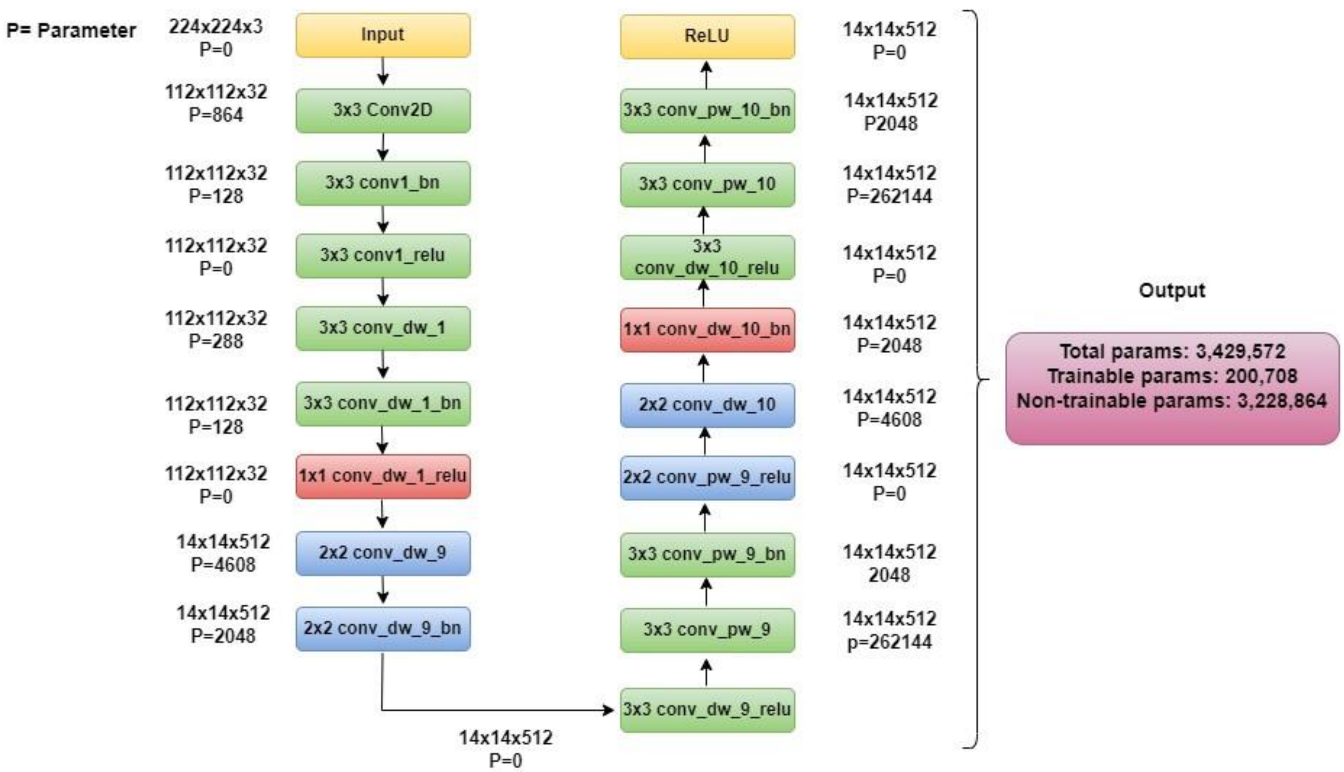

Figure 5. The architecture of MobileNet with parameters.

Since the MobileNet model is low-latency and lightweight and has shown encouraging results in some earlier tests, we adopted it in this work. The essay's remaining sections are organized as follows: We begin by providing a brief overview of the papers that have been published. We next sketch the model, explain the methodology, and discuss the model's performance in post-training classification of test dataset histopathological images. MobileNet is designed to effectively optimize accuracy while taking into consideration the limited resources of an on-device or embedded application. Low-latency and low-power MobileNet models can be adapted to the constrained resources of computing devices [25]. Similar to the large-scale models, MobileNet may be applied to tasks including segmentation, embedding, detection, and classification. MobileNet solely employs separable filters, which mix depth-wise and point-wise convolution. To reduce the computational expenses related to conventional convolution processes, it employs 1 x 1 filters. This lowers the network's size and computational complexity, as shown in Fig. 10. The ImageNet classification of MobileNet-224 has almost 5 million characteristics. Additionally, 224 x 224 x 3 is the required input size for MobileNet. The number of filters can vary from 32 to 1024, as illustrated in Fig. 5.

CHAPTER 4

Experimental Results and Discussion

4.1 Results and Discussion

The characteristics of true-negative (TN), true-positive (TP), false-negative (FN) and falsepositive (FP) are used in a confusion matrix to assess the study's performance. Colon and lung cancer classified by the models is represented by true-positive (TP) results. Models that are not classified as colon cancer are called true-negative (TN), non-colon cancer that the models have identified as lung and colon cancer is called false-positive (FP), and lung and colon cancer that the models have classified as non-colon cancer is called falsenegative (FN). Check for validity using measures like f1-score, recall, accuracy, specificity, and precision. These performance metrics' mathematical formulations are as follows:

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

$$Accuracy = \frac{TP+TN}{FP+TN+FN+TP} \quad (7)$$

$$Precision = \frac{TP}{TP+FP} \quad (8)$$

$$F1 - score = 2(\frac{Precision \times Recall}{Precision+Recall}) \quad (9)$$

This study's suggested CNN-based transfer learning (TL) model is used to classify and identify colon cancer. Twenty-five thousand colon cancer photos are preprocessed before being utilized for classification in order to get the best results. The ten CNN transfer learning models MobileNet, MobileNetV2, VGG16, VGG19, InceptionV3, ResNet50, DenseNet201, Xception, ResNet50V2 and ResNet101 used in this study are the best at detecting lung and colon cancer with the least amount of data loss and completion time. With the lowest calculation time and the highest accuracy of 98.58%, MobileNet exceeds all 10 of these models in the most successful colon cancer identification. Together with additional performance indicators, Table 2 shows the accuracy attained by the 10 transfer learning models.

Table 2. Accuracy table of models

Model	Accuracy	F1-score	Precision	Recall	Specificity
MobileNet	99.68	98.21	97.06	96.65	95.86
VGG16	97.3	96.46	91.95	90.07	93.03
VGG19	97.72	97.02	96.11	96.04	94.03
MobileNetV2	97.54	96.25	97.5	96.08	94.02
ResNet50	95.02	95.02	95.67	94.22	91.25
ResNet101	95.78	95.40	95.69	95.84	94.55
ResNet50V2	96.7	96.3	93.27	94.35	93.66
Xception	94.77	95.66	94.65	95.56	92.56
InceptionV3	94.70	94.02	94.75	93.96	95.56
DenseNet201	96.25	93.73	94.86	95.87	93.48

Figure 6 displays a confusion matrix for the proposed MobileNet architecture since it produces the best accuracy.

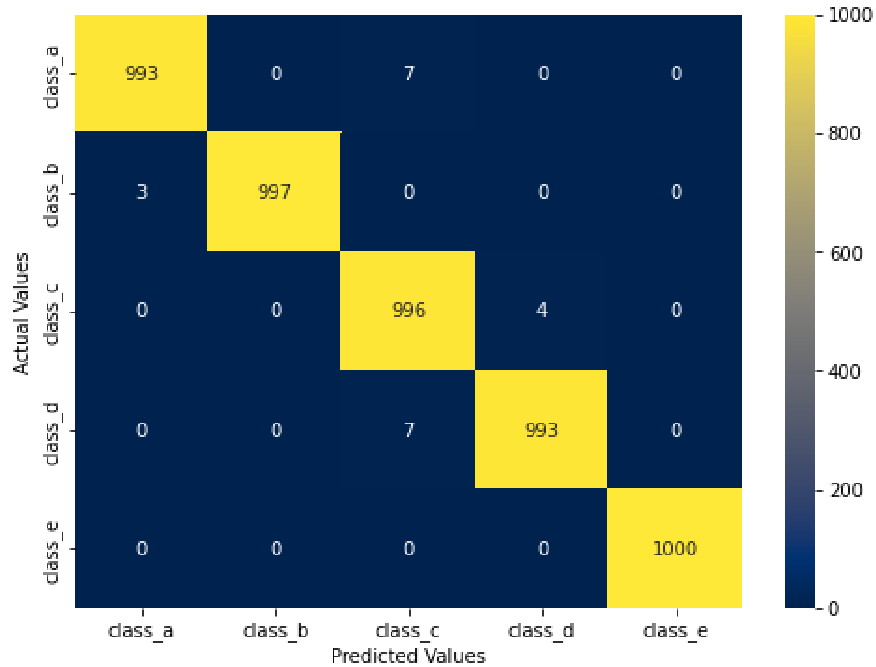

Figure 6. Confusion matrix for the intended Mobilenet architecture

In a confusion matrix of Figure 6, the column numbers indicate the anticipated scores that the Mobilenet network delivered, while the row values indicate the genuine labels. In the confusion matrix, the values that the models accurately predicted are positioned diagonally. It is evident from the confusion matrix values that the model works best for class_e, or lung squamous cell carcinoma, with a prediction rate of 0 misclassifications. With misclassifications cases as low as 7, 3, 4, and 7 for classes A, B, C, and D, respectively, the classification performance for the remaining four classes is encouraging. The model can be regarded as robust across all classes because it was developed with few misclassification cases.

Table 3. The accuracy of the suggested Mobilenet model is based on class

Class	Test accuracy
c_1	99.45%
c_2	99.32%
c_3	99.85%
c_4	99.52%
c_5	99.68%
Overall accuracy	99.58%

Table 3 illustrates that each class achieves a good level of accuracy. It suggests that there is no class bias in the suggested MobileNet model. All of these excellent accuracies for each class support the model's resilience. Figure 7 shows the accuracy and the loss curves so that we can confirm the model's overfitting problem.

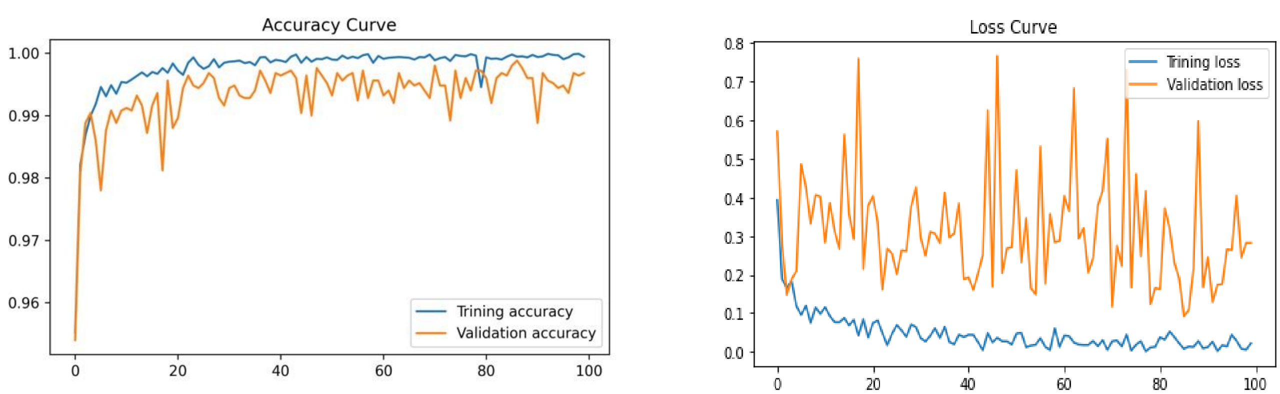

Figure 7. The Accuracy curve and the loss curve

The accuracy curve pattern confirms that there was no overfitting during network training because there is only a very little gap between the training and validation curves, which are both seen to be well converging. There is a tiny space between the accuracy curves and a steady decline in the loss curves over the epochs. During the training phase, no overfitting is noticed.

CHAPTER 5

Impact On Society, Environment And Sustainability

5.1 Impact on society

The benefits of deep learning to the prediction of lung and colon cancer has enormous potential for social impact, particularly in the healthcare industry. By offering a prompt and accurate diagnosis, it can significantly reduce the time between initial suspicion and the start of therapy, improving patient outcomes. Particularly in underprivileged regions with little specialized expertise, the technology offers the ability to democratize access to expert-level medical diagnostics. Additionally, by reducing the need for numerous diagnostic tests and avoiding unnecessary procedures, deep learning systems can help with cost control. By tailoring treatment plans to specific patient profiles, these technologies can also support customized medicine as they are incorporated more and more into clinical practice. This could result in improved lung and colon management as well as higher life rates.

5.2 Impact on the environment

A substantial impact on the environment may arise from the massive computer resources required for training and inference of deep learning models, especially those used in medical imaging. However, the environmental effect may be minimized by optimizing algorithms for efficiency, utilizing renewable energy sources for data centers, and developing models that can be trained using less computing power or data. Reliable remote diagnostics can also help to offset some of the environmental costs by reducing the need for physical diagnostic equipment and supplies and perhaps reducing patient travel.

5.3 Ethical Aspects

The use of deep learning to forecast lung and colon presents ethical questions about algorithm reliability, data security, and patient privacy. Ensuring patient data security and confidentiality is crucial, as is the openness of the algorithms used for diagnosis and their decision-making procedures. Eliminating biases in datasets that may contribute to differences in the effectiveness of technologies across various groups is also morally required. Maintaining patient trust and upholding ethical norms require robust, interpretable mechanisms that may be contested or corrected as necessary.

5.4 Sustainability Plan

Algorithms must be continuously reviewed and improved as part of a long-term plan for deep learning applications in lung and colon prediction in order to prevent obsolescence and guarantee their continued innovation. To utilize these technology effectively and morally, healthcare professionals must get training. Furthermore, environmental issues will be resolved if renewable energy sources are used to power these systems' computing requirements. The development of a sustainable ecosystem that benefits all parties and guarantees that deep learning advancements may be facilitated by establishing partnerships with stakeholders from a variety of healthcare sectors, including hospitals, insurance providers, and patient advocacy groups.

CHAPTER 6

Conclusion and Future Work

6.1 Conclusion

Models of transfer learning improve the performance of lung colon cancer detection. According to this study, a model effort has been developed to classify and diagnose colon cancer from colon photos into five groups. Ten deep learning models that could be employed for automatic colon cancer diagnosis were presented in this study. In contrast, the MobileNet model performed better than the others in terms of average calculation time, data loss, and test accuracy. VGG19 has the lowest rate of data loss; nevertheless, it is less accurate and takes longer to complete than MobileNet. Eventually, a hybrid transfer learning (TL) method will be able to assess and analyze a lot of photos while figuring out how much of the colon volume is contaminated.

6.2 Future Work

A more robust and precise model will be created to improve the accuracy of the framework for identifying lung and colon cancer. In addition to protecting people from dangerous effects, the application will significantly aid in the convenient location of lung and colon cancer.

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