EARLY IDENTIFICATION OF COLORECTAL CANCER USING CONVOLUTIONAL NEURAL NETWORK (DEEP LEARNING)

A THESIS SUBMITTED TO THE GRADUATE SCHOOL OF APPLIED SCIENCES OF NEAR EAST UNIVERSITY

By

MUFTAH EMTIR ALFRGANI ALI

In Partial Fulfillment of the Requirements for the Degree of Master of Science

in

Electrical and Electronics Engineering

NICOSIA, 2020

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Approval of Director of Graduate School of Applied Sciences

Prof. Dr. Nadire ÇAVUŞ

We certify this thesis is satisfactory for the award of the degree of Masters of Sciences in Electrical and Electronics Engineering

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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ACKNOWLEDGMENTS

My profound gratitude goes to my supervisor Assoc. Prof. Dr. Sertan Serte for his commitment and support during this study. Lastly, I will also like to appreciate my family for their support and backup as well as every other person that has contributed to the success of this study.

To my Family…

ABSTRACT

Artificial intelligence (AI) has contributed immensely in the field of medicine, especially in the Oncological sector. The use of different networks such as deep learning for the detection of cancer has proven to be very effective in performance. However, this study focuses on conducting an analytical study for the early identification of colorectal cancer using deep learning technique, trained with ResNet-50 and VGG-19. Several objectives were outlined for this study, which included the investigation of deep learning colorectal staging, quantitative data acquisition, utilization of ResNet-50 and VGG-19 for training and testing and interpretation of results. The methodology involved analyzing a dataset acquired for the study, using a high-level computation machine to increase the result performance. Nine different classification were used in the training and testing of ResNet-50 and VGG-19. At the end of the analysis, the results obtained from the study reported a high level of performance with an accuracy level of 99.3% and 95.5% for both ResNet-50 and VGG-19 respectively. Moreover, it was recommended that a network combination technique, can further increase the performance.

Keywords: Artificial Intelligence (AI); Deep learning; ResNet-50; VGG-19; and Colorectal cancer.

ÖZET

Yapay zeka (YZ) tıp alanına, özellikle Onkolojik sektörüne son derece yüksek katkılarda bulunmuştur. Kanserin tespiti için derin öğrenme gibi farklı ağların kullanımının performansta çok etkili olduğu kanıtlanmıştır. Bununla birlikte, bu çalışma, ResNet-50 ve VGG-19 ile eğitilmiş derin öğrenme yöntemi kullanılarak kolorektal kanserin erken teşhisi için analitik bir çalışma yapılmasına odaklanmaktadır. Bu çalışma için derin öğrenme kolorektal evreleme, kantitatif veri toplama, ResNet-50 ve VGG-19'un eğitim için kullanılması ve test edilmesi ve yorumlanması için araştırılmasını içeren çeşitli hedefler belirlenmiştir. Metodoloji, sonuç performansını artırmak için yüksek seviyeli bir işlem makinesi kullanarak, çalışma için elde edilen bir veri kümesinin analiz edilmesini içermektedir. ResNet-50 ve VGG-19'un eğitim ve testinde dokuz farklı sınıflandırma kullanılmıştır. Analiz sonunda, çalışmadan elde edilen sonuçlar, hem ResNet-50 hem de VGG-19 için sırasıyla % 99.3 ve % 95.5 doğruluk seviyesiyle yüksek bir performans seviyesi göstermiştir. Ayrıca, bir ağ birleştirme tekniğinin performansı daha da artırabileceği önerilmiştir.

Anahtar Kelimeler: Yapay zeka (YZ); Derin öğrenme; ResNet-50; VGG-19; Kolorektal kanser.

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ACC:	Accuracy
ADI:	Adipose
AI:	Artificial Intelligence
BACK:	Background
CNN:	Convolutional Neural Network
DEB:	Debris
FN:	False Negative
FP:	False Positive
LYM:	Lymphocytes
MSE:	Mean Square Error
MUC:	Mucus
MUS:	Smooth muscle
NORM:	Normal colon mucosa
SE:	Sensitivity
SP:	Specificity
STR:	Cancer-associated stroma
TN:	True Negative
TP:	True Positive
TUM:	Colorectal adenocarcinoma epithelium

CHAPTER 1
INTRODUCTION

1.1 Overview on Colorectal Cancer and Deep Learning

Cancer is responsible for an estimated 8.9 million fatalities globally. This makes it the second most fatal infection and the primary cause of about one in six deaths worldwide. Based on the frequency of incidence, colorectal cancer is the third most prominent form of cancer following lung and breast cancers. For efficient treatment, prompt detection and classifying of the cancer cells is necessary. According to statistics from the American Cancer Society 56% of clients with CRC obtain diagnosis at regional or later stages wherein the cancer has disseminated from the original tumor to infect other parts of the body. Fast advancements in technology in the domain of graphic processing as well as machine learning have introduced many affordable and computer assisted diagnostic methods. Routine traditional techniques have the general objective for performing pattern recognition dependent systems for rapid and automatic diagnosis of cancers. This technique involves the isolation of a fixed group of hand built characteristics from the tissue scans which rely on texture, features on morphology as well as the training of a classifier for these characteristics to categorize or identify these cancerous cells. In recent years, there has been the use of deep learning artificial neural networks which compose the isolation characteristic and categorization within a unified learning group.

Procedures of segmentation find relevant applications in a wide range of fields from systems which involve artificial visions to medical systems and mechanical engineering technology. Segmentation techniques in applications of mechanical engineering for instance have been involved with the analysis of materials at the microstructure scale (Boschetto et al., 2014).

In medical applications, the segmentation of soft tissues is a basic aspect in developing Computer Aided Diagnostic systems (CAD). This system is based on Computed Tomography (CT) scans. The segmentation of soft tissues like colon sectionalizing has been increasingly employed in modern medical practices. In these processes, CAD is utilized in obtaining a 3D overview of the organ structure. This process bypasses the possibility of human errors and increased reliance on experiential knowledge from medical practitioners and accurate results are obtained in an effective and timely manner (He et al., 2015).

By so doing, the sectionalizing of colorectal tissues in human CT scans is the fundamental aspect of analyzing and identifying tumor nidus. This provides relevant information like the prompt detection of polyps and hence decrease to a significant extent the possibility of colorectal cancers (Mittal et al., 2016).

In addition, the sectionalizing of colorectal tissues from CT scans can be engaged in as a pre-surgical procedure (Lorenzon et al., 2016). Adequate differentiation of colon (foreground) from the no colon (background) pixels, sensitive processes are utilized to avoid errors in segmentation, without which, colorectal pixels could be mistakenly identified in place of background noise, artefacts, limitations, unclear edges (Kim et al., 2006) as well as other internal organs of the gut.

Colorectal cancer (CRC) is accountable for an estimated 10% of deaths caused by cancers in Western countries. In the US and UK, it is considered the second leading cause of deaths (Bray 2018). Despite the fact that about half of these cancers are predominant in developed countries, significant distribution of these exist geographically. The most cases are found in Australia and New Zealand. Age-associated incidences are estimated at 45 per 100,000 for males and 32 per 100,000 for females (Arnold et al., 2017). The lowest incidences are recorded in Western Africa with estimated incidences of about 4 per 100,000. A number of predisposing factors contribute to the increased incidence of CRC such as ageing, diet, smoking, sedentary lifestyle as well as obesity (Brenner et al., 2014). Other factors include prolonged inflammatory bowel disease, family history of CRC, family adenomatous polyposis and hereditary polyposis colon cancer (HPCC).

Colorectal cancer is also referred to as colon cancer. This is a result of the abnormal, uncontrolled growth of cells through the colon. According to statistics from the American Cancer Society, the mean lifetime danger for coming down with CRC is 5%.. In line with the majority of cancers, prompt detection of CRC is crucial for enhancing the possibility of a successful therapy. CRC is often diagnosed via a microscope by the analysis of colon biopsy scans. Nonetheless, this procedure consumes much time and is subjective and this often causes relevant variability in observation both within and between examiners. Due to this limitation, a number of endeavors have been put in place for developing reliable techniques and methods for the automatic detection of CRCs.

Colorectal tumor is one of the most common forms of tumors globally. It is a major cause of fatalities related to cancers. Epidemiological statistics demonstrate that colorectal cancer is a significant form of cancer in a number of European states and is still responsible for high death rates (Marley et al., 2016). Therefore, prompt identification, differentiation and diagnosis of colorectal cancers is critical for ensuring the survival of majority of sufferers.

Traditional means of identification is performed by optical observation of tissue samples from biopsies under the microscope on slides fixed and stained with Hematoxylin and Eosin. The availability and extent of malignancy is examined by the observation of the organizational variations in the tissue samples that are revealed by the two stains. The limitation of this method however is the fact that it is subject to variability by the observer and between observers (Young et al., 2011). Therefore, the use of CAD techniques to enhance diagnosis focuses on two aspects:

Automated segmenting: this partitions the heterogeneous colorectal tissue samples into homogeneous sections of concern

Automated classification: the objective of this is for the categorization of the homogeneous tissue sample to generate a proportion of classes either as normal or diseased. This is dependent on quantitative characteristics obtained from the scan.

For both cases, the hurdle exists in tackling the intra-class and inter-dataset variations.

Much advancement has been made with respect to the automated segmentation and classification of tissue images of organs such as the brain, breast, prostate, lungs and different parts of the gut. Most of the previous techniques depended on automated assessment of texture in which a finite group of local features are computed from sections of the initial input graphics which are then later introduced to a classifier. These features which are used for describing texture are encoded into a compact reference system of visual words and are used as input of machine learning techniques like Support Vector Machines (SVM), Random Forests or Logistic Regression classifiers (Di Cataldo et al., 2017).

Regardless of the satisfactory nature of results gotten from these procedures, the reliance on a limited quantity of characteristics is a major limitation to the accuracy of these approaches. This is so as the utilization of these techniques require in depth knowledge for categorization and this is not always guaranteed. Secondly, these approaches place much constraints to the generalization and transfer abilities of the suggested categorizers, particularly in the availability of inter-set variations.

In response to such restrictions, the utilization of deep learning techniques, precisely Convolutional Neural Networks has increasingly gained prominence (Janowczyk et al., 2016; Korbar et al., 2017). With CNN, a proportion of convolutional and pooling layers acquires skills by back propagation; a group of characteristics which are well suited for categorization, hence bypassing the need for isolating handcrafted texture features. Nevertheless, there is till the need for exposing the networks with a large proportion of autonomous tissue samples. The utilization of transfer learning, which is the application of the pre-trained CNNs on another kind of scan with a more extensive dataset appears suitable for this limitation (Weiss et al., 2016).

Colorectal cancers have been proven to arise from adenomas. This is known as the adenoma-carcinoma sequence. Evidence for this is supported as the prompt detection and extrusion of adenomas effectively prevented the development of colon cancers. Most minute colorectal polyps are hyperplastic growths with rare or no possibility of developing into colorectal cancer. Hence, the accurate and objective diagnosis of little colorectal growths decrease unnecessary biopsies and colonoscopy exams. This aids in the reduction of complications linked with endoscopy exams.

Nonetheless, differentiating hyperplastic growths from adenomas by traditional white light microscopy, image enhanced endoscopy or chromatography is often challenging even for experienced colonoscopy examiners 5. Thus, the availability of accurate and objective technique for aiding diagnosis in classifying colon growths would be useful.

Even though colorectal growths are initiators of colorectal cancers, it takes several years for these polyps to ultimately develop into cancer. The early detection of colorectal growths would permit for their extrusion before the transformation into cancerous cells occurs. At present, the commonest screening testing procedure for colorectal growths is colonoscopy exams. In the year 2012, the American Multi-Society Task Force on colorectal cancer introduced updates on the guidelines on colorectal cancer monitoring following a colonoscopy exam. This surveillance is a vital factor and comprises of the assessment of risks as well as monitoring guidelines on the characterization of tissues diseased with polyps which were identified during the colonoscopy exam. Hence, the identification as well as histo-pathological description of colorectal growths are significant components of the screening and testing of colorectal cancers. From this screening, polyps which exert significant risk are distinguished from those with low risk potency.

This characterization determines the risk of these polyps developing into colorectal cancers and the timing of monitoring colonoscopy exams. Nonetheless, the proper description or characterization of some kinds of growths could be a challenge. Also there exists an extensive proportion of variation on the manner at which pathologists characterize and diagnose such growths.

For instance, sessile serrated polyps have the potential of aggressively developing into colorectal cancer in contrast to other forms of colorectal polyps. This is so because of the serrated process in tumorigenesis. This pathway relates to gene transformations in the BRAF or KRAS cancer-causing genes as well as the CpG island methylation. This can then cause a mismatching of repair genes such as MLH1 and hence a much more aggressive development into malignancy. As such, distinguishing sessile serrated polyps from other types of polyps is recommended for a proper screening test and monitoring. The only reliable technique for the diagnosis of sessile serrated polyps is the characterization of histopathology. The other screening techniques which are designed for detecting pre-cancerous lesions like occult fecal blood, fecal DNA or virtual colonoscopy are not adequate for distinguishing sessile serrated polyps from other forms kinds of polyps.

Even for pathologists, the differentiation of sessile serrated polyps from other kinds of polyps is a challenging activity. This results from the fact that sessile serrated polyps like hyperplastic polyps most times do not have dysplastic nuclear variations which are typical for adenomatous polyps. Also, the diagnosis of their histopathology is based on morphological characteristics like serration, dilatation and splitting. The adequate diagnosis of sessile serrated polyps as well as their distinguishing from hyperplastic polyps is required for ensuring that sufferers get the appropriate treatment as well as the right follow up and to spare them the arduous task of multiple screening tests. In a colorectal cancer investigation however, over seven thousand clients went through colonoscopy in thirty-two medical facilities, but to the dismay of not having a single sessile serrated polyp diagnosed in all these facilities. This unlikely outcome demonstrates that there exist much short comings in the performance as well as training of examiners with regard to the identification of histological characteristics of colorectal growths as well as the accuracy of diagnosis.

In recent years, automated and computational techniques have been introduced for aiding colonoscopy examiners analyze microscopic graphics. These graphic-assessment techniques have as points of interest, the fundamental architectural segmentation such as nuclear segmentation and the isolation of traits such as orientation, shape as well as textual characteristics. In some techniques, such isolated or hand crafted traits are utilized as input data into a standard machine learning categorization build like the support vector machine, or into a random forest for automatic categorization of the tissue as well as the grading of the infection.

In the sector of artificial intelligence, deep learning computational prototypes comprising numerous processing layers can be trained for multiple stages of abstraction for information representation 25. Such information abstractions have a significant improvement on the quality of computer visual identification functions and computer vision. In some instances, could even be superior to that of human performance.

At present, deep learning techniques are used in automatic mobile automatons and self-driven vehicles. The development of deep learning prototypes have increasingly become applicable as a result increased proportions of training information that is available on the internet, public information banks and novel high performance computing abilities which are commonly as a result of novel generation of Graphics Processing Units (GPUs) that are required for optimizing such patterns.

Several studies and investigations have been conducted and have demonstrated deep learning techniques to exceed in quality and standard to prior graphic processing methods with respect to activities concerned with classifying and segmenting on histology whole slide graphics. For instance, deep learning patterns have been built for the detection of metastatic breast cancer. They have also been developed for identifying mitotically active cells, for the identification of basal cell carcinoma and the classification of cerebral gliomas with the use of hematoxylin and eosin stained graphics.

Colorectal cancer is also known as bowel or colon cancer. It is the development of cancer from the colon or rectum. It is responsible for about 10% of cancers global. Adequate diagnosis is crucial for choosing the most adequate therapeutic plan as well as the clinical management of the patient.

Therefore, research is being undertaken for the improvement of the disease and the enhancement of accuracy in diagnosis and survival rate of the infection. One of the predictors of colorectal cancers have been the Tumor Node Metastasis (TNM) staging system. The limitation of this technique however is the fact that its patient precision level is low.

As a result of this observation, much research has been conducted in recent years in a bid to improve on this. This has led to the introduction of various machine learning techniques for the accurate diagnosis of colorectal cancers in patients. These deep learning techniques have been applied unlabeled whole slide histopathology images (WSIs). Some challenges addressed in these studies include:

- Impractical computational abilities with the equipping of classifiers with gigapixel whole slide histopathology images
- Effective ground truth annotation of unique graphic patches
- Determining biased patch subgroups
- The design of convolutional neural network (CNN) for the prediction of patch level
- The blending of patch level into graphic level forecast.

In the year 2018, the statistics from US provided evidence of the proportion of new cases of colorectal cancer to be estimated at 97,220 with about 50,630 infection associated fatalities. The total mortality rate of colorectal rate has dropped from 28 per 100,000 in 1975 to 14 per 100,000 in 2015. This decline as a result of increased testing and screening, reduction in incidence rates as well as the enhancement of treatment. The importance of screening in efficiently preventing colorectal cancers is the identification as well as subsequent extrusion of early forms of pre-metastatic forms. Early screening also exposes a wide range of elements which predispose patients with the likelihood of developing colorectal cancers.

Some of these predisposing risk factors are colorectal adenomas, hereditary factors like Lynch syndrome and adenomatous polyposis, individual clinical history of prolonged chronic ulcerative colitis and alcohol abuse.

Even though the recommendations of screening for colorectal cancers do not differentiate males from females, some statistics provide evidence that the proportion of male cases is 17% higher than that for females. They also provide evidence that females beyond the age of 65 present with higher fatality rate and a decrease five –year survival rate of colorectal cancer in contrast to males in same age group. Nonetheless, colorectal cancers are highly treatable and curable if limited to the bowel following a surgery. However, colorectal cancer becomes incurable when the cancer cells have metastasized to other organs. In such a scenario, proper options of management including chemotherapy could be beneficial for improving the standard and longevity of life. Thus, prompt diagnosis and accurate prediction of the aggressive nature of the cancer as well as the outcome of the patient are of significance.

1.2 Aim of the Study

The aim of this study is to conduct a quantitative analysis on the effect of deep learning in the detection and diagnosis of colorectal cancer using two networks (ResNet-50 and VGG-19).

1.3 Objectives of the Study

The objectives of this study were outlined as:

i) To investigate the impact of deep learning in the staging of colorectal cancer.
ii) To acquire datasets for the quantitative study of colorectal.
iii) To use ResNet-50 and VGG-19 for the training and testing of the classified dataset.
iv) Interpretation of results as well as comparison with related studies to resolve a high performing technique.

1.4 Significance of Study and Contribution to Knowledge

The use of ResNet-50 and VGG-19 for the staging of colorectal cancer have been very effective in the area of oncology for many years. The death counts recorded in the area of colorectal cancer has been a major threat, and has called for an intervention in different fields, especially in the area of Artificial Intelligence (AI). Results from this study as well as results obtained from related studies, will be very effective in the diagnosis of cancer, thus improving the diagnosis measures in the area of Oncology.

CHAPTER 2

LITERATURE REVIEW

2.1 Colorectal Cancer Grading or Staging and Prognosis

The current clinical practice predicting factors for colorectal cancer constitute:

- Depth of penetration of the tumor into the walls of the colon T
- The absence or presence of the involvement of nodes N
- The presence or absence of metastasis M

These three factors are the basis of the 5 level TNM grading system.

The first level is Stage 0. This stage is of the least severity. All blisters are limited to the mucosa and the lamina propria. The treatment option here is just a simple region excision or simple polypectomy with definite boundaries.

In Stage 1, the tumor would have penetrated the muscularis mucosa or into the muscularis propria but not into the muscle walls of the colon, peripheral lymph nodes or distant regions. At this stage, colorectal cancer infection is still localized and so a high possibility of been cured with extensive surgical resection and anastomosis.

Stage II is characterized by the tumor spreading beyond the serosa and possibly into regional tissues or organs safe lymph nodes. Also, it has not disseminated to other organs and other distant regions. A surgical resection is the gold standard treatment. Nevertheless, high risk sufferers like those who suffer from t4 infection could be given chemotherapy.

Stage III is featured with the involvement of lymph nodes and the recommended therapy in this case involves extensive surgical resection and anastomosis as well as adjuvant chemotherapy.

With Stage IV, the infection is characterized by metastasis. Treatment at this point relies on the regions where the infection has disseminated to. The involvement of the liver constitutes about 50% of Stage IV as well as colorectal cancer. The options for therapy comprise all previous mentioned strategies as well as palliative radiation therapy, palliative chemotherapy as well as target therapy.

Some studies utilized digitized whole slide graphics of preserved diagnostic histopathological tissue sections which have been with hematoxylin and eosin (H&E) as shown in the below.

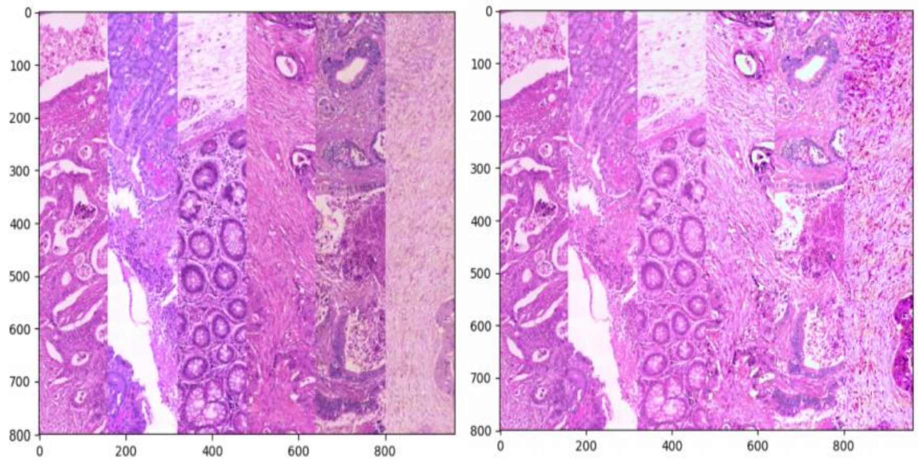

Figure 2.1: Chromatic normalization examples (left & right: original & normalized tiled strips) H&E staining

The acidic dye eosin colors the basic organs like protein organs red or pink in the cytoplasm. Hematoxylin is a basic stain which colors acidic organs blue or purple like the DNA within the nucleus.

A colon section stained with H&E gives nuclei a purplish-blue apparition, the cytoplasm appears red, red blood cells appear cherry red in coloration and collagen as well as mitochondria appear pale pink. The gastrointestinal tract describes a system of organs which are responsible for digestion. Just like every other organ system, this tract could suffer from many infections like inflammatory infections, autoimmunity, tumors and so on. The diagnosis of these infections requires clinical exams. These clinical exams may include tests like fecal occult blood, endoscopy and so on.

Colonoscopy exams are considered most accurate for the identification of blisters in the colon. More so, colonoscopy procedure is also utilized for therapeutic purposes. Statistics provided by the National Statistical Office in 2016 provide evidence that colorectal cancers are among the leading forms of cancer infections, particularly in Western countries. According to adenoma-cancer continuum hypothesis, 95% of colorectal cancers develop from adenoma. Hence, prompt detection as well as exclusion of polyps at the adenoma stage is vital for the prevention of colorectal cancer. The diagnosis of colorectal cancer is performed by a physician and the accuracy had been heavily reliant of expertise. Even with the fact that some objectivity is involved to ensure accuracy in diagnosis, most examiners follow a subjective guideline, giving the outcomes a subjective limitation. This subjective disadvantage is overcome by the presentation of artificial intelligence which ensures greater accuracy in results and decreases human faults. Endeavors to analyze clinical scans with the use of computer assisted diagnostic tools have come a long way. Computed Aided Diagnosis (CAD), as a concept was introduced in the 1970s when scanned clinical pictures were analyzed on a computer. In the 90s, rule dependent systems and expert systems were broadly utilized.

Rule dependent systems utilize low grade picture development to isolate features and lines with the use of filters. Computational systems were utilized to tally circles as well as ellipses to get and analyze structures. Expert systems are assessed as Good Old-Fashioned Artificial Intelligence (GOFAI). This was by assessing the outcomes of pictures with the use of numerous conditional clauses.

In the later 90s, the training of data for enhancing the performance of the system increasingly gained prominence. This involved two steps known as the extraction or isolation of features or characteristics or traits and classification or grading.

Traits like color, shape and texture are isolated during this extraction stage. Critical for the extraction are significant traits which represent the picture. These traits are analyzed with the use of different machine learning techniques. Some studies following this approach involved trait isolation steps with numerous linear classifiers for grading. Nevertheless, such techniques depend on the assessment of texture and requires expertise knowledge on the traits during the isolation phase. Therefore, there is the absence of generalization and are inapplicable for transfer capacities.

At present, deep learning techniques are broadly utilized in assessment of clinical pictures. Artificial intelligence employing deep learning techniques have demonstrated satisfactory outcomes in different sectors like the recognition of speech, the discrimination of language, the recognition of behavior, as well as the retrieval of picture. In most instances, the analysis of clinical graphics is involved with the diagnosis of infections as well as the detection of diseased regions. The diagnosis of infections with the use of artificial intelligence is a booming area in research which results from the development and top-quality performance of deep learning techniques. In recent times, convolutional neural networks have been shown to be useful in endoscopy. Some studies investigated with convolutional neural networks diagnostic tool for the localization and grading of EGD pictures efficiently. Subsequently, this was applied to colonoscopy pictures for the detection and classification of colorectal polyps. From this investigation, it was proven that convolutional neural network techniques yielded better results in contrast to routine hand-crafted trait techniques. Other routine implications of deep learning for the diagnosis of infections include the screening for skin cancer as well as the diagnosis of diabetic retinopathy.

Studies conducted by (Esteva et al., 2017), utilized Google's Inception v3 prototype for the recognition of 757 kinds of skin cancer. More so, convolutional neural networks were utilized to assess the intensity of knee osteoarthritis in X-ray pictures as well as the detection of lymph nodes. Adequate results have also been achieved with the use of convolutional neural networks for the detection of cerebral tumors and the grading of lung nodules. Albeit the presence of extensive amount of information has greatly improved the performance, standard quality data are also required for increasing the diagnostic capacity of the network. Nonetheless, since clinical pictures are gotten from regulated situations, these are stereotypic and can generate proper generalization performance even with very little data group. More so, the proportion of layers in the network contributes to the isolation of deep traits from pictures.

In recent times, the incidence of colorectal cancers among people aged below 50 years is on the rise hence calling for the increased need for screening. Cancers are characterized by uncontrolled cell division and exists in living anomalous cells in different organs. When these abnormal cells appear and divide in the colon, leads to colorectal cancer.

The initiation of colorectal cancer involves 70% development from adenomatous growths or polyps which have the possibility of developing in the lining of colon. This progressive growth occurs slowly over close to two decades. The assessment of colorectal cancer is for diagnosis is critical because the prompt detection increases the likelihood for survival as with all cancers. The main techniques for this diagnosis involve medical imaging through which patients' visceral organ are displayed so as to help improve on rapid screening as well as diagnosis by medical practitioners for continuous and follow up therapeutic protocol.

Such clinical pictures display the visceral organs of patients from every angle. For the identification and grading of colorectal polyps, colonoscopy makes use of a scanning machine for the acquisition of an overview picture of the colorectal region for the identification of abnormalities of polyps for prompt extrusion before metastasizing into a cancer. Nevertheless, as mentioned before, this diagnostic procedure has a number of shortcomings. Some of these include the manual interpretation of the picture, which is demanding, time consuming, biased and subjective.

2.2 Tissue Sampling

Clinical imaging is involved with digitized pictures which can be used for assessment by a computer. Hence, the examination of images based on computer assisted diagnostic systems for the grading of clinical pictures is necessary for the detection of infections, screening as well as diagnosis. The application of computer assisted screening for the grading of colorectal polyps and their screening with multiple media summarization techniques, has the advantage of improving the diagnosis of colorectal growths.

Since the late 90s, deep learning techniques have developed prominence for application in the medical field. This was particularly obvious with the introduction of an early deep learning method known as LeNet with a convolutional neural network for the recognition of digitized handwriting.

As from 2006, deep learning techniques became even more popular with the possibility of fine tuning. This property was used for producing a much advanced model of digitalized handwritten picture grading than the biased learning technique. Reducing dimensions of images by the adoption of deep learning was already described by (Yu et al., in 2016). This suggested technique was an improving in contrast to the traditional technique of Principal Component Analysis (PCA).

The development of deep learning technique like the convolutional neural network system has been linked with the grading of images by ImageNet. From then, there has been the development as well as application of deep learning in different applications as well as the medical practice. In clinical medicine, deep learning aids medical practitioners by decreasing the amount of time used to screen patients and also increase the effectiveness of diagnosis. The deep learning technique particularly convolutional neural network has been extensively applied in a number medical procedures like the reconstruction of medical images, the grading of clinical reports, diagnosis, the recognition of diseases, the detecting of cancer, the screening of infection and the grading of clinical pictures. With procedures involving the screening and diagnosis of colorectal polyps, much has been achieved by convolutional neural network systems. A number of investigations have been performed with the application of convolutional neural networks for the provision of solutions for challenges in clinical images with colorectal cancers and colorectal polyps. Some of these investigations utilized convolutional neural network systems for the segmenting with magnetic resonance imaging wherein the combination of three dimensional convolutional neural networks and three-dimensional level set for automatic segmenting of colorectal cancers generated a segmentation accuracy of 93.78%.

Studies conducted by (He et al., in 2016), suggested a convolutional neural network hybrid loss for the automated segmenting of colorectal cancer and outperformed with a mean surface distance of about 3.83mm and an average dice similarity coefficient of 0.721.

With respect to computed tomography imaging, functions of convolutional neural networks by transfer learning for electronic cleansing could enhance accuracy from 89% to 94% for visualization of pictures of colorectal polyp.

Among the world ranking cancers, colon and rectum cancers top. The likelihood of survival increases with early or prompt diagnosis. Therapy can significantly improve the possibility of eradicating the infection. A reliable source for cancer statistics is the Surveillance Epidemiology and End Results SEER. An estimated 30% of the US populace is covered by SEER and this proportion represents various races through different geographical sites.

Neural networks with more than two latent layers are considered deep. These have been utilized to successful resolve challenges associated with the recognition of speech and the grading of text. Some investigations have applied deep neural networks to prognosticate the survival chances of patients suffering from colorectal cancers following diagnosis after a one-year, two-year and five-year period.

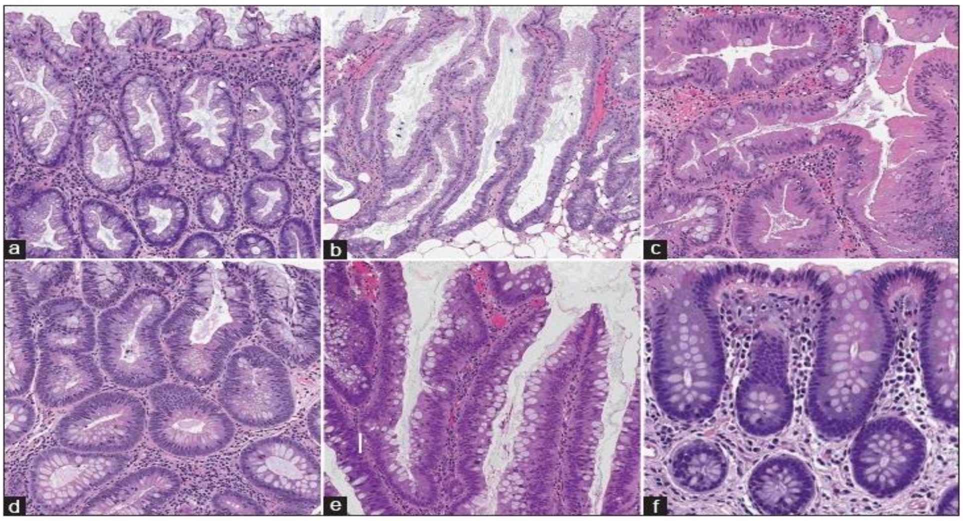

Figure 2.2: Tissue samples with colorectal polyps:(a). Hyperplastic (b). Sessile serrated (c). Traditional serrated (d). Tubular(e). Tubulovillous/villous and (f). Normal (H&E)

2.3 CRC Screening and Monitoring

The practice of colonoscopy is the gold standard of screening for CRC. It paves the way for early identification of cancerous wounds. It also enables for the monitoring of other screening exams. Sticking to frequent guidelines for colonoscopy exams will help decrease the likelihood of a progression into cancer (Jacob et al., 2012). CRCs originate from serrated polyps and are frequently found in the proximal colon (Church J. 2014; Sanduleanu et al., 2015). These serrated polyps are responsible for an estimated 3 to 9% CRCs. The likely explanation for an interval CRC could be:

- The initial polyp could be very tiny and thus go undetected during early examination
- Inadequate preparedness of the patient for colonoscopy exam
- Incomplete visualization of the caecum
- Difficult pathologic interpretation
- Inadequate resection of the polyp (Benedict et al., 2015).

Tandem colonoscopy exams have proven that medical practitioners miss out on tiny colorectal polyps and even bigger ones (Rex et al., 1997). According to a study conducted by Hixson and colleagues, a tandem colonoscopy was conducted by two alternating physicians to ascertain the proportion of tumors missed out on in the course of a colonoscopy exam. The investigation totaled ninety subjects, identified in three classes on the basis of the size of the lesion. In the first class, fifty-eight lesions were identified in thirty-one subjects with no neoplastic lesion more than or equal to 10mm in diameter was missed out on. For the second class, 16% of the neoplastic lesions 5mm and below in diameter were missed out on by the first investigator. In the third class, 12.3% of mid-sized neoplastic tumors of diameter between 6 to 9mm were missed out on by the first investigator. The conclusion from the investigation was therefore that even an experienced practitioner has the possibility of missing out on about 15% of the colorectal neoplastic tumors which are below 10mm in diameter. Nevertheless, tumors with diameter 10mm or greater are seldom missed out on (Hixon et al., 1990). Therefore, the procedure of colonoscopy is highly dependent on the operator with respect to the detection of polyps.

It has been statistically proven that these factors associated with human errors account for more than 75% of interval cancers as well as lesions missed out on or incompletely resected (Huang et al., 2012; Le Clercq et al., 2012). These limitations have spun the desire for more research for better techniques for enhancing the standard of colonoscopy exams as well as training which would ultimately decrease the incidence of CRCs.

2.4 Quality Measures in Colonoscopy

As a result of the operator-dependent nature of colonoscopy exams, measures on quality assurance have emerged. This area of research continues to evolve especially as regards the benefits and shortcomings of each strategy as well as the degree to which each measure can decrease the load of CRC. The three major measures which necessitate consideration include:

The assessment of the adenoma detection rate (ADR). This refers to the quantity of screening colonoscopy exams in which at least one adenoma is identified. At present, the ADR benchmarks are 20 to 25% or greater for males and 15% or more for females (Rex et al., 2006). The measure is considered the most accurate and practical surrogate metric. A patient with a colposcopy exam with results which show less than 20% ADR was shown to be 10 times higher with the risk of developing CRC than a patient with ADR greater than 25% (Corley et al., 2014).

The second strategy is the frequency of intubation of the caecum. It is a quality which reflects the capacity of the colonoscopy examiner to conduct a complete analysis of the caecum in all procedures. At present, the benchmark which reflects this is for colonoscopy examiners to be able to exhibit the capacity of intubating the caecum in at least 90% of analyzed cases. As a matter of significance, clients with caecum intubation rates of at least 95% showed decreased likelihood of developing interval CRCs, in contrast to clients with caecum intubation frequencies of less than 80%. Hence, the examination of the caecum intubation rate is a significant measurement parameter in evaluating the standard of a colonoscopy exam (Hoff et al., 2017).

The third measurement parameter is the withdrawal time (WT). This parameter is utilized to investigate if the colonoscopy examiner has put in enough time for conducting a meticulous mucosal exam between the intubation of the caecum to the removal of the colonoscope from the client. At present, the standard amount of time for this procedure is 6 minutes or greater for analyses void of biopsies or polypectomies (Rex et al., 2006). The variation in results obtained from colonoscopy exams is dependent on the technique used for examination during the withdrawal time. A study proved that the colonoscopy withdrawal time is shorter than the standard recommended time in an unmonitored exam, but greater when examiners are aware of their being monitored. Hence, the execution of routine monitoring as well as an investigation of each examiner's withdrawal time records could help increase the ADR (Vavricka et al., 2016). The greater the withdrawal time, the greater the quality or standard of the operation (Lee et al., 2013).

The main challenges facing this technique are the ability in differentiating between hyperplastic polyps and adenomas with the use of white light observations as well as chromo-endoscopy (Pohl et al., 2008). Present studies on deep learning techniques especially convolutional neural networks provide evidence of surmounting these challenges.

A number of new technologies have been built for the purpose of improving the adenoma detection rate including enhanced vision (resolution, zoom, wide angles, chromo-endoscopy, digital auto-fluorescence, extra lenses for side and forward viewing), attachments as well as alterations to help view behind and between folds, cap aided methods and balloon aided devices (Bond et al., 2015).

Recent methods of deep learning like the Convolutional Neural Network (CNN) has been employed in the medical field for the analysis of images and CT scans for the detection of tissues (Haj-Hassan et al., 2017) as well as the segmentation of tissue (Codella et al., 2015). This application is employed over a wide range of medical fields such as ophthalmology, pathology, radiology as well as the investigation of diseased tissues for unique diagnosis (Razzak et al., 2018). CNN thus finds applications for the analysis of colorectal tissues for classification of pathological regions (Haj-Hassan et al., 2017).

The use of CNN has been proven to generate efficient and accurate results in the assay of colorectal scans. These, diagnosis is achieved on the basis segmenting the scan which contain diseased colorectal tissue sample (Kainz et al., 2015).

2.5. Adenoma Detection Rate (ADR)

Colorectal cancers develop from pre-metastatic polyps with an average incubation period of about ten years. Statistics from the National Polyp Study reveal that 70 to 90% of colorectal cancers are avoidable through routine colonoscopy exams and the prompt excision of polyps. However, even with regular colonoscopy exams, there is the likelihood of missed polyps or incomplete excision of polyps which ultimately result into interval cancers. Some statistics reveal that the incidence of pre-metastatic polyps in the screening populace beyond 50 is about 50%. Of these precancerous polyps, the most prevalent are adenomatous polyps. The proportion of screening colonoscopy exams with one adenoma located is known as the adenoma detection rate (ADR). This proportion is represented as a percentage. It is an assay of the ability of a colonoscopy examiner to locate an adenoma. The adenoma detection rate should be reflection of the prevalence of adenomas.

However, the adenoma detection rate differs between 7 to 53% among colonoscopy examiners. In some cases, in tandem colonoscopy exams missed out on 22 to 28% of polyps and 20 to 24% of adenomas. As such colorectal cancer had a diagnostic miss rate of 5%. Therefore, the adenoma detection rate relies on the expertise of the colonoscopy examiner, amount of time spent as well as the method utilized during withdrawal, standard of preparation and a host of other elements (Anderson et al., 2015).

Results from an extensive Kaiser Permanente study revealed that for every 1% increment in the adenoma detection rate, the interval rate cancer had a decrease of about 3% (Corley et al., 2014). Another investigation with almost one million person-years of surveillance in Poland demonstrated a 6% reduction in the frequency of interval cancer for every 1% rise in adenoma detection rate (Kaminski et al., 2017). This investigation also demonstrated an 82% reduction in the frequency of interval cancers among colonoscopy examiners who improved their adenoma detection rates to the top quintile.

Colon adenomas are predisposing factors to CRC in a large proportion of the cases. About 20 to 53% of US population above 50 suffer from these adenomas. Adults have an estimated 5% possibility of coming down with adenocarcinomas (American Cancer Society 2014). The morphology of these adenomas could be flat, sessile, sub-pedunculated or pedunculated. The development of CRC could be through any of three different mechanisms (Erichsen et al., 2016):

Firstly, about 50 to n75% of all CRCs developed from traditional adenomas via unstable pathways in the chromosome or through unstable microsatellite pathways which result in gene alterations by a process known as adenoma-to-carcinoma sequence. At the microscopic level, these variations involve the Wnt pathway, TP53, KRAS as well as BRAF alterations. With pathway sequences such as the Wnt, a destruction nexus is formed when the APC tumor suppressor protein binds to beta catenin (White et al., 2012). This leads to the phosphorylation of beta catenin by GSK3 which results to deterioration into a proteasome (Kanczuga-Koda et al., 2014). Sequences of events leads to the disruption of the APC/axin1/GSK3 complex as well as assemblage of unphosphorylated beta catenin (Bouroul et al., 2016). These variations are associated to apoptosis. A portion of this develops into malignancy via a hyper mutation sequence and this leads to the alteration of protein structures and the production of highly unstable microsatellites.

The second mechanism is the Lynch syndrome alteration sequence which accounts for 3 to 5% of cases. Though Lynch syndrome has been known as a non-polyposis syndrome, some patients develop symptoms of an attenuated polyposis-like phenotype (Zhu et al., 2019).

The third mechanism involves a sessile serrated sequence which accounts for about 15 to 20% of cases. These are often located in the proximal colon. Such lesions are heterogeneous in nature but can be distinguished from traditional adenomas. From their morphology, they possess saw-toothed and luminal serrations with basal dilations of their crypts. Serrated polyps can be grouped into three different kinds: hyperplastic polyps, sessile serrated adenomas and conventional serrated polyps. The last two of these are implicated with the production of CRC (Singh et al., 2016). Elements which determine their transformation to become cancerous include size of the polyp, ageing, smoking, family predisposition and the non-utilization of non-steroidal anti-inflammatory drugs (NSAIDS) (Øines et al., 2017). Previous investigations report the decrease in colorectal cancers in the left colon as opposed to the right. The majority of cases which end in fatality could be due to a miss-diagnosis of significant adenomas especially sessile serrated adenomas at primary colonoscopy (Brenner et al., 2010; Baxter et al., 2009).

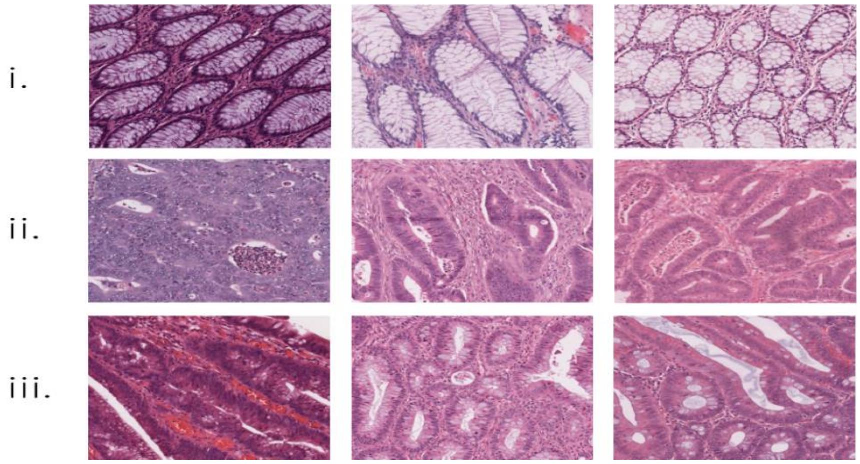

Figure 2.3: Histological H&E images of colorectal tissues (cropped patches). i) Healthy tissue; ii) Adenocarcinoma; iii) Tubulovillous adenoma

2.6 Convolutional Neural Network

CNNs form a branch of deep learning techniques and originated from the discovery of natural visual perception systems in animals. As far back as the early 1960s, David Hubel and Torsten Wiesel had a significant discovery in the visual system, visual cortex as well as visual processing. The outcome of this study as well as the record of the electrical activity in each neuron of cats' brains led to further investigation which also comprised the 1980 works of Kunihiko Fukushima and LeCun and colleagues in 1990. Research conducted by Fukushima birthed the term 'neocognition' which is a mechanistic self-structured neural network prototype for pattern recognition (Fukushima, 1980). LeCun and colleagues described the framework of CNN (LeCun et al., 1998). This was subsequently developed by the introduction of artificial neural network system made of multiple layers known as LeNet-5.

With the passing of time, more investigations led to the further establishment of more methods to fix the challenges in developing deep learning CNNs. The work of Krizhevsky and colleagues generated a significant development in the classification of images via the introduction of AlexNet (Krizhevsky et al., 2012). More studies and research led to the development of ZfNet, VGGNet, GoogLeNet as well as ResNet (Zhao et al., 2019).

The applications of CNN in detecting colon polyps as well as in other applications are:

2.6.1 The Classification of Images

The foremost CNN build which exhibited the ability for classifying graphics is AlexNet. This method of classifications are on the basis of dispensing data with the use of a structural organization of classes.

Some methods are dependent on the disintegration of an activity into a sequence of steps leads to fine classification categories as well as more processing. This is referred to as the coarse-to-fine classifying method.

Other models are on the basis of sub-category classification. For instance, the structural organization of a CNN technique could generate a system for the classifying of colorectal tumors into sub-categories which improve the frequency of right diagnosis as well as enhance the standard of colonoscopy exams. Komeda and colleagues demonstrated that the 10-fold validation had an accuracy of 0.751. This accuracy is analyzed as the ratio of the proportion of correct answers to the overall proportion of answers generated by the CNN (Komeda et al., 2017).

2.6.1 Detection of Object

This involves the utilization of CNNs in detecting and localizing objects. The techniques that are currently used are dependent on obtaining general measurements for determining if a sampled window is a likely object or not. It also further subjects the proposed object to a detector for distinguishing between a particular object from the surrounding matrix or background. This method is based on the utilization of CNNs for the automated detection and localization of polyps (Urban et al., 2018). This method is concerned with the search of the precise location of a polyp within a graphic, regardless of difficulties encountered with size, shape, texture as well as color. The challenges also involve those encountered with the camera angle, lighting conditions, reflection and a host of relevant obstacles for the localization of polyps encountered with colonoscopy. Therefore, the degree of accuracy provided by CNN with respect to this could aid decrease the frequency at which polyps are miss-detected and thus enhance the accuracy of diagnosis and quality.

2.6.2 Tracking of Objects

This process depends on the robustness of the representation of the appearance of the target against challenges such as variations in viewpoint, variations in lighting. The structure of CNN is developed in a way as to discriminate against object patches from their background with the use of the available low-level signals. Therefore, the build of CNN can group scan frames as well as the differentiation of polyps from non-polyp scans. Therefore, it is utilized to enhance the diagnostic capacity of colonoscopy (Blanes-Vidal et al., 2019).

2.6.3 The Detection of Visual Saliency

The objective of this technique is the localization of significant sites and signals in a scan. This application is relevant for the identification of variations which could confirm diagnosis. Another close characteristic is sparse representation. This reflects the capability for performing tasks involved with the improvement of the standard of the image by generating novel versions such as the removal of noise, high quality resolution as well as compressive sensing. Such applications are necessary for improving the accuracy and biased abilities of the CNN build. An example is the re-development of scans as well as the ultra-magnification of a type of tissue as well as characteristics of the nucleus followed by a machine learning examination and categorization (Kainz et al., 2017).

2.7 Clinical Applications of CNNs In Colonic Polyps

The clinical uses of CNN for the early detection of colorectal tumors can be classified as follows:

i. Identifying and classifying colorectal polyps or tumors
ii. The prediction of the nature of tissue and sequestrating of glands
iii. The distinguishing of benign from malignant tumors
iv. Categorization of tissues based on histopathology of the scans of CRCs
v. The re-development of the topography of the mucosa of the colonic mucosa from the CNN scans (Mahmood et al., 2018).

Convolutional neural networks are feed forward artificial neural networks which are inspired by the mammalian visual cortex. CNNs which are composed of multiple latent layers are the de facto standard for numerous uses of visual recognition such as the recognition of objects, segmenting, and tracking. This is because they have accomplished top notch performance from other techniques. Nonetheless, the training of such deep learning approaches from scratch requires a large proportion of data set with labels. The feasibility of such could be challenging particularly for biomedical datasets in which the annotated data is rare and often limited as a result of aspects involved with privacy. In addition, training is costly with respect to time and computational supplies. Also, biomedical scan labeling is expensive and tedious. These limitations hinder the wide scale employment of this technique.

Transfer learning has grown in prominence in the scientific research sector as a possible alternative to the training of deep CNN from scratch. It involves the re-utilization of CNN pattern which has been trained on an extensive but unrelated data. The initial build of the pre-trained prototype is retained and re-utilized either as a characteristic isolator or is fine-tuned by the resumption of training with the use of available information. Regardless of the obvious discrepancy between natural graphics as well as biomedical imaging information, deep CNN prototypes trained on an extensive scale of natural data groups can efficiently be tuned to obtain consistent and accurate outcomes for the assessment of biomedical scans.

Another technique for the alleviation of the challenge of limited sets of data is the use of augmentation and enriching techniques for the refining and virtual enrichment of the available data. In the examination of diseased tissues, various patch generation as well as data transformation techniques are frequently used. The enrichment of data is also employed by the integration of a segmentation stage as a prerequisite to the isolation of characteristics as well as classifying. This technique involves the removal of the background and the emphasis of sections of concern by the localization of sections of tumor. Nonetheless, the extent of variation which could add significant information to the available data is restricted. More so, the majority of preprocessing approaches depend on manual or semi-automatic user-reliable techniques which present significant subjectivity and feasibility aspects. Another crucial aspect with respect to this is the restricted variation in the data group. This is recognized by the proportion of distinct patients from which information was obtained. Even among data groups with increased number of graphics, the quantity of sufferers is decreased. This absence of diversity restricts proper validation and cannot be fixed by the augmenting data or by an enriching procedure.

Computer assisted diagnostic techniques is increasingly becoming prominent in clinical practice. A number of investigations have been performed with CAD for the detection of colon growths and have proven to help solve the limitation involved with colonoscopy exams. In addition, the increased frequency with the utilization of CAD systems points to the enhancement in the standard of colonoscopy exams. Apart from traditional CAD, convolutional neural networks using artificial intelligence have been developed.

Studies suggest that a convolutional neural network system dependent on CAD employing artificial intelligence has the potency of achieving higher accuracy in diagnosis than routine computer assisted diagnostic systems void of convolutional neural networks or artificial intelligence for colorectal growths.

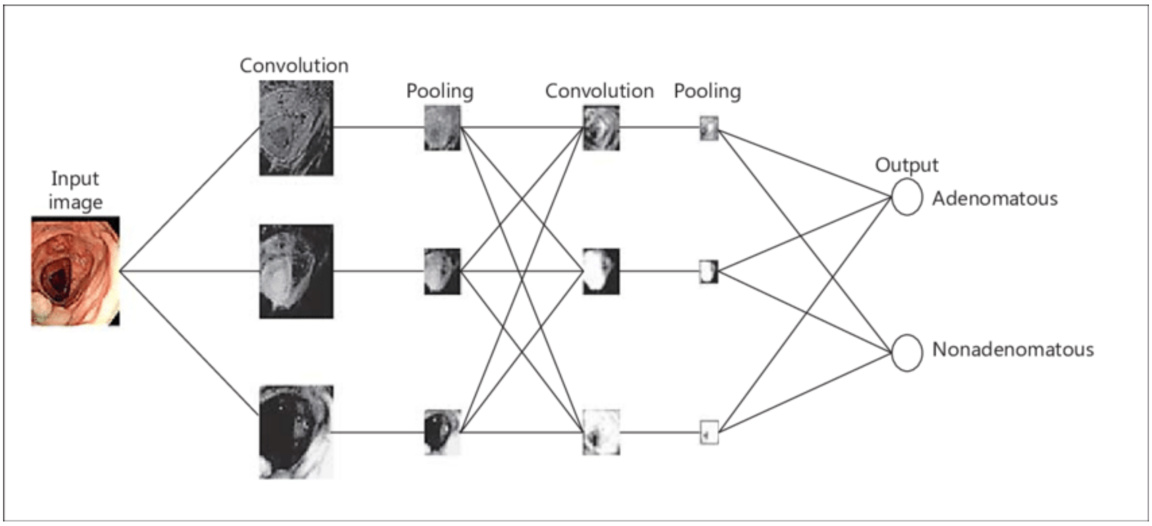

Figure 2.4: Functional architecture of a CNN

Manually reporting H&E dyed tissues with the use of a microscope or whole slide imaging on a computer screen for TNM grading is demanding. It is also heavily dependent on the expertise of the examiner and thus is subjective. Spun by these limitations, much research has been undertaken and still is, on the applications of machine learning for analyzing whole slide images. Being a data dependent and end to end technique that is trained with high level feature void of subjectivity, functions of convolutional neural networks (CNN), computer assisted interpretation instruments stem as far back as the 1990s. At this early times, convolutional artificial neural networks were presented as they attempted to resemble the analytic process of the radiographic scans of radiologists. The applications of CNN build have been suggested for assessment of intima media thickness in ultrasound scans, cerebral tumor segmenting in Magnetic Resonance Imaging graphics, the segmenting of neuronal membrane in electron microscopy.

With respect to the examination of whole slide histopathological images, convolutional neural networks have been utilized for solving limitations like automated nuclear atypia scoring as well as the distinguishing of epithelial tissues from stromal tissues. In recent studies, there have been evidence to prove that finely regulated pre-trained convolutional neural networks performed better than convolutional neural networks which were trained from initial stages in lesser time frames.

Traditionally, equipping a convolutional neural network from scratch involves the random initialization of all factors in the structure of an artificial neural network. In contrast however, the fine regulation of a convolutional neural network entails the initialization of the weight and discriminatory values with the parameters of a previously trained convolutional neural network with same structure.

The assertion is that early layers of convolutional neural networks learn the low level graphic parameters that are almost same for various vision challenges. The deeper layers which learn high level parameters are definite as regards the task of classification.

2.8 Patch-Based CNNs

Despite the fact that convolutional neural networks are extensively taken to be top notch models in a wide variety of applications with respect to the classification of graphics, the examination of whole slide histopathological scans is still a hurdle because the equipping of deep convolutional neural networks with gigapixel whole slide images is still a challenge in practice. As a result, most previously mentioned techniques utilize down sampled graphics. Nevertheless, there is the inherent loss of biased data at finer scales. A prototype on patches of high-resolution graphics was equipped by Hou and colleagues in 2016. From these images, prognostications for complete whole slide histopathological images were done with an algorithm based on expectation maximization that was autonomously used to decide biased patches. Subsequently, many other techniques which depend on the utilization of graphic patches as well as convolutional neural networks have demonstrated satisfactory outcomes in differentiating whole slide histopathological images of polyps from normal tissues. It also makes it possible for the segmenting of precursor blisters.

With respect to tackling the challenges presented with prognosis, an adaptive sampling technique was employed in an end to end frame work to set of graphics with distinct content. This framework is made of four vital levels:

- The adaptive production of patches from whole slide histopathological images
- Phenotypic amalgamation of patches
- Autonomic amalgamation of selection

- Aggregation of cluster level prediction

But as a result of the decreased resolution of down sampled phenotypes as well as the absence of an efficient manner of aggregating patch-wise prognostications, this technique only accomplishes 57% mean accuracy.

A convolutional neural network architecture set up by studies conducted by Tieleman in 2012 provided evidence of enhanced performance in the grading of colorectal polyps by the area under the curve of 86 and an accuracy of 83% on computed tomography data groups.

A number of investigations laid emphasis on endoscopic graphic data groups like those of (LeCun and colleagues, 1998). These developed a convolutional neural network for the detection of polyps in real time as well as the validation of novel colonoscopy graphic set with detected polyps. The investigation demonstrated an area under the curve of 0.984%, a sensitivity of 94.38% and a specificity of 95.93 %. The creation of a convolutional neural network for the detection of polyp enabled the precise detection at 88.6% and recall at 71.6%.

A method which involved the segmenting of polyp with total convolutional neural network for various sizes and shapes of colorectal polyps utilized as ground truth pictures for assessment was investigated by Akbari et al., 2018. In this investigation, a segmentation accuracy of 97.77% was obtained.

A convolutional neural network for real time assessment of endoscopic videos was suggested in studies conducted by Byrne et al., in 2019 for the identification of colorectal polyps and accomplished an accuracy of 94%. Enhanced site-dependent training of convolutional neural network on wire-free capsule endoscopy pictures in studies conducted by (Sornapudi et al., 2019), experienced a precision on performance of 98.46%, a recall of 95.53%, an F1 score of 96.67% as well as F2 score of 96.10%.

With the use of picture datasets, investigations performed by Ponzio et al., 2018 led to the developing of an experimental convolutional neural network with transfer learning and fine regulation for tissues in the diagnosis of colorectal cancer. In this study, the convolutional neural network made provision for proper testing grading accuracy of 90%.

In studies conducted by (Muhammad et al., 2019), extensive dimensions of images were applied with convolutional neural networks and assessed for the classification of colorectal cancer. An accuracy was achieved for two classes of 99.28% and three classes of 95.70%.

In investigations conducted by (Kather et al., 2019), a convolutional neural network was equipped by transfer learning and accomplished an accuracy of 94.3% with the use of an external testing dataset in 9 classes.

A number of studies have proven the importance and significance of convolutional neural networks in the grading of colorectal polyps in the context of screening for the generation of extremely accurate and excellent outcomes with the use of various types of clinical image data groups as well as magnetic resonance imaging, computed tomography and endoscopic graphics. Nevertheless, a computational neural network technique has not been used yet with colorectal topogram graphics.

Since 2012, much improvement has been accomplished with convolutional neural network designs. The classic of these designs, AlexNet, depicted fundamental enhancements over previous versions for the grading of graphics. In the past couple of years, a number of convolutional neural networks have been built for the enhancement of grading of pictures. Some of these convolutional neural network architectures include VGGNet in 2014, GoogLeNet otherwise known as Inception as well as ResNet, built in 2015. Such convolutional neural networks were built under six major enhancement features. These are: layer of convolution, pooling layer, activation application, loss application, regularization as well as optimization.

Extreme Inception otherwise referred to as Xception was built in 2017. This is a derivative of the Inception group developed at Google. This concept of this design is dependent on the Inception module. It has adjustments and a mix of convolutional layers, inception modules, depth-wise detachable convolutions as well as extra links for the improvement of the performance of the convolutional neural network. The outcomes of Xception demonstrate that the grading operation was enhanced in contrast to VGGNet, ResNet and Inception v3. The initial Xception structure utilized rectified linear unit (ReLU) for activating the application. This function known as Swish has the possibility of enhancing the accuracy of NASNet Mobile (developed, 2018) and of InceptionResNet v2 (established, 2016) for grading the image. Putting Swish in place of ReLu inside Xception could improve the grading operation in contrast to the initial Xceptionand other convolutional neural networks.

Investigations were conducted to provide a new adjustment of Xception by the application of Swish activation function for the determination of the likelihood of developing of a primary a screening system for colorectal polyps by equipping the suggested Xception with Swish prototype with a colonoscopy topogram scan dataset. This suggested system screens for colorectal polyps into two categories: absent and present. In addition, the results with the original Xception system and other instituted current convolutional neural network systems which are also altered with Swish as well as the operation of Xception provided evidence of superior results in contrast to other convolutional neural network architectures.

Fathy et al. (2011) conducted investigations on colorectal cancers prediction survival rates versus the quantity of hidden junctions in the Artificial Neural Networks (ANN). A clinical protocol for colorectal cancer was developed by (Stojadinovic et al., 2013) with the use of Bayesian Belief network (BBN). Wang and colleagues in 2013 examined the survival rates of patients with colorectal cancers on a number of varied indices like stage, age, gender as well as race.

The progress and continuous achievement of deep learning in the sectors of computer visuals as well as the recognition of speech, and the improved availability of medical records in electronic formats have aided the increase in research of varied kinds of neural networks on electronic health records.

A convolutional neural network architecture was suggested by Cheng for the isolation of characteristics and conduct the prognostication of chronic infections on patient electronic health records.

Data from the intensive care unit was used by (Lipton and colleagues, 2015) and assessed the capacity of Recurrent Neural Networks (RNN) with the use of Long Short-Term Memory (LSTM) units for the classification of 128 diagnosis given thirteen measurements.

Sirinukunwattana et al. (2015) introduced a deep learning technique for the detection of nuclei and classification on hematoxylin and eosin stained graphics of colorectal cancer. This technique is dependent on a standard eight-layer convolutional neural network for the identification of nuclear centers as well as grouping them into four classes of epithelial, inflammatory, fibroblastic and miscellaneous classes.

Another study conducted by (Janowczyk and colleagues, 2016) published a survey of the functions of deep learning in pathology, with exploration of sections like the detection of lymphocytes, mitosis, aggressive ductal carcinoma and the categorization of lymphoma. Every technique in the investigation employed the convolutional neural network suggested by (Krizhevsky and colleagues, 2012).

The increase use of whole slide digital scanners, there is the possibility of enhancing colonoscopy examiners in histopathology exams of microscopic graphics, the diagnosis of infections and the proper management of sufferers. Other enhancement factors for assisting pathologists accomplish such feats that are connected to the use of whole slide digital scanners include high throughput histology reservoirs and the archiving of digitized histological examinations

2.9 Colorectal Cancer and Deep Learning

Conventional monitored strategies for the testing of cancer is generally involved with a step concerned with the isolation of features. This then followed by the training of a classifier for these extracted features. With regards to the challenge of detecting binary colorectal cancer, an investigation was performed for varied combinations of eighteen isolated characteristics as well as those based with texture that are obtained from the grey level co-occurrence matrix, GLCM. A classifier based on Support Vector Machine (SVM) was then equipped for the accomplishment of a satisfactory precision as regards detection of 96.6% on a data group composed of 60 graphics which are equally spread out among two classes.

Another study was conducted which evaluated a number of textual characteristics coupled with various classifiers. The step involved with the isolation of characteristics was augmented by a decrease in dimension operation based on Principal Component Analysis (PCA). Classifiers were equipped for a three-step categorization task with the use of isolated characteristics from a data group comprising twenty-nine multiple graphics. Each of these contained sixteen channels which corresponded to various wavelengths. Multiple scale local binary patterns and then a support vector machine dependent classifier made possibility great accuracy with respect to classification (Peyret et al., 2015).

In another investigation, an extensive group of characteristics were computed over a data group of forty-eight graphics of breast cancer tissues with the use of nuclear structural features aside the frequently utilized characteristics based on texture. For the activity for the detection of cancer, a support vector machine dependent categorizer that was equipped on Gabor filter characteristics depicted quality outcomes with 95.8% accuracy. To ensure the isolation of extremely biased characteristics, the step involved with the isolation is commonly preceded by a sectionalizing task to highlight the sections of interest (Doyle et al., 2008).

In a different investigation, a by-product of the active contour dependent sectionalizing technique based on progressive sub-sampling of the graphic is presented for the sectionalizing of multiple scans. This was followed by the extraction of Haralick-dependent characteristics. Following this was the equipping of a probabilistic neural network for the classification. Characteristics from eighteen graphics were utilized for equipping the network and a subsequent number of forty-five graphics were utilized for testing (Chaddad et al., 2011).

In a similar manner, an active contour dependent pre-processing step was employed for the identification of sections of interest. A number of texture-based characteristics are isolated from here. These traits were used to equip three different classifiers and were evaluated through a data group of 480 sixteen channel multiple spectral scans. These images were gotten from biopsy samples of thirty patients.

Convolutional neural networks provide top quality outcomes for various computer visual tasks like the detection of objects as well as their recognition. Nevertheless, adequate equipping necessitates a vast proportion of graphics. This is a critical impediment to their routine use for clinical field challenges in which the annotated information is frequently in short supply. With the particular instance with the analysis of images from diseased tissues, patch generation as well as methods involved with the augmentation of information are the commonest strategies engaged for artificially improving the proportion of annotated samples utilized for equipping.

Patch generation is involved with isolating small fragments of patches from the initial graphic. Every single patch is assumed to bear same annotation as that of the initial graphic and is handled as a distinct data point. Following this is the stage concerned with the augmentation of data. This involves the application of geometric changes like rotation and flipping for further increasing and enriching the equipping data. In studies conducted, 70,000 distinct patches were obtained from 250 initial equipping scans which were then utilized for equipping a convolutional neural network for four-class classification of breast cancer. Equipping the CNN for categorization as well as training a classifier with the use of CNN characteristics both accomplished about 80% accuracy with respect to the diagnosis of cancer (Araujo et al., 2017).

In like manner, studies conducted by (Spanholl et al., 2016) involved the use of CNN dependent on the classical structure of AlexNet. This was equipped from its initial stages with the use of BreaKHis dataset. Of the 7,909 graphics used, up to 1,000 patches were obtained from each. This investigation reported an image accuracy of 90%. Further research on this involved the cropping of each image from same data set to generate a square patch and applied affine changes to get a more extensive pool of equipped samples. This was further utilized to equip a custom convolutional neural network structure which comprises three convolution blocks, three completely connected layers and then a soft max categorization layer. This technique proved superior to handcrafted methods and accomplished a mean recognition frequency of about 83.25%.

In contrast to the diagnosis with breast cancer, one of the major challenges with diagnosis involving colorectal cancers is the absence of an extensive dataset. In some investigations conducted, multiple spectral 16 channel graphics from just thirty sufferers were gotten and sectioned with the use of the contour technique. These sectioned images were then employed to equip a convolutional neural network comprising two convolutional layers interspaced by max pooling, and a completely connected layer. Despite the achievement of a 99% accuracy, much subjectivity is observed. This is due to the preprocessing sectioning step as well as the restricted variation of the test group which had graphics from just nine sufferers.

As earlier mentioned, equipping a deep CNN from its initial stage across a limited number of annotated data is not feasible. More so, the degree to which patch generation as well as data enhancement alleviates this challenge is limited. As an alternative, transfer learning dependent techniques are presented to make up for the limited availability of data.

In the field of biomedical science for the analysis of medical scans, the application of transfer learning for the detection of thoraxo-abdominal lymph node was investigated coupled with the categorization of interstitial lung infection. For this purpose, prototypes for prominent CNN structures of AlexNet and GoogLeNet that had been trained were utilized. These prototypes were tested by utilizing them as isolators of traits and by finely regulating via training of the last completely connected layer from initial stages and then resuming equipping for the bottom convolutional layers with the use of lower learning frequency.

With respect to visual and quantitative stability, transfer learning dependent techniques were found to be superior. For the activity of classifying cancers from histology scans, a number of techniques dependent on transfer learning have been conducted. In this study, the proposed technique involved the application of a two-step transfer learning process on the data group 23. After patch generation and the enhancement of data, a VGG16 prototype which had been pre-equipped on ImageNet data group is utilized for transfer learning. The completely linked layers of the prototype are randomly initialized and equipped with the use of target data group. This was then followed with fine regulation with a smaller learning frequency across same equipped data. This technique proved superior to the techniques involving equipping from initial stages for same group of graphics.

Same activity for the detection of cancer was conducted by (Chougrad et al., 2017) on the BCDR data group. This comprised digitalized mammogram for over 300 sufferers. Several augmentation strategies were employed on a pre-equipped Inception V3 pattern. Furthermore, a strategy which involved the correction of the learning rate in which this was decreased for every single lower layer.

On a data group consisting 400 high resolution scans for four various categories of breast cancer, a stain normalization was applied on patches prior to utilizing them to regulate already prepared InceptionV3 as well as ResNet50 prototypes. The top completely linked layers of the networks were replaced with a mixture of mean pooling, a completely linked layer and then by a soft max categorization layer (Vesal et al., 2018). Many investigations have been performed for the automatic detection for analyzing and classifying colorectal cancer tissues. Fu and colleagues developed a computer assisted diagnostic system for the classification of colorectal growths with the use of sequential scans characteristic selection and support vector machine (SVM) categorization (Fu et al., 2014).

Kumar and colleagues proposed a processing pipeline as well as the utilization of graphic categorization microscopically, the isolation of characteristics and categorization for the automatic detection of colorectal cancers from biopsy graphics (Kumar et al., 2015).

An investigation dependent on clinical, molecular and characteristics on morphology depict the significance of such characteristics for diagnosing and treating CRC (Jass et al., 2007). A blend of characteristics based on geometry, morphology, texture and scale invariance was also assessed in studies conducted by Rathore and colleagues. This technique involved the classification of colon biopsy scans with an accuracy of 99.18% (Rathore et al., 2015). In another experiment conducted, a similar group of hybrid characteristics was utilized with an ensemble classifier for the enhancement of the accuracy of classification (Rathore et al., 2014). Rathore et al also performed investigations with structural characteristics dependent on the white run length as well as percentage cluster region and was depicted to be significant for the classifying of biopsy graphics (Rathore et al., 2013).

A study conducted by Chaddad and colleagues utilizes three-dimensional gray level co-occurrence matrix characteristics for the classification of CRC tissue kinds in multiple spectral graphics (Chaddad et al., 2016). In recent times, convolutional neural networks have led to state-of-the-art performance on a wide diversity of computer visual activities like face recognition, (Krizhevsky et al., 2012), broad range classifying of object, as well as the assessment of documents. In contrast to traditional techniques based on manual expertise, these techniques which involve the use of CNN have the capacity of developing top quality characteristics from low level features in a data directed manner. In clinical applications, the utilization of CNN has demonstrated satisfactory possibility for diverse applications like the recognition of medical scans, the detection of diseased tissues and the classifying of tissues.

New techniques have been suggested for the assessment of the progression of CRC which uses CNNs for multiple spectrum scans. In these studies, the progress of CRC is patterned with the use of three kinds of diseased tissues:

- Benign Hyperplasia (BH) which represents abnormal growth in the proportion of non-cancerous cells.
- Intra-epithelial neoplasia which represents an abnormal proliferation of tissue for the formation of a tumor
- Carcinoma which corresponds to the abnormal tissue developing into a cancer.

The utilization of CNN is for the determination of the kind of tissue for biopsy scans obtained with a light microscope at various wavelengths. By the identification of the kind of tissue, the progress of CRC can be tracked hence providing guidance on the best possible diagnosis and treatment plan.

Studies by (Kim and colleagues, 2015) reveal that females over 65 years of age have higher likelihood of mortality from colon cancer in contrast to men of same age group. With such women, the cancer is often of an aggressive nature and infects the proximal colon. Factors which are likely to contribute to the increased rates of proximal colon cancer in women may include:

- Social and cultural impediments which prevent females from signing up for screening programs and getting a prompt diagnosis.
- Difficulties experienced with detection as well as the increased rates of missed diagnosis during colonoscopy exams.
- Asymptomatic nature of the infection as patients with proximal colon cancer seldom develop signs such as rectal bleeding or abdominal pain and hence unlikely to seek medical help unless at later stages of the infection.

In view of these difficulties, there is the necessity for exploring techniques to improve the screening for cancers of the right colon. The combined use of CNN along with colonoscopy could help improve the rates of detection and hence diagnosis.

Several studies have been conducted on the early diagnosis of colonic polyps with the use of convolutional neural networks.

In 2017, Komeda and colleagues conducted a study on this. The main objective of the investigation was on the possibility of a computer-aided diagnosis (CAD) dependent on CNN make possible the classifying and diagnosis of colon polyps. The method made use of a convolutional neural network with a system based on computer-aided diagnosis as well as artificial intelligence for examining the colonoscopy graphics. The results of the investigation proved that findings of the CNN were accurate in 7 out of 10 instances. Therefore, the procedure could be utilized in the rapid detection of colorectal tumors as well as their classification. However, the efficiency of CNN-CAD systems in everyday colonoscopy calls for further research (Komeda et al., 2018).

In 2016, Ribeiro and colleagues explored databases' deep learning techniques for the automatic categorization of colon tumors. The method used include distinct structures 'off the shelf' pre-trained CNNs which are tested on an 8 HD colonoscopy graphic, with 1200 graphics isolated from the endoscopy videos. The outcomes from the investigation showed that convolutional neural networks trained from scratch could be very significant for automatic categorization of colon polyps. These findings were compared to those of commonly utilized characteristics of colon polyp categorization (Ribeiro et al., 2016).

In 2018, Urban and colleagues experimented on the capacity of computer aided graphic analysis with convolutional neural networks to enhance the detection of polyps. The CNN tried twenty colonoscopy videos, a total of 5 h.S.A.AS. The findings revealed an additional eight growths without CNN utilization which had not been isolated and identified, as well as another 17 growths with the use of CNN. The convolutional neural network traced growths with an area below the operating feature graph of 96.4%. The false positive proportion of the CNN was 7% (Urna et al., 2018).

Qadir and colleagues (2019) set on an investigation on enhancing the total performance of CNN dependent detection of growths on colonoscopy scans. The procedure involved two stages: a section of interests prompted by CNN detector and a false positive decrease unit. The results proved that the two directional temporal data in the system pattern aided in the estimation of growth locations as well as in the prediction of false positives thereby improving on the sensitivity and precision. The accuracy of this method was better in contrast to convolutional false positive learning techniques (Qadir et al., 2018).

Billah and colleagues (2017) performed an investigation on the possibility of automatic systems in supporting the detection of gastrointestinal growths. The method used a combination of CNN with linear support vector machine (SVM). From the findings, it was observed that the identification of growths with the use of computer assistance decreased the frequency of missing out on polyps as well as aided in exploring colonic sections of interest. This suggested method provides more accuracy than the majority of gold-standardized methods, with an accuracy of 98.6%, a sensitivity of 98.8% and a specificity of 98.5% (Billah et al., 2017).

In 2017, Zhang and colleagues conducted an experiment on the development of fully automatic technique for the detection and classification of hyperplastic as well as adenomatous colorectal growths. The method utilized a new transfer learning application which uses characteristics obtained from extensive non-clinical data with close to 2.5 million scans with the use of deep learning CNN. The outcomes of the experiment identified growth scans from non-polyp graphics at the initial stage. This was subsequently followed by the prediction of polyp histology. Automated techniques can aid colonoscopy examiners identify growths which are adenomatous but have been wrongly labelled hyperplastic. In contrast to the visual observation by colonoscopy examiners, the outcomes of this investigation prove that this technique bears a similar precision of 87.3% versus 86.4% but a greater recall rate of 87.6% in contrast to 77.0%. It also has a greater accuracy of 85.9% in contrast to 74.3% (Zhang et al., 2017).

Blanes-Vidal et al. (2019) explored two suggested techniques on enhancing the acquisition and examination of information gotten from capsule colonoscopy on colorectal growths. The method utilized information from the Danish National screening program colorectal capsule endoscopy (CCE). Information on colonoscopy and histopathology of all growths was also utilized. The technique developed complemented CCE as well as colonoscopy growths. The deep convolutional neural network enabled automatic identification and spotting of growths. The results from the investigation showed that the technique objectively quantified similarities between colorectal capsule endoscopy and colonoscopy growths. In contrast to previous techniques, this proposed technique demonstrated an accuracy of over 96%, a sensitivity of 97% as well as a specificity of 93% (Blanes-Vidale et al., 2019).

Haj-Hassan and colleagues (2017) conducted an experiment on the possibility of CNN being able to predict the kinds of tissues that are associated with the progression of colorectal cancer. The technique used the CNN and multiple spectral scans of thirty patients with colorectal cancer graphics at three various histopathology stages. The results of this experiment showed that CNN has proven the capacity of detecting tissue types of colorectal cancers accurately. The accuracy of the method was found to be 99.2%, which significantly outperforms current techniques which rely on traditional characteristics, isolation and categorization techniques (Haj-Hassan et al., 2017).

Kainz and colleagues (2017) examined the capacity of deep learning for segmenting of glands as well as the classifying of glands for differentiating between benign and malignant colon tissues. The method was based on deep neural dependent technique patterned for segmenting and classifying glands in colon tissues into benign or cancerous. The outcomes of this method showed the capacity of differentiating between benign and cancerous tissues with increased accurate results. The accuracy of the technique in the segmenting and classifying of tissues was found to be 98% and 95% respectively (Kainz et al., 2017).

Mahmood and Durr (2018) presented a method which used CNN-conditional random field for reconstruction of topography of the colon mucosa from convolutional colonoscopy scans. The method involved the training of unary as well as pair-wise applications of conditional random field incorporated in a CNN structure as well as the utilization of information obtained from colonoscopy scans. The outcomes showed that the estimated depth maps could be utilized in the reconstruction of the topography of the colon mucosa. The system can be incorporated into available colonoscopy system and the technique enables the detecting, segmenting as well as classifying of growths (Mahmood et al., 2018)

Sirinlukunwattana and colleagues (2016) conducted a study for the detection and categorization of diseased tissue scans of colorectal malignant tissues among regionally sensitive deep learning. The technique involved the utilization of a spatiality constrained CNN for performing the detection of nucleus as well as for the categorization of new peripheral ensemble predictor along with CNN. The results showed an extensive dataset of scans of colorectal adeno-cancerous cells (20,000 labelled nuclei from four distinct patients). This technique generated the greatest mean F1 proportion compared to other newly published techniques (Sirinukunwattana et al., 2016).

Men and colleagues (2017) suggested a technique, a new deep dilated convolutional neural network dependent technique for rapid and consistent automated segmenting of colorectal cancers. This technique showed that the deep dilated convolutional neural network technique can be utilized with much accuracy and effectiveness in contouring and streamlining radiotherapy. This suggested technique outperformed U-Net in all categorizations. The mean dice similarity coefficient was more than 3.8% greater than that for U-Net.

Shin and colleagues (2016) applied a section dependent structure in automated detection of growths in scans gotten from colonoscopy exams. The technique utilized a deep CNN prototype for the detection. Graphic enhancement techniques were examined for training deep networks. Two post learning techniques were incorporated for the detection of false positives as well as enable reliable detection of growths. This method demonstrated an enhanced performance with respect to the detection of colon polyps (Men et al., 2017).

CHAPTER 3
METHODOLOGY

3.1 Dataset

The dataset that was used in this study was derived from a "100,000 histological images of human colorectal cancer and healthy tissue" by (Kather et al., 2018). The entire images in this database was 224x224 pixels. However, it has a 0.5MPP and it was color normalized utilizing Macenko's method. Nine different classifications were utilized in the testing and training of ResNet50 and VGG-19: Adipose (ADI), Background (BACK), Debris (DEB), Mucus (MUC), Normal colon mucosa (NORM), Lymphocytes (LYM), Smooth muscle (MUS), Cancer-associated stroma (STR), and Colorectal adenocarcinoma epithelium (TUM). Figure 3.1 reveals the colorectal images used for ResNet and VGG-19 classification.

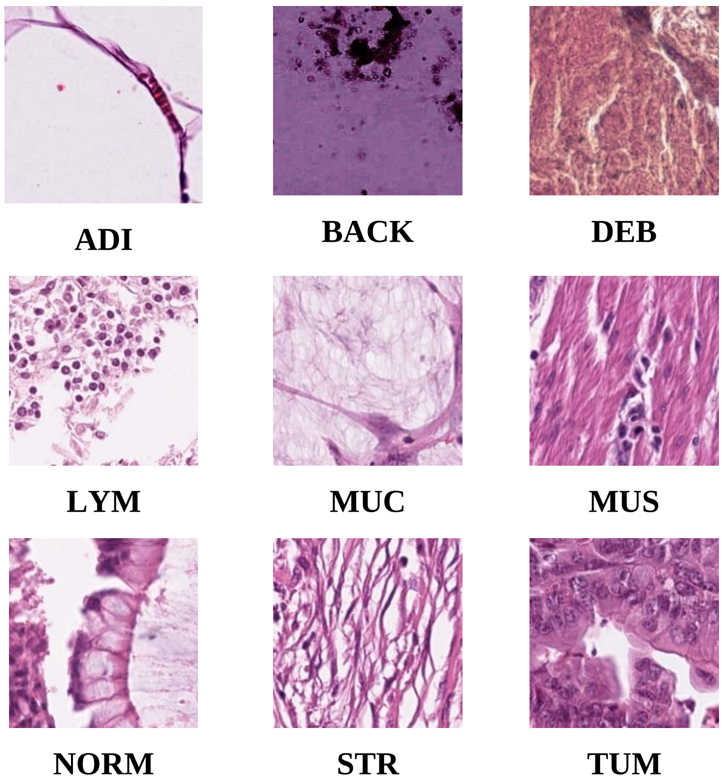

Figure 3.1: Normal and Abnormal MR images for data training

The images used in this study were adopted from the NCT Biobank from a gastrectomy specimen. The total images used was 7180 derived from a patch of 50 patients with colorectal adenocarcinoma. The data used for training was splinted 80% for training and 20% for testing.

Table 3.1: Colorectal images

Classification Label	**Image Count**
ADI	1338
BACK	847
DEB	339
LYM	634
MUC	1035
MUS	592
NORM	741
STR	421
TUM	1233
Total Count	7180

3.2 Study Parameters

The parameters used for this study to determine the level of testing include Accuracy (ACC), Specificity (SP) and Sensitivity (SE). Equation (1), (2) and (3) was a very effective tool in determining the different study parameters. The true positive, true negative, false positive, and false negative derived from the confusion matrix was inputted in the equations.

$$\text{Accuracy (ACC)} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \tag{3.1}$$

$$\text{Specificity (SP)} = \frac{TN}{TN + FP} \tag{3.2}$$

$$\text{Sensitivity (SE)} = \frac{TP}{TP + TN} \tag{3.3}$$

Where TP = True Positive , TN = True Negative , FP = False Positive and FN = False Negative.

3.3 ResNet-50

Various enhancements in CNN have been produced using 1989 to date. These enhancements can be arranged as parameter streamlining, regularization, basic reformulation, and so on. In any case, it is seen that the primary purpose in CNN execution improvement originated from rebuilding of handling units and structuring of new squares. A large portion of the advancements in CNN have been made in connection with profundity and spatial misuse. Contingent on the kind of compositional changes, CNNs can be extensively sorted into seven unique classes in particular; spatial abuse, profundity, multi-way, width, highlight map misuse, and consideration based CNNs (Asifullah et al., 2015).

Different upgrades in CNN have been delivered utilizing 1989 to date. These upgrades can be orchestrated as parameter streamlining, regularization, essential reformulation, etc. Regardless, it is seen that the basic role in CNN execution improvement started from reconstructing of taking care of units and organizing of new squares. An enormous segment of the headways in CNN have been made regarding significance and spatial abuse. Dependent upon the sort of compositional changes, CNNs can be widely arranged into seven remarkable classes specifically; spatial maltreatment, significance, multi-way, width, feature map abuse, and thought based CNNs (Asifullah et al., 2015).

3.4 VGG-19

Visual geometry group (VGG) is a type of CNN that can perform multifunctional layers of computation. The VGGNet is very effective in analyzing images from datasets. VGG-19 is one of the simplest CNN because of its 3x3 convolutional layers, which multiplies in several depths. The VGG-19 consists of two FC CNN layers with neurons of 4096 and another FC layer of 1000 neurons.

However, the performance of VGG-19 was compared with other networks used in this study to determine the level of accuracy and performance during the testing and training of the dataset. In spite of the fact that the size of association definitely dropped, it despite everything leaves such a large number of parameters to settle. Another suspicion for rearrangements, is to keep the neighborhood association loads fixed for the whole neurons of the following layer. This will associate the neighbor neurons in the following layer with the very same load to the nearby locale of the past layer. In this manner, it again drops numerous additional parameters, and lessens the quantity of loads.

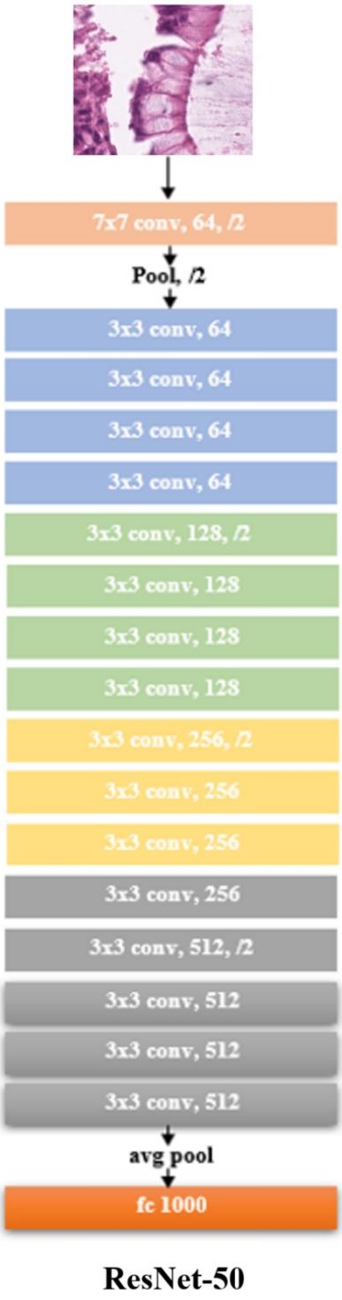

Figure 3.2: ResNet-50

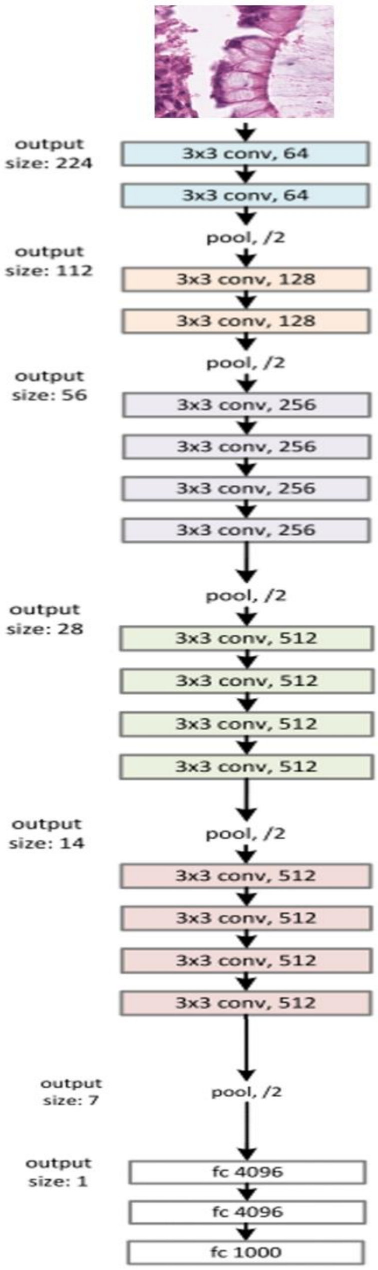

Figure 3.3: VGG-19

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Experimental Results

Results obtained from the two different networks used in this study (ResNet-50 and VGG-19) was reported in this section. The accuracy for ResNet-50 was 99.3% and VGG-19 was 95.5%. The learning rate for this study was 0.0001 for both ResNet-50 and VGG-19. It should be noted that during the training of the data, the dataset was splinted into 80% for training and 20% for testing. A plot of the classification accuracy against the Epoch for both ResNet-50 and VGG-19 is visualized in Figure 4.1 and Figure 4.2 respectively.

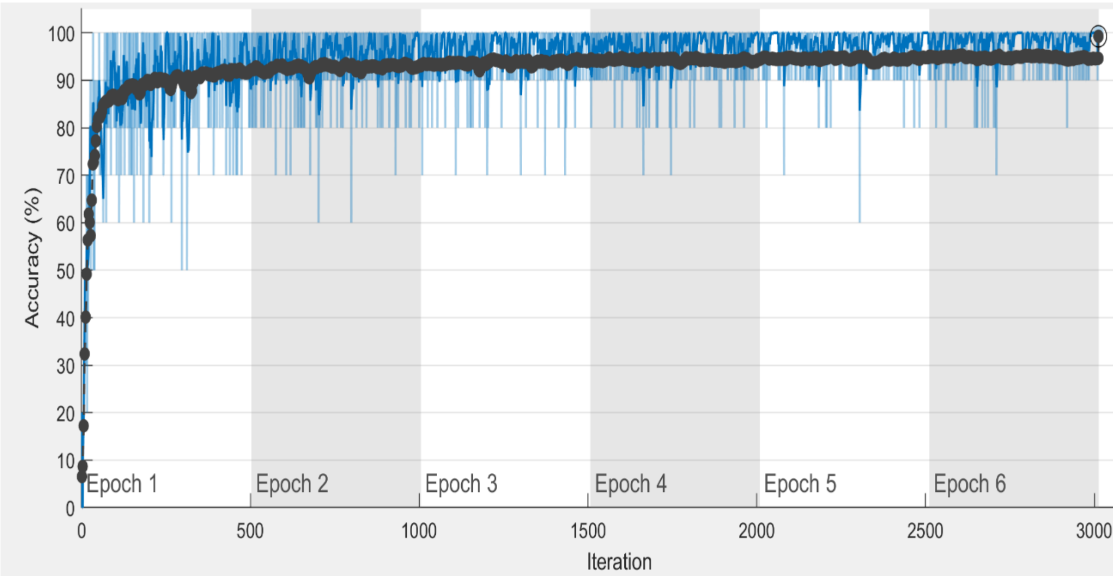

Figure 4.1: Plot of Classification accuracy against Epochs (ResNet-50)

The learning parameters for the networks (ResNet-50 and VGG-19), had an epoch of 100 and 100 respectively. The training time for both ResNet-50 and VGG-19 was 1 hour and 2 hours respectively.

Table 4.1: Models learning parameters

Models	ResNet-50	VGG-19
Parameters	**Values**	**Values**
Epoch	100	100
Learning Rate	0.0001	0.0001
Training Time	1 hour	2 hours
Testing Accuracy	99.3%	95.5%
Training Accuracy	100%	100%
Mean Square Error (MSE)	0.065	0.043

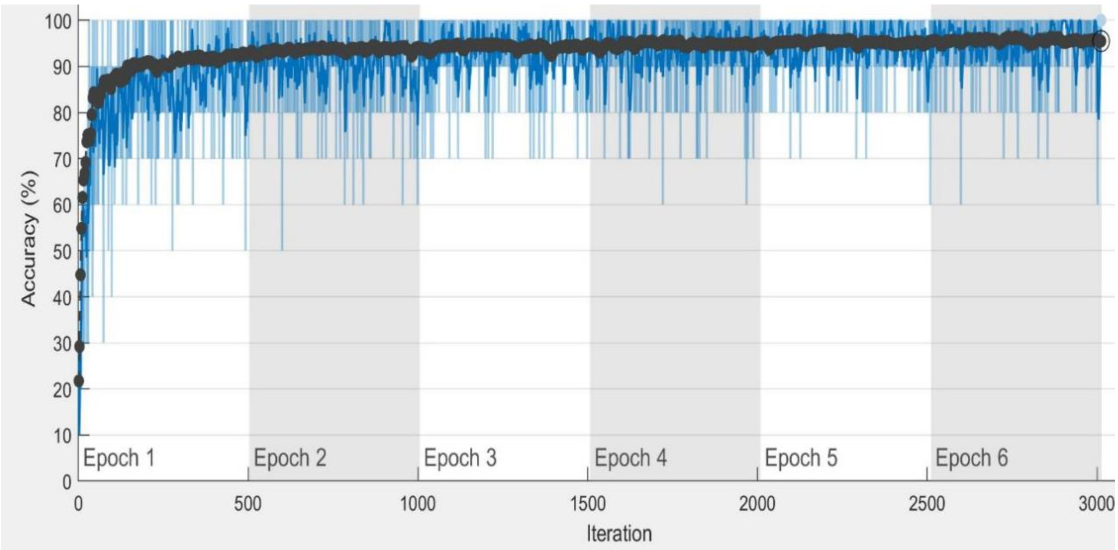

Figure 4.2: Plot of Classification accuracy against Epochs (VGG-19)

ResNet-50 had a better accuracy result in comparison to VGG-19. The training and testing time as well as the processing capacity of the simulating machine were all contributing factors to the training and testing accuracy. Moreover, the Mean Square Error (MSE) of both Resnet-50 and VGG-19 were 0.065 and 0.043 respectively.

Table 4.2: Performance parameters of dataset

Network	Models	ACC	SP	SE	AUC
ResNet-50	ADI	98.8%	1.000	1.000	0.967
	BACK	97.8%	1.000	1.000	0.981
	DEB	98.7%	0.981	0.980	0.977
	LYM	99.5%	0.984	1.000	0.971
	MUC	98.4%	1.000	0.967	0.968
	MUS	99.2%	0.977	0.938	0.955
	NORM	98.6%	0.995	0.959	0.943
	STR	98.8%	0.927	0.913	0.968
	TUM	98.5%	0.963	0.992	0.911
VGG-19	ADI	96.5%	0.987	0.995	0.895
	BACK	95.7%	1.000	1.000	0.899
	DEB	96.2%	0.951	0.971	0.914
	LYM	95.3%	0.962	0.979	0.927
	MUC	95.8%	0.827	0.981	0.972
	MUS	96.8%	0.911	0.959	0.986
	NORM	94.4%	0.954	0.954	0.978
	STR	95.8%	0.955	0.724	0.991
	TUM	95.9%	0.969	0.939	0.962

Table 4.2 gives information on the different parameters of ResNet-50 and VGG-19. The AUC value of both networks was analyzed and compared. The confusion matrix is formulated based on the “True Positive (TP)”, “True Negative (TN)”, “False Positive (FP)” and “False Negative (FN)”. Table 4.3 reports results obtained from the overall data parameters (Accuracy, Specificity, Sensitivity, and the Area Under the Curve.

Table 4.3: Overall data parameters

Network	ACC	SP	SE	AUC
ResNet-50	99.3%	0.981	0.972	98.9%
VGG-19	95.5%	0.946	0.945	96.2%

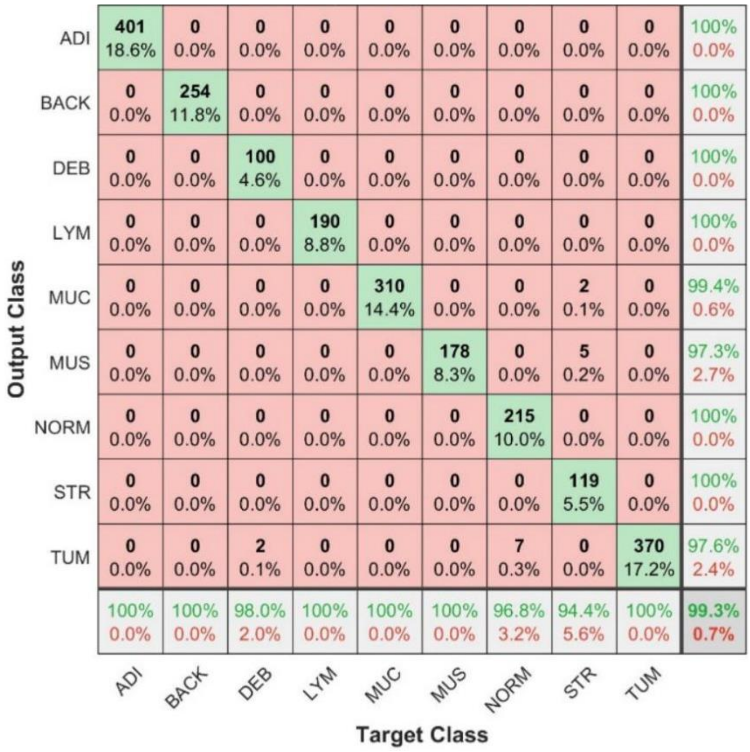

Figure 4.3: ResNet-50 Confusion Matrix

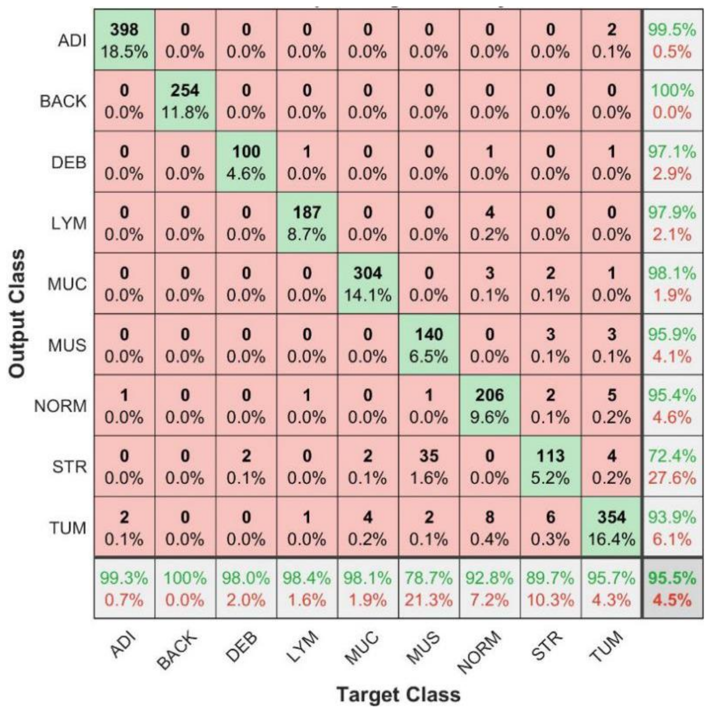

Figure 4.4: VGG-19 Confusion Matrix

4.2 Comparison of Model Performance

In this study, a comparison between ResNet-50 and VGG-19 was analyzed, to analyze. Results obtained from this study, indicated ResNet-50 to have the highest accuracy (99.3%) compared to the accuracy of other networks. VGG-19 had an accuracy of 95.5% which is lower than ResNet-50.

Abubaker et al. (2019) conducted a study on colorectal cancer using deep learning and AlexNet as a classification network for adipose tissue, back tissue, debris tissue, lymphocytes tissues, mucus tissue, smooth muscle, normal tissue, cancer associated stroma and adenocarcinoma epithelium. Their study had the highest level of accuracy (97.8%) amongst the other comparisons, as well as the specificity (1.000) and sensitivity (1.000).

Table 4.4: Comparison of our study and previous studies

Studies	Network	ACC	SP	SE	AUC
Our Study	ResNet-50	99.3%	0.981	0.972	98.9%
Our Study	VGG-19	95.5%	0.946	0.945	96.2%
Abubaker et al. (2019)	AlexNet	97%	0.98	0.97	-
Xiaomei et al. (2020)	ResNet-50	95.0%	0.721	0.804	-
Esmaeil et al. (2020)	ResNet-50	69.7%	0.993	0.807	-
	VGG-19	82.7%	0.902	0.688	-
	VGG-16	63.5%	0.856	0.424	-
	AlexNet	74.1%	0.820	0.923	-
	GoogleNet	51.2%	0.994	0.132	-
Hyo-Joon et al. (2018)	ResNet-50	95.0%	85.7%	67.6%	86.0%

However, results reported by Xiaomei et al. (2020) and Hyo-Joon et al. (2018) had the second highest accuracy (95.0%) for ResNet-50. Esmaeil et al. (2020) conducted a similar study on the staging of colorectal cancer using deep learning with several networks (ResNet-50 (69.7%), VGG-19 (82.7%), VGG-19 (63.5%), AlexNet (74.1%), GoogleNet (51.2%), Modified Network (98.1%)), had a better accuracy than ResNet-50 (99.3%).

The comparison between our study and previous studies as indicated in Table 4.4 was analyzed on different parameters, which consist of accuracy, specificity, sensitivity and the area under the curve. Results have shown ResNet-50 to be a better convolution neural network compared to GoogLeNet. Hyo-Joon et al. (2018), also reported an accuracy of 95.0% which reveals a very high level of performance.

However, results from these comparisons have revealed the modified networks to have the highest level of accuracy, specificity and sensitivity. Thus, with the high level of accuracy recorded from this study, it is evident that a modified network for our study will yield a better result.

CHAPTER 5
CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

Deep learning has been very effective in the area of colorectal cancer detection. Different networks were used during the testing and training of this study. ResNet-50 and VGG-19 were used in testing and training nine different classification. The accuracy, specificity and sensitivity result of this study reveals that ResNet-50 (99.3%) has a better accuracy compared to VGG-19 (95.5%). Comparison between our study previous studies were carried out in this study to ensure the validity of the study. However, several factors can contribute to the efficiency of the result, some of these factors include, the processing speed of the simulating machine, and several interferences that may occur.

Deep CNN learning alludes to the class of AI techniques that utilize progressively increasingly dynamic portrayals of the info information to play out a particular task. These techniques use preparing information to figure out how these portrayals ought to be created in a way suitable for the given undertaking. On the other hand, conventional AI utilizes carefully assembled highlights to make portrayals of the information that are applied to play out the errand. In numerous applications, profound learning has been demonstrated to be better than other machine learning strategies and is relied upon to change current clinical practice. Convolutional neural systems have exceeded expectations in many picture understanding undertakings and could be conjectured to recover extra data from histopathology pictures. The point of this examination was to utilize profound figuring out how to investigate regular entire slide pictures to build up a programmed prognostic biomarker for patients resected for essential colorectal malignant growth. Moreover, several recommendations and limitations exists in this study that might upgrade and optimize the performance rate of ResNet-50 and VGG-19 during the training and testing of different networks.

5.2 Recommendations

Diagnosis in oncology needs a high level of accuracy and the general performance of a CNN network needs to be at a very high optimized state. However, the result obtained in this study has shown a very high-performance rate of both ResNet-50 and VGG-19. The need to explore higher optimization results and performance is needed. Several combination techniques can be used to further enhance the results obtained in this study. The use of Support Vector Machine (SVM) as a combination technique can yield a very effective result. ResNet50-SVM and VGG19-SVM can provide a very high-performance result during testing and training, as evident in previous studies.

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APPENDIX I

ETHICAL APPROVAL LETTER

NEAR EAST UNIVERSITY YAKIN DOĞU ÜNİVERSİTESİ

ETHICAL APPROVAL LETTER

TO GRADUATE SCHOOL OF APPLİED SCİENCES

REFERENCE: MUFTAH EMTIR ALFRGANI ALI (20163825)

I would like to inform you that the above candidate is one of our postgraduate students in Electrical and Electronics Engineering department he is taking thesis under my supervision and the thesis entailed: EARLY IDENTIFICATION OF COLORECTAL CANCER USING CONVOLUTIONAL NEURAL NETWORK (DEEP LEARNING).
The data used in his thesis does not require any ethical report.

Please do not hesitate to contact me if you have any further queries or questions.

Thank you very much indeed.

Best Regards,

Assoc. Prof. Dr. Sertan Serte

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Mersin 10 – Turkey.
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APPENDIX II

SIMILARITY REPORT

	AUTHOR	TITLE	SIMILARITY	GRADE	RESPONSE	FILE	PAPER ID	DATE
	Muftah Emtir Alfrgan...	Abstract	0%	--	--		1333527241	28-May-2020
	Muftah Emtir Alfrgan...	Chapter 1	4%	--	--		1333527910	28-May-2020
	Muftah Emtir Alfrgan...	Chapter 2	11%	--	--		1333528399	28-May-2020
	Muftah Emtir Alfrgan...	Chapter 3	12%	--	--		1333528733	28-May-2020
	Muftah Emtir Alfrgan...	Chapter 4	7%	--	--		1333528972	28-May-2020
	Muftah Emtir Alfrgan...	Chapter 5	0%	--	--		1333529241	28-May-2020
	Muftah Emtir Alfrgan...	Conclusion	0%	--	--		1333527522	28-May-2020
	Muftah Emtir Alfrgan...	MSc Thesis	11%	--	--		1333525918	28-May-2020