LUNG AND COLON CANCER CLASSIFICATION USING MEDICAL IMAGING THROUGH TRANSFER LEARNING

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled **"Lung and Colon Cancer Classification Using Medical Imaging Through Transfer Learning,"** submitted by Kayes Uddin Fahim, ID No:191-15-2764 and Chaity Mondol, ID No:191-15-2688 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 B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 01 February 2023.

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ABSTRACT

Carcinomas of the lung and colon are among the most common sources of invasive cancer and are the two most common causes of cancer deaths in worldwide. Detecting and treating cancer at an initial stage can diminish death rates worldwide. At present, transfer learning is the very extensively used, compelling and successful imaging approach for the recognition of lung and colon cancer. As part of this study, 10 CNN architectures are analyzed to find ascertain which model provides the best performance for detecting colon and lung cancer with the minimum amount of data loss and completion time: VGG16, VGG19, MobileNet, MobileNetV2, InceptionV3, ResNet50, ResNet50V2, ResNet101, DenseNet201 and Xception. Performance, data loss, and completion time are compared using an evaluation matrix. MobileNet performs with the highest accuracy, VGG19 performs with the second-highest accuracy, and VGG16 performs with third highest accuracy. The dataset contains 25,000 images. MobileNet achieved the best 99.90% training accuracy, 99.88% validation accuracy, and 99.58% test accuracy. It takes the lowest completion time, 45 seconds per epoch, with 0.3323 % of data loss and gives the highest result with the least epoch. Based on image processing and transfer learning, the recommended method yields the highest accuracy, the least completion time, and the least data loss.

TABLE OF CONTENTS

CONTENTS
Page

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Introduction

Colorectal cancer is the third prominent origin of cancer-related fatality in males and females. In current years, the occurrence of colorectal cancer (CRC) has risen at a shocking rate all over the world. In 2017, 614,000 women and 746,000 men were identified with colorectal cancer, which accounts for 9.2% of all latest cancer instances worldwide [1]. According to estimates, 1.93 million new instances of CRC will be detected in 2020, with 0.94 million fatalities, reporting for 10% of the worldwide cancer prevalence (for an aggregate of 19.29 million additional instances) and 9.4% of all cancer-related fatalities. There will be an overall 9.96 million fatalities due to CRC. Approximately 515,637 males and 419,536 females are expected to die. CRC has affected more than 5.25 million individuals worldwide in the past five years, only a little less than breast cancer, which impacts 7.79 million people [2]. Approximately 13 million people are projected to die from cancer by 2030, an increase of 60% in the next 15 years [1][3]. CRC derives as adenomas or flat dysplasia and develops into cancer across the span of a period [4]. The American Cancer Society (ACS) defines stage 0 as the earliest stage of colorectal cancer, followed by stages I (1) through IV (4). Cancer has generally spread less when it has been detected earlier. In the late phases of CRC, patients frequently endure a superior mortality rate after surgery since the cancer has advanced further or a lot, such as stage IV [5]. The mortality of the patients are high in late stages of CRC even after surgery [6]. The initial testimony that colorectal cancer (CRC) screening can decrease mortality was presented 20 years ago [1]. CRC survival rates differ significantly even in developed countries. It has been suggested that CRCs have a substantial disparity in survival rates because they are diagnosed at different clinical stages [7]. In recent years, technology has advanced at a breakneck pace, affecting every aspect of life, including surgery [8]. CRC is primarily detected with endoscopes with magnification, localization capabilities, and variable stiffness. Medical local excision, endoscopic resection, radiation therapy, ablative therapies, chemotherapy, and immunotherapy have all contributed to a better understanding of the pathophysiology of CRC and expanding treatment possibilities, with endoscopic resection, local clinical excision, targeted therapy, radiation therapy, ablative therapies, chemotherapy, and immunotherapy, all of which have improved total survival of progressive CRC to three years [9]. Machine learning methods have been utilized to predict different types of biological signals. Deep learning systems enable machines to procedure high-dimensional data for example images, multidimensional anatomy images, and videos. A learning algorithm encouraged through the shape and brain function is known as Deep Learning [10]. Computer vision and medical image processing use deep learning, a part of machine learning. Over the last six years, deep learning has achieved high attention for a combination of an increase in computing power and lower hardware prices, as well as a large number of new data sets. Since deep learning procedures can isolate sophisticated attributes straight from raw pictures, they effectively detect and diagnose cancer and segment tumors. A deep learning technique can help doctors provide secondary ideas and identify connections between images. Moreover, a particular deep learning model has been demonstrated to be helpful in diagnosing CRC as well as medical procedures [11]. In medical image processing, ANNs have gained prominence due to their success in improving pattern recognition abilities. Many Deep Learning system exist currently, however not all have been appraised for their efficiency in identifying colon cancer. Fully automated detection and classification are made possible by these algorithms, which extract critical features from images without the need for human intervention. Transfer learning (TL) can assist in improving diagnosis performance while the amount of images needed to train a Deep CNN system is insufficient or not sufficient. This is particularly relevant when dealing with colon cancer's complicated features. Recently, intellectuals have come to be interested in fine-tuning transfer learning (TL) systems with pre-trained weights for performing complex classification tasks.

1.2 Problem Statement

As was explained previously, when it comes to lung and colon cancer, time is a crucial component in protecting lives. Many nations lack the technology and human resources necessary for patients to receive prompt colon cancer monitoring, diagnosis, and treatment services. Numerous tactics and approaches for detection and diagnosis have been proposed by researchers; nevertheless, these systems frequently provide false positive and false negative results. By improving models and image preprocessing methods for early colon cancer diagnosis and detection, this study aims to reduce radiologists' workload and misdiagnosis rates. The development of a quick and inexpensive method could save lives in underdeveloped, rising, and even advanced countries. It is described how to get good accuracy of colon cancer using best image preprocessing techniques and models.

1.3 Research Objectives

a) To investigate research gaps of the existing deep learning-based systems to correctly classify different categories of lung and colon in their classes.
b) To apply a straightforward deep learning-based approach for improving the accuracy for classifying the cancer.

1.4 Research Questions

a) How can we investigate the gaps of the existing deep learning based systems that can correctly classify different categories of lung and colon cancer?
b) How can we develop a deep learning based approach for improving the accuracy of differentiating different kinds of lung and colon cancer correctly in their class?

CHAPTER 2

LITERATURE REVIEW

2.1 Related Works

The last three decades have seen several algorithms for supervising learning developed, and they are reasonably competent at handling biological data. Utilizing CNN models with max polling, MobileNetV2 and average pooling layers aimed to analyze imaging data of colon cells like classification and to figure out the learning rate of a classification accuracy 97.49% and 95.48 % for the max polling and average pooling layers respectively and 99.67% for MobileNetV2 with 1.24% of data loss [12]. Artificial intelligence based deep learning can be used to identify cells in immunohistochemistry-stained slides as a foundation for measuring nuclear staining biomarkers through a streamlined but robust annotation process and cell identification models. Artificial intelligence (AI)-based deep learning can be used to identify cells in immunohistochemistry-stained slides as a foundation for measuring nuclear staining biomarkers through a simplified but robust annotation process and cell identification models. [13] .To analyze diagnostic images using deep-learning cell identification algorithms with two CNN working series like a detection network and a classification network [14]. Techniques for Deep Learning and Digital Image Processing utilized to analyze histopathological images aimed for classification framework and maximum 96.33% accuracy for identifying cancer tissues from the framework [15]. The verifiability of colon cancer was classified using Fourier Transform Infrared (FTIR) spectroscopy signals. Before categorizing the signals with SVM and ANN, they collected numerous statistical features or characteristics from the signals. ANN had a classification accuracy of 95.71%. Extracted eighteen ordinary characteristics by using the Gray-Level Cooccurrence Matrix (GLCM) approach including, grayscale variance, grayscale mean, and 16 texture features to figure out the 96.67% accuracy of SVM based classifier and 83.33% and 89.51% respectively F1-score and recall. To diagnose and prognosis colon cancer based on high-level characteristics extracted from colon biopsy images, transfer learning architectures are utilized. The image characteristics are separated using a pre-trained convolutional neural network (CNN), which is then employed to train a Bayesian optimal Support Vector Machine classifier. Based on the analysis, Alexnet, VGG-16, and Inception-V3 pre-trained neural networks framework had the highest accuracy for colon cancer detection, which is 96.5 to 99%. [16]. For biological image analysis, a deep learning algorithm offers very dependable and repeatable results. Use ResNet-18 and ResNet-50 on colon glands images and figure out that ResNet-50 gives the most consistent results in terms of accuracy, sensitivity, and specificity when evaluated to ResNet-18[17]. For comparison, the texture feature - Local binary pattern (LBP) and shape feature - Histogram oriented gradient were extracted using traditional machine learning approaches - Random Forest (RF) and k-nearest neighbor (KNN) by removing texture feature - Local binary pattern (LBP) and shape feature - Histogram oriented gradient (HOG) and the accuracy of the suggested technique for colon segmentation using CNN (87 percent) outperformed RF 85% and KNN in the trial 83%, CNN's polyp identification accuracy (88%) is higher than that of Random Forest (85%) and KNN (80%)[18]. Using images from various sources, Selvanambi et al. proposed a glowworm swarm optimization (GSO)-based lung cancer prediction approach in 2018 [30]. Their learning algorithm was the Recurrent Neural Network (RNN), and they attained a maximum accuracy of 98%. In 2020, Suresh and Mohan introduced an algorithm that learns feature patterns from nodule areas of interest (ROI). To expand the study, they used Generative Adversarial Networks (GANs) to generate more data from IDRI's and LIDC's CT scan databases. Maximum classification accuracy of 93.9% was achieved by CNN-based classification methods [31]. Hatuwal et al. build up a Lung cancer detection method established on the CNN model. Employing the CNN model, they obtain training and validation accuracy of 96.11 and 97.2% [32].

2.2 Scope of The Problem

As was explained previously, when it comes to colon cancer, time is a crucial component in protecting lives. Many nations lack the technology and human resources necessary for patients to receive prompt colon cancer monitoring, diagnosis, and treatment services. Numerous tactics and approaches for detection and diagnosis have been proposed by researchers; nevertheless, these systems frequently provide false positive and false negative results. By improving models and image preprocessing methods for early colon cancer diagnosis and detection, this study aims to reduce radiologists' workload and misdiagnosis rates. The development of a quick and inexpensive method could save lives in underdeveloped, rising, and even advanced countries. It is described how to get good accuracy of colon cancer using best image preprocessing techniques and models.

2.3 Challenges

There are some research challenges focused on this study which are following:

a) **Data Collection:** In medical imaging real medical data is important but in our study we face some difficulties to collect real medical data. For this reason, we took datasets from online open source platform Kaggle. Therefore, it was very arduous work to accumulate the image data from the lung and colon cancer’s field.

b) **Raw Image Processing**: There is a lot of noise and artefacts in lung and colon cancer dataset images, so this study focuses on improving the model's accuracy through image processing techniques. Because images are usually filled with noise and artefacts, image processing is the first step in training a deep-learning model.

c) **Select deep learning Approach**: Several researchers use different deep learning techniques to complete the tasks effortlessly. So, the selection of optimum deep learning technique which can correctly classify different categories of lung and colon cancer.

d) **Accuracy Improvement:** Another challenging issue is to improve the accuracy of the deep learning model as well as selecting the optimum model.

CHAPTER 3
MATERIALS AND METHODS

3.1 Working Process

There are four different stages to accomplish the entire work. These are the following: a)

Original dataset

b) Image Pre-processing
c) Model selection
d) Result analysis

The total working process starting from image collection to result in the analysis is presented in figure 1 and explains elaborately in the following sections.

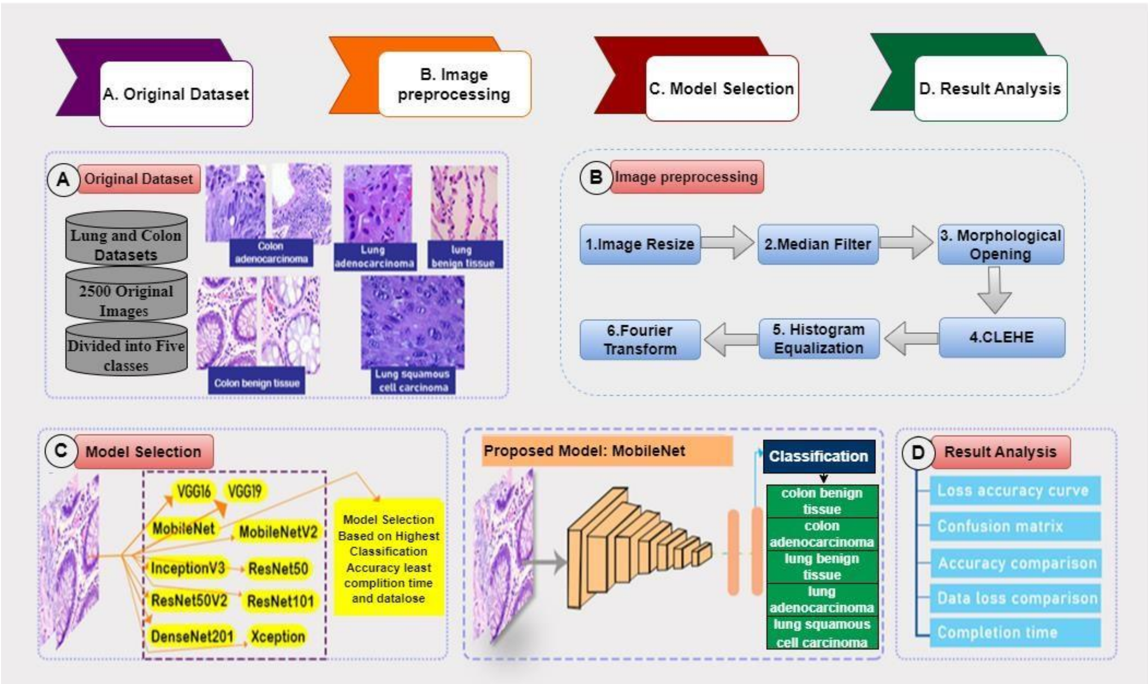

Figure 3.1.1: An overview of the entire classification process

3.2 Dataset Preparation

In this study, 25000 histopathological images from the Kaggle Lung and Colon Cancer Histopathological Images dataset are analyzed [19]. There are five types of images in this dataset. Each class image has a resolution of 768 X 768 pixels.

A total of 750 images of lung tissue (250 benign lung tissue, 250 lung adenocarcinomas, and 250 lung squamous cell carcinomas) and 500 images of colon tissue (250 benign colon tissue, 250 colon adenocarcinomas) were generated from an original sample of HIPAA compliant and validated sources and augmented to 25,000 using the Augmentor package. Colon adenocarcinoma, which makes up more than 95% of all incidences of colon cancer, is the generally familiar type. It is created when a polyp known as an adenoma grows inside the large intestine before turning cancerous. Adenocarcinomas of the lung, which account for across 60% of each occurrences of lung cancer, often develop in the glandular cells in the outer part of the lung before spreading to the lung's alveoli. The second highest familiar type of lung cancer, lung squamous cell carcinoma, occurs in the lungs' bronchi or airways and accounts for around 30% of all cases. Table 3.2.1 provides a summary of the dataset's description,

Table 3.2.1: Summery of the dataset

Class ID	Name	Description
C1	Colon benign tissue	5000
C2	Colon adenocarcinoma	5000
C3	Lung benign tissue	5000
C4	Lung adenocarcinoma	5000
C5	Lung squamous cell carcinoma	5000

Sample images of the diverse classes of colon cancer dataset has shown in Figure 3.2.1

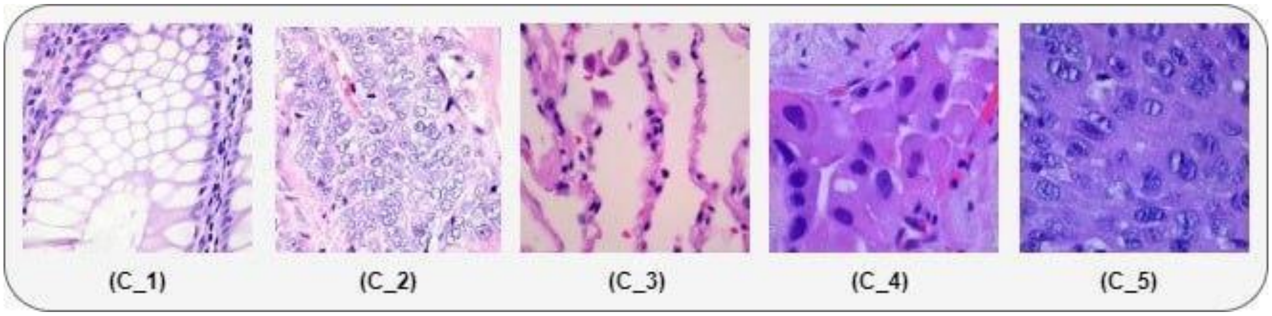

Figure 3.2.1: Example images of the dataset

3.3 Image Pre-processing

There is a lot of noise and artefacts in lung and colon cancer dataset images, so this study focuses on improving the model's accuracy through image processing techniques. Because images are usually filled with noise and artefacts, image processing is the first step in training a deep-learning model. First, we resize the images then a median filter is used to remove noise from this image, then a morphological opening is used to remove artefacts. After that we apply CLAHE for enhancing the quality of images, then we used histogram equalization on the CLAHE images to adjust the intensity of the images. Lastly, we applied Fourier transform.

3.3.1 Image Resizing

Through the process of resizing, we can reduce the size of an image without losing quality. When an image's dimensions are changed, it often results in a loss in quality and an increase in file size [33].With smaller images, our transfer learning models can train more quickly. If the dimension of the input image is doubled, our network will have to learn from eight times as many pixels, which takes more time. In our dataset there are many large and small combined images. We resized our dataset's images into 224 X 224 [34] from 768 X 768 pixels to get the perfect shape of images.

3.3.2 Median Filter

The images of our dataset have some noises that's why the edges were not clear. And that can lead to misclassification. So, we applied a median filter. In order to clean up noisy images and signals, a median filter is applied. In image processing, the median filter is crucial because of its proven ability to keep edges intact while simultaneously reducing noise. In our dataset, a two-dimensional median filter is being applied [35].

3.3.3 Morphological Opening

An image's morphological opening consists of two processes that use the same structuring element: erosion and dilation [36]. Opening pushes small objects into the background of an image by removing them from the foreground (typically taken to be the bright pixels). We used morphological opening on our image dataset after applying the median filter. The dilation of the destruction of a set A by a structuring element B is known as opening in mathematical morphology,

$$A \circ B = (A \ominus B) \oplus B \quad (1)$$

Where $\oplus$ and $\ominus$ denotes dilation and erosion respectively.

3.3.4 Contrast Limited Adaptive Histogram Equalization (CLAHE)

CLAHE is an adaptive histogram equalization technique used in image processing to improve the contrast of images. It is an advanced version of the traditional histogram equalization technique that works by dividing an image into small non-overlapping tiles, and then applying histogram equalization to each tile separately. Ragab et al. [26] compared the two algorithms and discussed their reasoning for selecting CLAHE over AHE. For the purpose of enhancing the quality of complicated structures in medical imaging, CLAHE was created [27].The legibility of medical images is improved by CLAHE's local enhancement of contrast [28]. The author of this paper provides a brief explanation of the

CLAHE formula and mathematical equations [29]. This is done to reduce the amount of noise in an image and to make the image look more natural.
Mathematically speaking, CLAHE works by transforming the intensity value at a given pixel location x, denoted by I(x), as follows,

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

where min(I) and max(I) are the minimum and maximum values of the image's intensity values, respectively, and L is the number of intensity levels. This transformation effectively stretches the image's histogram to cover the entire dynamic range of the image. Additionally, the CLAHE algorithm is detailed in [29].

3.3.5 Histogram Equalization

A technique for changing image intensities to enhance contrast is histogram equalization. After applying CLAHE we then applied histogram equalization on the CLAHE images to adjust the intensity of the images. The following is a quick explanation of the CLAHE's mathematical equations and formulas [37]. Let f be a given image with integer pixel intensities ranging from 0 to L − 1 and represented as a m_r by m_c matrix. L, frequently 256, is the total amount of potential intensity values. With a bin for each potential intensity, let p stand for the normalized histogram of f so,

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

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

Fourier transform is a powerful tool used in image processing to extract useful information from an image. Fourier domain images are created by comparing a spatial domain image with a Fourier domain image [38, 39]. It is used to analyze the frequency content of an image and can reveal features that are not visible to the human eye. The Fourier transform of an image can be expressed mathematically as:

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

Where F (u,v) is the Fourier transform of the image f(x,y) at the frequency (u,v). The variable x and y denote the spatial coordinates in the image, and the variable u and v denote the frequency coordinates. The integral is calculated over the entire image and the result is a complex number. The magnitude of the complex number represents the strength of the frequency at that point in the image. The Fourier transform can be used to extract features from an image such as edges, lines, and shapes. It can also be used to remove noise from an image, compress an image, and improve the contrast of an image.

All the image processing steps are illustrated in Figure 3.3.6.1.

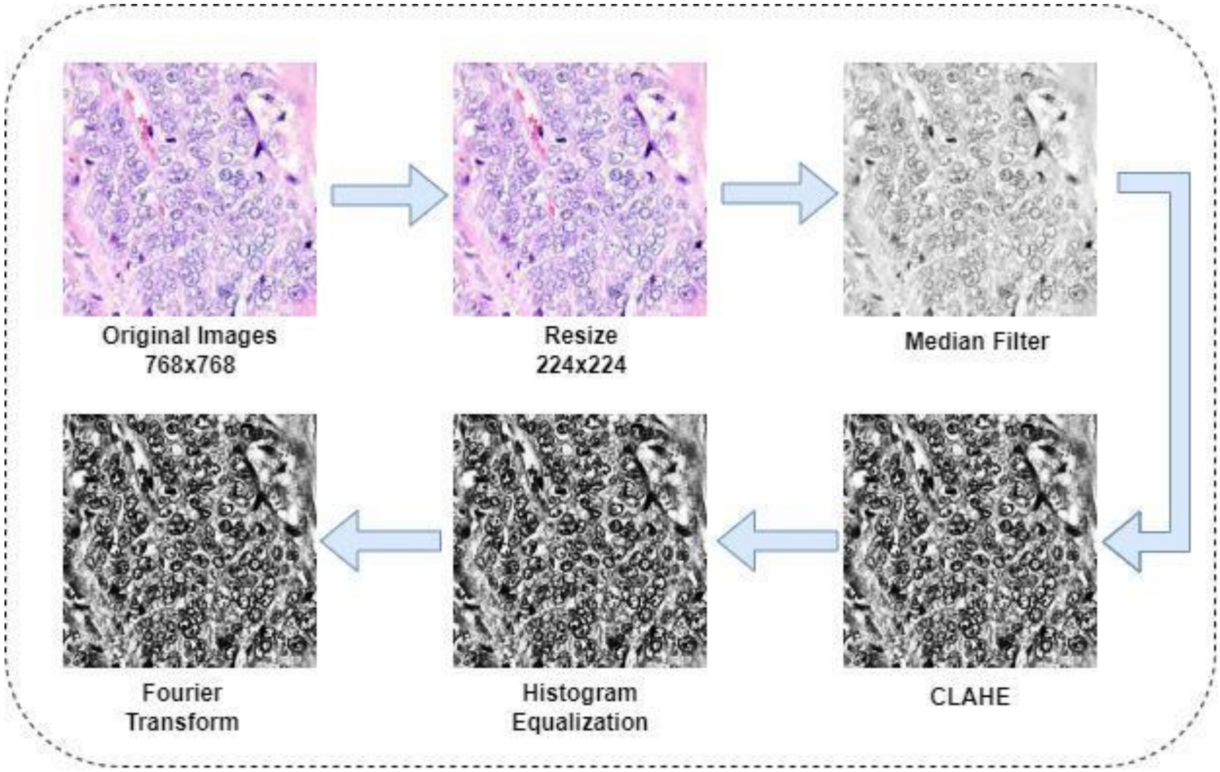

Figure 3.3.6.1: Image processing steps

3.4 CNN Transfer Learning Development

The remarkable performance of convolutional neural networks (CNN), a subcategory of neural networks that may be employed to recognize objects based on images, has made them quite popular in recent years [20, 21]. Convolution, pooling, normalizing, and fully linked layers are just a few of the layers that make up a typical CNN architecture. The network is built using convolution, pooling, and normalization layers that are implanted sequentially. Convolution and pooling processes together create high-level features that are then utilized for classification. The fully linked layer of the CNN architecture is where the classification is done. There are a ton of parameters in the CNN architecture that need to be changed during training. The traditional back propagation approach is typically used for

CNN training. For increasingly sophisticated models, extra layers can be used. Figures 4 and [22] both show examples of a conventional CNN [40].

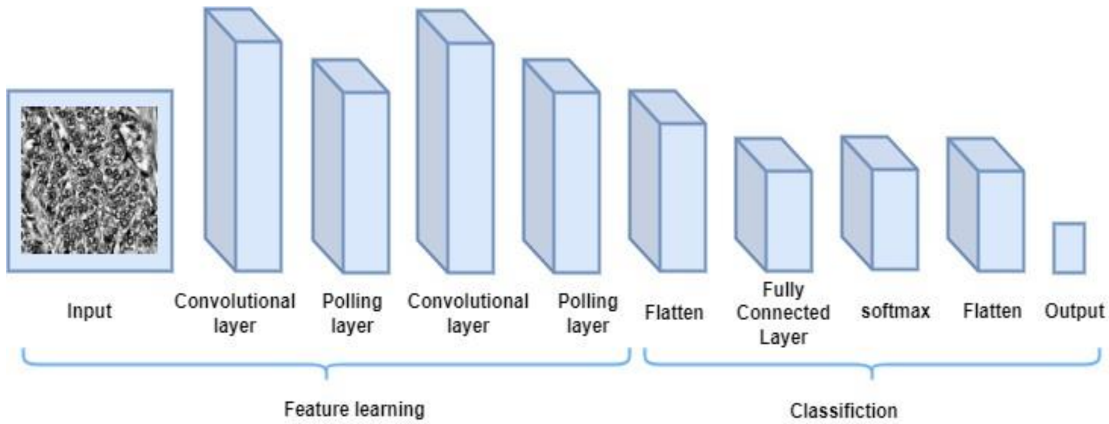

Figure 3.4.1: The standard CNN model architecture

3.5 Selection of Transfer Learning Models

Models are developed and trained for specific tasks using the deep learning approach known as "transfer learning" before being used on another closely related activity. It describes a scenario in which lessons learned in one context are used to enhance optimization in a different setting [23]. Transfer learning has frequently employed when a new datasets is lesser than the original dataset that was used to train the pre-trained model. [24]. This study focuses on ten transfer learning models which give standard accuracy and MobileNet gives us highest accuracy. To identify which model performs the best, ten pretrained models — VGG16, VGG19, MobileNet, MobileNetV2, InceptionV3, ResNet50, ResNet50V2, ResNet101, DenseNet201 and Xception — are trained on training data and assessed on testing data. Short description of these models is given below:

VGG16

VGG16 is a convolutional neural network model proposed by K. Simonyan and A. Zisserman from the University of Oxford in the paper "Very Deep Convolutional Networks for Large-Scale Image Recognition" in 2014. VGG16 is a deep convolutional neural network model which is composed of 16 convolutional layers [41] and is capable of not only recognizing objects in an image but also classifying them. It takes an image as input and then applies a series of convolutional, pooling and fully connected layers to produce an output that tells the model what objects are in the image. VGG16 has been widely used in applications such as automatic image captioning, object detection and segmentation, and image classification. It has also been used in transfer learning, where it has been used to initialize weights of other neural networks. VGG16 is known to be one of the most accurate image recognition models available. It has achieved a top-5 error of 7.3% on the ImageNet challenge and is often used as a baseline model for new image recognition tasks.

VGG19

VGG19 is a convolutional neural network that was developed by Karen Simonyan and Andrew Zisserman in 2014. It was a part of the Visual Geometry Group (VGG) network family and was the 19th network in the series. VGG19 is a 19-layer network [42], which is commonly used for image recognition and classification tasks. VGG19 is a simple yet powerful architecture that can be used to solve a variety of computer vision tasks. VGG19 is composed of five convolutional blocks and three fully connected layers. The convolutional blocks consist of multiple convolutional layers with non-linear activation functions, pooling layers, and batch normalization layers. Each convolutional block is followed by a max-pooling layer with a stride of 2. The three fully connected layers are composed of 4096, 4096 and 1000 neurons respectively. The output of the VGG19 network is a 1000-dimensional vector representing the predicted class for an image.

InceptionV3

A new InceptionV3 design aims to reduce the needed computational power by modifying earlier Inception designs. It is possible to decrease the computational cost by regularizing, reducing the dimension, factoring convolutions, and parallelizing computations. Comparing InceptionV3 [43] to earlier Inception models, there are some significant updates, label smoothing and factorized 7x7 convolutional layers are included, and the transfer of label information across the network using an auxiliary classifier.

Xception

This network was introduced by Francois Chollet who works at Google. Xception is usually classified as the "extreme" form of an Inception module as well as two blocks or convolution and ReLU activation has been used in convolutional layer. Xception [44] is a 71-layer deep convolutional neural network architecture that solely uses depthwise separable convolution layers.

ResNet50V2

A conversion was introduced to the dissemination formulation of the links between blocks in ResNet50V2 [45], an altered version of ResNet50 that works well than ResNet50. ResNet50V2 can classify images into different object categories.

ResNet101

ResNet-101[46] has 101 layers also there are almost 44.5 million trainable parameters. The pre-trained network is efficient in detecting objects in images. As a consequence, the architecture has acquired large feature representations for a number of images. The architecture will only recognize images that are also 224x224 in size.

ResNet50

The ResNet50 architecture combines convolution filters of various shapes and sizes to address the CNN models' deterioration issue and decrease the training time caused by deep structures. ResNet50 [47] includes an average pool layer and a maxpool layer in addition to 48 convolutional layers; also there are almost 23 million trainable parameters.

MobileNet

Mobilenet is a type of convolutional neural network (CNN) designed to run efficiently on mobile devices with limited computing power. It was developed by Google and was the first of its kind to be used in mobile applications [48]. The main goal of MobileNet is to reduce the size of the network while maintaining accuracy. This is done by using depthwise separable convolutions, which essentially reduce the number of parameters and computations required by a network. MobileNet can be used for a variety of tasks, such as image classification, object detection, and semantic segmentation. Additionally, it is relatively easy to train and can be deployed on a wide variety of platforms, including mobile phones and embedded devices.

MobileNetV2

MobileNetV2 is a convolutional neural network architecture developed by Google in 2018[49]. It is a lightweight network designed to run efficiently on mobile devices, providing improved accuracy over its predecessor MobileNetV1. MobileNetV2 introduces a new set of residual blocks called 'inverted residual blocks' which are designed for efficient computation on mobile devices. These blocks use a combination of depthwise convolutions and pointwise convolutions to reduce the computation time while improving the accuracy of the model. MobileNetV2 also uses batch normalization layers to reduce overfitting and a depth multiplier to control the number of parameters in the model. The result is a model that is both lightweight and accurate, making it suitable for applications such as object detection and image classification.

DenseNet201

DenseNet201 is composed of a series of dense blocks and transition layers. Each dense block contains several convolutional layers and is connected to a transition layer. The transition layer reduces the spatial size of the output from the dense block. The output from the dense block is then passed to the next dense block. This architecture allows the model to capture more complex features and patterns. DenseNet201 has several advantages over other image recognition architectures such as ResNet and InceptionNet. It has significantly lower number of parameters, which makes it more efficient and easier to train. It also has a faster inference time and is less prone to overfitting.

3.6 MobileNet Architecture

In this study, we used the MobileNet model since it is a lightweight, low-latency model that has demonstrated promising performance in certain previous experiments. The remainder of the essay is structured as follows: We start out by giving a quick rundown of published papers. Next, we describe the approach, outline the model, and talk about how well it performs post-training classification of histopathology images from the test dataset.

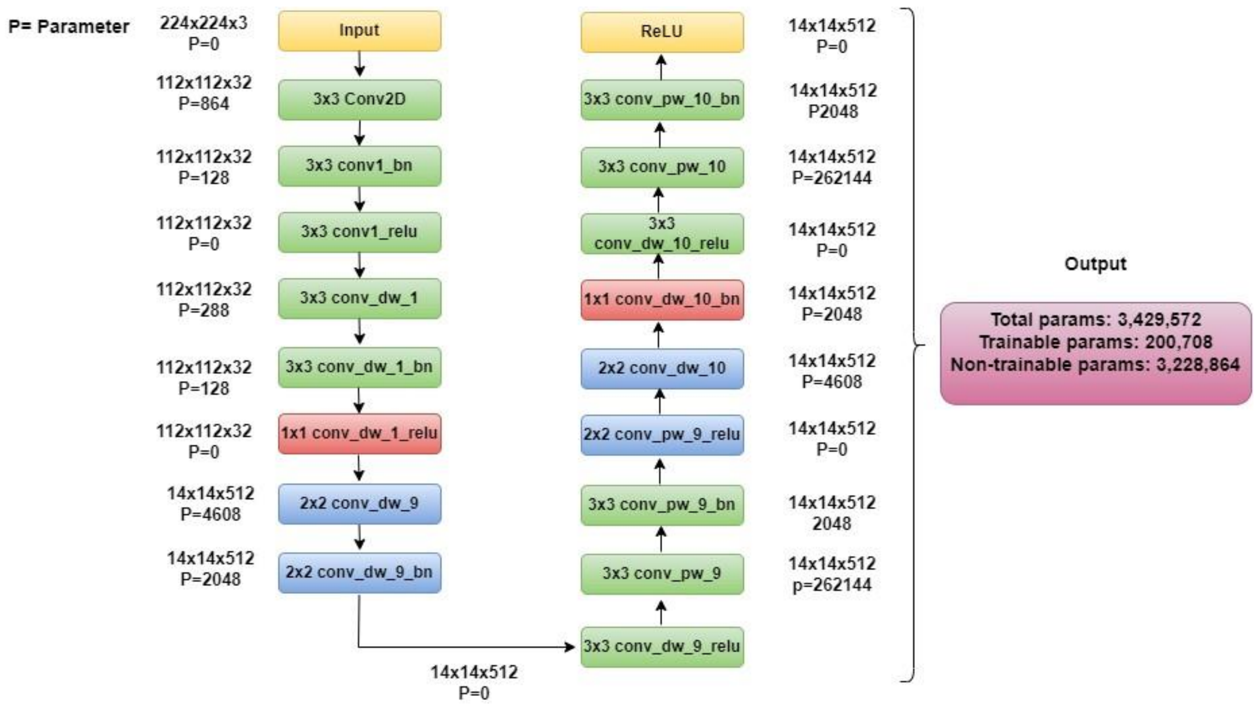

Figure 3.6.1: MobileNet architecture with parameters.

MobileNet is built to efficiently maximize accuracy while considering the constrained resources of an embedded or on-device application. MobileNet has low-latency, low-power models that may be customized to fit the computing devices' resource limitations [25]. MobileNet can be utilized for applications like classification, detection, embeddings, and segmentation, just as the large-scale models can. Separable filters, which combine depth- and point-wise convolution, are the only filters used by MobileNet. It uses 1 x 1 filters to cut down on the computing costs associated with standard convolution operations. As can be seen in Fig. 10, this reduces both the size and computational complexity of the network. There are around 5 million parameters in MobileNet-224's ImageNet categorization. Furthermore, MobileNet necessitates an input size of 224 x 224 x 3. As shown in Figure 3.6., the number of filters can range from 32 to 1024.

CHAPTER 4

RESULT ANALYSIS

4.1 Results and Discussion

Using confusion matrix to determine the success of the study, parameters are truepositive(TP), true-negative(TN), false-positive(FP) and false-negative(FN) where : Truepositive (TP) represents colon cancer classified by the models, True-negative (TN) indicates models that are not classed as colon cancer, False-positive (FP) indicates noncolon cancer that the models have classified as colon cancer, False-negative (FN) denotes colon cancer classified as non-colon cancer by the models. Measure some validity metrics such as accuracy, specificity, recall, precision, f1-score. The mathematical formulas for these performance metrics are as follows,

$$Accuracy = \frac{TP+TN}{FP+TN+FN+TP} \quad (6)$$

$$recall = \frac{TP}{TP+FN} \quad (7)$$

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

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

The proposed model of this study can classify and detects colon cancer based on CNN which is a transfer learning (TL) model. To obtain the best result 25,000 colon cancer images are preprocessed and then used for classifying. In this study there are ten CNN transfer learning model (VGG16, VGG19, MobileNet, MobileNetV2, InceptionV3, ResNet50, ResNet50V2, ResNet101, DenseNet201 and Xception) has used for analyze and the model provides the finest performance to detect colon cancer with least completion time and data loss. Among all of these ten models, MobileNet outperforms with the best accuracy of 98.58% in identifying colon cancer most successfully, with least computation time. Table 3 depicts the obtained accuracy by the ten transfer learning models along with other performance metrics.

Table 4.1.1: Performance evaluation matrix for different applied models

Model	Accuracy	Specificity	Recall	Precision	F1-score
MobileNet	99.58%	95.88%	96.65%	97.06%	98.21%
VGG19	97.73%	94.3%	96.4%	96.11%	97.02%
VGG16	97.6%	93.3%	90.7%	91.95%	96.46%
MobileNetV2	97.53%	94.2%	96.8%	97.5%	96.25%
Xception	94.75%	92.56%	95.56%	94.65%	95.66%
ResNet50	95.03%	91.22%	94.22%	95.67%	95.2%
ResNet50V2	96.5%	93.66%	94.35%	93.27%	96.3%
ResNet101	95.77%	94.55%	95.85%	95.69%	95.40%
DenseNet201	96.28%	93.47%	95.88%	94.87%	93.77%
InceptionV3	94.75%	95.56%	93.94%	94.77%	94.02%

As the suggested MobileNet architecture yields the highest accuracy, a confusion matrix for this architecture is shown in Figure 4.1.1.

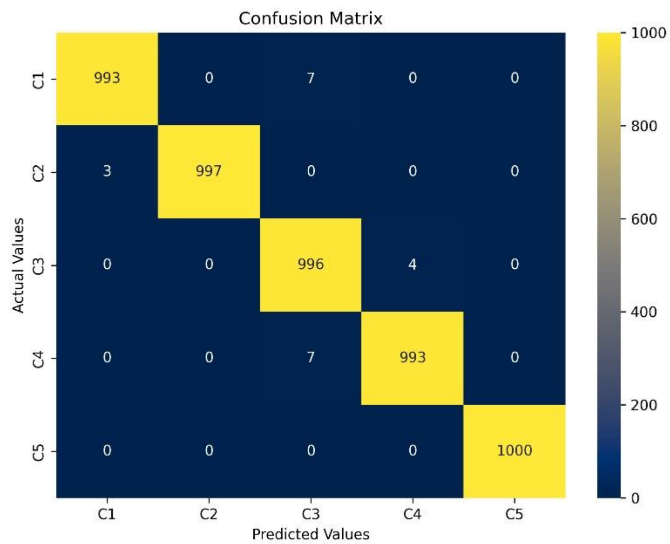

Figure 4.1.1: Confusion matrix of proposed MobileNet model

And Figure 4.1.2 shows the normalized form of the above confusion matrix.

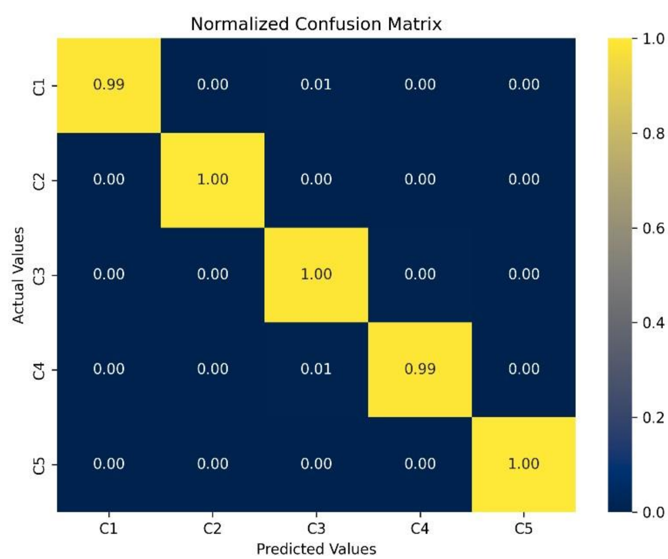

Figure 4.1.2: Normalized Confusion Matrix of proposed MobileNet model

In the confusion matrix of Figure 4.1.1, the row values point to the true labels and the column values denote the predicted scores provided by MobileNet network. The correctly predicted values by the models are placed diagonally in the confusion matrix. From the values of the confusion matrix, it can be observed that the model performs with the highest prediction rate for class_e which is lung squamous cell carcinoma with 0 misclassifications. For the other four classes, a promising classification performance is observed with misclassifications cases as low as 7,3,4 and 7 for class a, class b, class c and class d respectively. Established on the low misclassification cases, the model can be considered robust across all the classes. The test accuracies for individual classes are also derived for the proposed MobileNet model as shown in Table 4.1.2.

Table 4.1.2: Class based accuracy of the proposed MobileNet model.

Class	Test accuracy
C1	99.45%
C2	99.32%
C3	99.85%
C4	99.52%
C5	99.68%
Overall accuracy	99.58%

Table 4.1.2 demonstrates that a good accuracy is obtained for each class. It indicates that the proposed MobileNet model is not biased to any specific class. All these high accuracies of every class justify the robustness of the model.

So that we may verify the overfitting issue of the model the accuracy and loss curves are demonstrated in Figure 7.

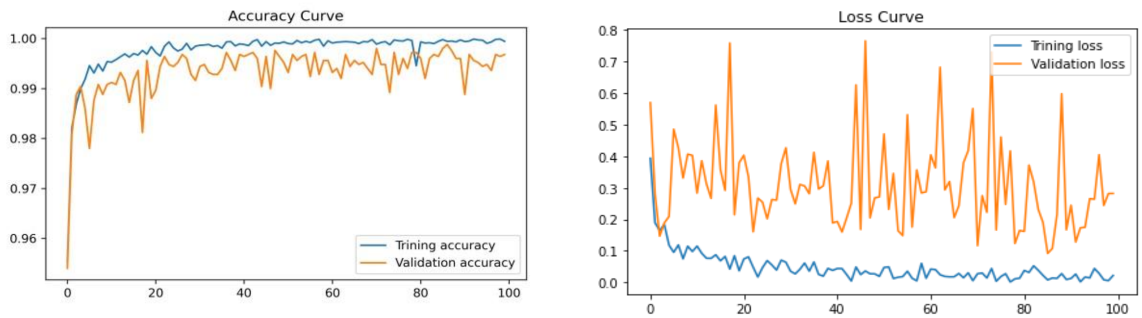

Figure 4.1.3: Accuracy curve and loss curve

The pattern of the accuracy curve validates that no overfitting occurred while training the network as both the training and validation curves are observed to be well converging with a very slight gap amid them. The loss curves are gradually decreasing over the epochs, having a small gap between the accuracy curves. No overfitting is observed throughout the training period.

A Receiver Operating Characteristic (ROC) curve is a graphical representation of the performance of a binary classifier system as the discrimination threshold is varied. The ROC curve is created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. The left-upper corner of the unit square, where TPR and FPR are equal to 1, is where the ROC of a flawless test crosses. The more closely a curve approaches this point, the better the exam. In Figure 4.1.4, ROC curve for our proposed model which is MobileNet is demonstrated.

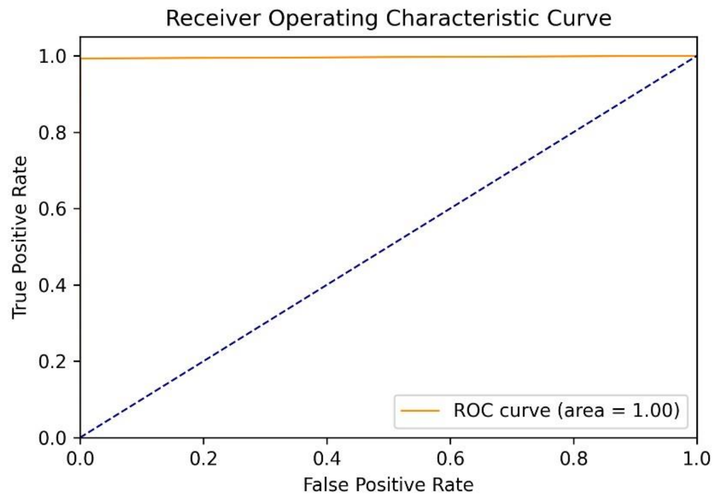

Figure 4.1.4: ROC curve

4.2 Accuracy Comparison

According to Zarrin et al. [12], the accuracy was 99.67%. For SVM models, Jiao et al. [15] achieved an accuracy of 96.63%. Babu et al. [16] achieved 96.67% accuracy with Inception-V3 and SVM. Additionally, Akshay et al. [17] and Selvanambi et al. [30] achieved an accuracy of 98% and 88%. Using our approach, we can overcome the limitations of previous studies. By optimizing the performance of the MobileNet model, we achieve a maximum accuracy of 99.58 %. The table 4.2.1 shows a comparison of our model with existing work.

Table 4.2.1: Comparison the Accuracy between Previous Works

Reference	**Year**	**Best Model**	**Data Size**	**No. of Class**	**Accuracy**
Zarrin et al.[12]	2021	MobileNetV2	25000	2	99.67 %
Jiao et al.[15]	2021	SVM	25000	5	96.33%
Babu et al.[16]	2021	Inception-V3, SVM	1348	2	96.67%
Akshay et al.[17]	2020	CNN	25000	5	88%
Selvanambi et al.[30]	2020	RNN	765	6	98%
Suresh et al.[31]	2020	CNN	5188	3	93.46% 93.9%
Hatuwal et al.[32]	2020	CNN	25000	3	97.2%

CHAPTER 5
CONCLUSION

5.1 Conclusion

Transfer learning (TL) models improve diagnosis performance of colon cancer. According to this study, a model attempt has made to classify and detect colon cancer from colon images into five classes. This study presented ten deep learning models that might be used to automatically diagnose colon cancer. However, the MobileNet model outperformed other models in terms of test accuracy, loss of data and computation time on average. There is the lowest rate of data loss with VGG19, but its completion time is higher and less accurate than MobileNet. In the future a hybrid transfer learning (TL) approach capable of evaluating and performing on a large number of images while determining how much of the colon volume is infected

.

5.2 Limitation and Future Work

We conduct our study with a limited number of image dataset. A large dataset can be used to make the diagnosis more accurate. There is absence of real world data. A variety of image pre-processing technique and updated model architecture can be used. Moreover, our proposed approach can’t detect the cancer progression.

We will try to meet the above mentioned limitations in our future work. A more exact and vigorous model will be developed for upgrading the precision of the lung and colon cancer identification framework. After that we will deploy the model and make an application. The application will make a significant contribution in detecting lung and colon cancer location and to shielding humans from harmful impacts.

5.3 Complex Engineering Statement

Complex engineering involves research in engineering principles, problem solving and critical analysis. To conduct this study, we ensured all these terms. We explored the existing engineering principles related to this study. By acquiring knowledge from that we designed the image pre-processing steps to feed into the models and we critically analyzed all the results. Throughout the whole study process we tried to solve a problem and that is to detect cancer at an early stage. We trained the computer with a set of images to evaluate and recognize new and unique images from patients and render a diagnosis.

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