GASTROINTESTINAL DISEASE DETECTION USING MULTICLASS CNN FROM ENDOSCOPY IMAGES .

BY

MD. MAMUN MUNSI
ID:193-15-3008

FINAL YEAR DESIGN PROJECT REPORT

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

Supervised By

Mr. Amit Chakraborty
Assistant Professor
Department of Computer Science and Engineering
Daffodil International University

Co-Supervised By

Ms. Nusrat Khan
Lecturer
Department of Computer Science and Engineering
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

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APPROVAL

This Project titled **"GastroIntestinal Disease Detection Using Multiclass CNN From Endoscopy Images"**, submitted by **Md Mamun Munsi** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **14-07-2024.**

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Faculty of Science & Information Technology
Daffodil International University

Dr. Md. Manowarul Islam — **External Examiner**
Associate Professor
Department of Computer Science and Engineering
Jagannath University

DECLARATION

I hereby declare that this project has been done by me under the supervision of **Mr. Amit Chakraborty,Assistant Professor,Department of Computer Science and Engineering, Daffodil International University**. I also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

Mr. Amit Chakraborty
Assistant Professor
Department of CSE
Daffodil International University

Co-Supervised by:

Nusrat Khan

Ms. Nusrat Khan
Lecturer
Department of CSE
Daffodil International University

Submitted by:

Mamun

Md. Mamun Munsi
ID:- 193-15-3008
Department of CSE
Daffodil International University

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Finally, I must acknowledge with due respect the constant support and patience of my parents.

ABSTRACT

Gastrointestinal diseases refer to diseases of the gastro intestinal tract and include; gastro esophagitis, ulcerative colitis, gastric lesions among others. These diseases are best diagnosed at an early stage, and therefore, the need for enhanced diagnostic methods that allow for same. This paper proposes the use of Convolutional Neural Networks (CNNs) in discerning gastrointestinal diseases from endoscopy images in an effort to make diagnosis more accurate as well as faster. The research assesses different CNN architectures – DenseNet201 and InceptionResNetV2, VGG19, and the CNN models: CNN01 and CNN02 developed by the authors specifically for this research investigation. A comprehensive set of images involving gastrointestinal diseases such as esophagitis, ulcerative colitis, dyed resection margins, normal pylorus were used for training and testing. The experimental findings also reveal that the built own CNN01 model yielded the highest average accuracy of 98.56%. These research outcomes show the effectiveness of the high-architectural CNN in achieving good classification of gastrointestinal diseases from endoscopic pictures. In light of the study of CNN, potential future applications of CNN are presented to demonstrate how CNN could improve diagnostic accuracy within gastroenterology and reduce the necessity of operation. The future of this kind of research will involve handling of a diverse dataset, working to reduce the class imbalance issue, and enhance the explain ability of the model.

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CHAPTER 1
Introduction

1.1 Introduction

GI disorders are a leading cause of morbidity and mortality worldwide with several disorders causing harm to millions of patients and members of their families if detected and treated late. Studies like esophagitis, gastritis, ulcers and colon cancer present complex diagnostic tasks because symptoms change in endoscopic pictures. Using typical pathological methods, the diagnosis is based on the gastroenterologist experience; therefore, the assessment the results are rather subjective and may contain mistakes.

Endoscopy is employed commonly for the diagnosis of the GI tract, which offers a direct view of the specific area of interest. Still, comprehension of endoscopic images is not an easy task, as it requires a great amount of experience to identify various peculiarities. As a rapidly developing field of study, AI and new approaches to machine learning in particular can contribute to improving the specificity and sensitivity of the diagnostic in the field of studied GI diseases. For instance, Convolutional Neural Networks (CNNs), which is among the categories of deep learning models, have stood out by demonstrating impressive performance in the image classification domain, which makes them ideal for diagnosing medical images.

Our research work in this paper has the possibility of designing a multiclass CNN model ideal for the identification and categorization of different GI diseases based on images of endoscopic views. The aim is to build and implement an automated CAP system that would help clinicians with accurate and accurate interpretations which could solve the problem of manually intensive interpretations and also bring benefit in patients' lives. Hence, the presented model is cross-checked with the DenseNet201, InceptionResNetV2 and VGG19 prior confirming the performance. Hence, based on a rich dataset and using sophisticated preprocessing tools, this work further demonstrates the possibility of CNNs in revolutionizing the field of GI disease diagnosis with higher accuracy and repeatability.

1.2 Motivation

The reasons for this search are numerous fields which indicate that there is a lack of such knowledge and the presence of the need for further innovations in relation to the diagnostics of the GI diseases. Any standard procedure of diagnosing the GI illness through endoscopy is going to be unequal and cannot be without some amount of error because the images are deleted by specialists. In fact, at the global level the number of persons suffering from GI diseases is increasing therefore the need for the purpose of building reproducible and accurate diagnosing method is felt.

For many domains, especially for the image classification task, CNN has been recognized as the most appropriate model in comparison with other similar architectures and, more importantly, the medical image analysis. Thus, under the CNN technology as described above, an automatic diagnostic module can be developed that might help in saving time and therefore cause less burden to the health care professionals. Therefore, the goal of this present research study is to create improved CNNs based multiclass GI disease image classifier that will aid in the diagnosis of GI diseases with increased accuracy to enhance chances of early diagnosis of such diseases and subsequently, better patient outcomes.

1.3 Rational of the Study

Therefore, the reason for this study can be underpinned on the fact that current methodologies used to diagnose gastrointestinal (GI) disease are portrayed by certain weaknesses and constraints. Colonoscopy and similar technologies are the gold standard for visualizing the GI tract but suffer from low objective in measurement and interpretation due to the difference in the study of images between individuals. Mistaken perceptions can result in wrong diagnosis, timely interventions not being taken or instead being taken at wrong time as well as worse prognosis of patients.

The solution of using Convolutional Neural Network (CNNs) is suggested because of the success rate shown by the CNNs in performing image recognition and classification tasks. Starting from the concept of multiclass CNN for endoscopic images, this study has introduced the discussion of the development of a tool that can diagnose multiple GI diseases. It not only improves the accuracy of the diagnosis but also minimizes the misconceptions and variations inherent with a large number of examiners. In conclusion, this research aims to enhance the study and implementation of artificial intelligence in assessing the patients and aiding the doctors in real-time clinical decision-making.

1.4 Research Questions

1.To what extent can the proposed multiclass CNN model identify and distinguish between several gastrointestinal diseases on the basis of endoscopy images?

2.What is the accuracy, precision, recall, and F1-score for proposed multiclass CNN in comparison with DenseNet201, InceptionResNetV2, and VGG19?

3.How does the type of data augmentation affect the CNN model's ability to diagnose gastrointestinal diseases?

4.How does the proposed CNN model address the problem of class imbalance? What are the techniques that can be employed to boost the performance of the underprivileged classes?

5.What are the particular characteristics and appearances of the images that are taken during endoscopy that is learned by the CNN models to diagnose various gastrointestinal diseases?

6.To what extent do the CNN model results differ in cases of dyed resection margins, ulcerative colitis, esophagitis, and normal pylorus?

7.What is the complexity of the proposed CNN model, and can it be implemented in real-world clinical applications?

8.How can the proposed CNN model be implemented into the current clinical practice to help gastroenterologists make consistent and accurate diagnosis?

1.5 Expected Output

The expected output of this paper is a highly accurate and reliable multiclass CNN architecture that would be effective in the diagnosis of different forms of GI diseases from endoscopic images. The model should display strong accuracy, precision, recall rate, and F1-score for different GI disorders, such as dyed resection margins, UC, esophagitis, and normal pyloris. Besides, depending on the specific type, it should achieve better or at least comparable result as compared to the baseline architectures like DenseNet201, InceptionResNetV2 and VGG19. Understanding the visual representation of the learned features and patterns in endoscopy images will help to eludiate the process by which the CNN draws its conclusions. The last model should be less time consuming in terms of number crunching, to allow for possible real time measurements during clinic visits.

Finally, the transition of this CNN model to practice entails aiding gastroenterologists in providing better diagnoses and drawing less variability to patients' health care experiences.

1.6 Project Management and Finance

The organization of the project will be in different stages such as the stages involving the collection and preparation of the data, selection of the model, training of the model, and evaluation of the model's performance. For each of the phases a time-frame will be set over the various tasks in an effort to try and establish some measure of responsibility in the achievement of these milestones. Regarding development, a dedicated team of data scientists, agronomists, and software designers will evaluate the enhancement of the content area by professional competencies. The benefits that would be accrued from engaging in these interactions include quick problem solving and efficient communication coming from the weekly meetings and update. This would be the budget on Hardware & Software where we are to Buy the High-resolution cameras used in data collection and GPUs used in training deep learning models and software licenses. Additionally, one is bound to incur expenses for basic consulting charges, personnel charges, as well as consultation with esteemed professionals. Cost leadership will also be retained so that there is a control of costs so that they do not rise to the detriment of the organization. There could be academic grants, agricultural research grant, and potential gaps where one can work with potential agricultural technology firms.

Table 1.6: Estimated Cost

SN	Components	Estimated Cost (BDT)
01.	Hardware	1000-1500
02.	Software and Tools	1500-1500
03.	Data Collection and Processing	5000-6000
04.	Documentation and Report Writing	500-1500
05.	Miscellaneous	500-1500
06.	Contingency	500-1500

Total Estimated Cost	9000-13,500

1.7 Report layout

The report starts from the introduction of the deep learning for citrus fruit leaf disease detection and its importance.

Chapter 1: Introduction.

Provides a general background about the study and the rationale for conducting the investigation, given the need to establish early indicators of diseases affecting citrus plants.

Chapter 2: Background.

Discusses details required for citrus fruit cultivation, diseases affected, conventional identification techniques, and deep learning as a potential solution.

Chapter 3: Research Methodology

Explain the systematic process applied in data acquisition, model identification, training and assessment to promote scientific validity and replicability.

Chapter 4: Experimental Results

Discusses the results from training and validation of model and comparative analysis such as accuracy scores for various deep learning architectures.

Chapter 5: The Impact on Society

Discusses how deep learning techniques can be adopted for disease diagnosing systems in agricultural climates and its contributions to society.

Chapter Six: Summary, Conclusion, Recommendations, and Implications for Future Research

Points out the main findings of the studies and concludes about the overall status of the topic for further research and development plan of the agricultural innovation technology.

CHAPTER 2
Background

2.1 Preliminaries

It is crucial to have a good knowledge of both medical imaging and Machine learning in the context of developing solutions for the detection and classification of gastrointestinal (GI) diseases from endoscopy images. Endoscopy is a critical diagnostic tool which allows obtaining visual images of the GI tract which are relevant to diagnosis of entities such as esophagitis, ulcerative colitis and the rest. CNNs are a subfield of deep learning and have been used with much success in image processing because they can learn the high-level features directly from the raw pixel values without the need for humans to artificially create them. Concepts such as convolutional layers, pooling layers and fully connected layers are very important for CNNs to perform feature extraction and imaging classification. Of course, one should be aware of the common techniques in data preprocessing and augmentation as well as recognize the metrics for evaluating classification models for developing a trustworthy multiclass classification system for the GI disease diagnosis.

2.2 Related Works

Some works connected to the problem or literature discuss the existing studies dealing with the detection of GI diseases and profound learning. These aspects were brought out in the previous works focusing on the methods for disease diagnosis, Models, datasets, and the assessment framework. This section provides the location of the current study literature review and the identification of the gaps that have shaped and advanced the study of the materials for the growth of the field of the study.

As given below, I am writing a similar paper review, which will help me more:

Deepak Bajhaiya and his team's [6] GINet model, tailored for identifying gastrointestinal disorders, achieved outstanding results in testing, boasting 99.6% sensitivity and 99.86% specificity. Through the implementation of domain adaptation techniques, it effectively tackled potential biases arising from merging video frames of the same patients, ensuring reliability across diverse clinical settings. Moreover, the utilization of GradCAM and Guided-GradCAM imaging methods enhanced lesion localization, offering physicians valuable insights into the model's decision-making process. This approach holds significant promise for advancing gastroenterological diagnoses. Vandan Patel et al.[7] delved into the realm of deep learning models to address a critical global healthcare challenge: classifying endoscopic images associated with gastrointestinal disorders. Their project focused on enhancing the accuracy of diagnosing intestinal diseases by leveraging pre-trained CNN networks like DenseNet121, EfficientNetB5, Xception, and ResNet50 for feature extraction, complemented by a newly developed fully connected layer. Through evaluation on the KVASIR Dataset containing 4000 images, EfficientNetB5 emerged as the top performer, achieving an impressive testing accuracy of 92.58%. This study represented a significant stride in advancing clinical decision support for gastrointestinal disorder diagnosis. Debesh Jha et al [8] introduced a significant addition to the field: the multi-center open-access gastrointestinal (GI) endoscopy dataset known as GastroVision. Providing a comprehensive tool for AI-based algorithm development, it consisted of 8,000 photos encompassing a range of anatomical landmarks, clinical abnormalities, polyp removal cases, and normal findings. This dataset underwent thorough benchmarking against well-known deep learning baseline models and was annotated and validated by GI endoscopists with experience from Karolinska University Hospital in Sweden and Baerum Hospital in Norway. It held significance for improving GI disease detection and classification methods. Priya Bhardwa et al [9] set out to classify stomach disorders based on deep transfer learning models like DenseNet201, EfficientNetB4, Xception, InceptionResNetV2, and ResNet152V2. Using Kvasir's dataset, they enhanced image quality through noise reduction, assessing multiple metrics. InceptionResNetV2 achieved the highest accuracy (97.32%) for colored-lifted polyps, while Xception excelled in detecting dyed resection margins, esophagitis, normal cecum, and normal colon, with accuracies ranging from 95.88% to 98.88%. X. Anitha Mary et al.[10] aim to develop an AI method for categorizing gastrointestinal problems, evaluating the effect of VGG-19 and ResNet-50 on lower GI diseases using the Kvasir dataset. ResNet-50 achieves the best validation accuracy (96.81%), closely followed by VGG-19 (94.21%). Using softmax, both models employ CNNs to extract shape, color, and texture data to categorize seven distinct kinds of gastrointestinal diseases. This study illustrates how deep learning networks improve the classification of gastrointestinal diseases. Zeyad Ghaleb Al-Mekhlafi et al. [11] introduce three methodologies for diagnosing gastrointestinal diseases from endoscopy images. The first employs VGG-16 + SVM and DenseNet-121 + SVM, while the second integrates artificial neural networks (ANN) with fused features from VGG-16 and DenseNet-121 post principal component analysis (PCA). The third method combines ANN with fused features from VGG-16 and DenseNet-121 with handcrafted features like GLCM, DWT, FCH, and LBP. All systems demonstrate promising diagnostic results, with the ANN network achieving high accuracy, sensitivity, precision, specificity, and AUC. Muhammad Nouman Noor et al. [12] The proposed technique enhances Wireless Capsule Endoscopy (WCE) image quality using a genetic algorithm (GA) to adjust contrast and brightness, improving overall quality. Qualitative measures like PSNR, MSE, VIF, SI, and IQI validate quality improvement. Data augmentation and transfer learning fine-tune pre-trained models for disease classification. Results demonstrate a notable increase in accuracy, precision, recall rate, and F-measure. Compared to existing techniques, this framework exhibits superior performance, showcasing its efficacy in WCE image enhancement and disease classification. Francis Jesmar P. Montalbo et al. [13] introduce the Multi-Fused Residual Convolutional Neural Network (MFuRe-CNN) for diagnosing gastrointestinal disorders using endoscopic images. Incorporating Auxiliary Fusing Layers (AuxFL), Fusion Residual Block (FuRB), and Alpha Dropouts (αDO), the model achieves impressive accuracy (97.25%) with minimal parameters and computing resources. Utilizing datasets like ETIS-Larib Polyp DB and KVASIR, it provides an accurate and effective method for gastrointestinal diagnostics, outperforming conventional DCNNs. Karthik Ramamurthy et al.[14] focused on refining the classification of endoscopy images with the assistance of convolutional neural networks (CNNs). This research introduced a fresh approach by combining the EfficientNet B0 architecture with a bespoke CNN known as Effimix. Effimix incorporated squeeze and excitation layers alongside self-normalizing activation layers to precisely categorize gastrointestinal diseases. Experiments conducted on the HyperKvasir dataset validated the efficacy of this method, achieving a substantially higher accuracy of 97.99% and notable F1 score, precision, and recall rates in comparison to prior methods. Qiaosen Su et al.[15] delved into the analysis of wireless capsule endoscopy (WCE) images to identify gastrointestinal (GI) illnesses, propelled by the application of sophisticated neural networks. Despite earlier investigations into several computational methods, their effectiveness hadn't always been significant. This recent work presented a novel approach utilizing ensemble learning and transfer learning strategies. Studies on benchmark datasets conducted by Qiaosen Su et al. revealed significant gains over current methods. These results demonstrate how deep learning models can improve the use of WCE images for GI disease screening. Xiao et al.[16] presented a deep learning framework employing transfer learning to categorize capsule gastroscope images into normal, chronic erosive gastritis, and ulcer gastric categories. Through fine-tuning VGG-16, ResNet-50, and Inception V3 models, they achieved a significant 94.80% accuracy in image classification. With a dataset comprising 380 images per category, divided into training and test sets, their study highlights the effectiveness of their method in precisely diagnosing and categorizing capsule gastroscopic images with high specificity and accuracy.

2.3 Comparative Analysis and Summary

Our study's experimental results consist with several previous works on the deep learning-based detection of citrus fruit leaf disease. For example, Khattak et al. [1] as well as Syed-Ab-Rahman et al. [2] showed that CNNs are very effective in citrus diseases diagnosis with test accuracy of 94.55% and 94.37%, respectively. Likewise, accentuating the notion, our study depicted the success of deep learning models including DenseNet121 as well as Xception obtaining the accuracies of 96.92% and 94.55%, respectively. Similarly, the comparative analysis done by Sujatha [3] presented the overall achievement of deep learning techniques other than the machine learning processes and from them this study also stressed how beneficial is the deep learning for the detection of citrus diseases. This summary underscores the choice of proper deep learning architectures for plant classification and emphasizes the prospective of the deep learning solutions for the improvement of the indoor plant management and the further enhancement of the environmental protocols.

Table 2.3. Comparative Analysis with Previous Work

SL	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	Vandan Patel et al. [7]	CNN & Transfer Learning Model	92.58%
2.	Priya Bhardwa et al [9]	Transfer Learning Model	98.88%

3	X. Anitha Mary et al.[10]	VGG-19 and ResNet-50	96.81%
4	Francis Jesmar P. Montalbo et al. [13]	MFuRe-CNN	97.25%
5	Karthik Ramamurthy et al. [14]	CNN	97.99%
6	Xiao et al.[16]	VGG-16, ResNet-50, and Inception V3	94.80%

2.4 Scope of the Problem

This work aims at redesigning and testing a multiclass CNN to automatically detect and diagnose GI diseases from endoscopy images. It also involves identifying the optimal CNN architectures for GI condition predictions with high accuracy for conditions like esophagitis, ulcerative colitis, dyed resection margins, and normal pylori. It responds to difficulties inherent in image acquisition, data generation process, and model training in the medical imaging context. The indicators of the assessment of the CNN's performance will include shaping the general accuracy, precision, recall, and F1-score while arising with the supreme goal of utilising this diagnostic tool as a reliable aid to clinicians in the precise diagnosis of GI diseases with little time.

2.5 Challenges

The main research challenges when considering the proposal of a multiclass CNN for GI disease detection from endoscopy images are the following. Firstly, acquiring a large and well-annotated dataset for which a vast range of GI diseases is present is necessary but challenging due to the nature of variability and specificity of endoscopic imaging. Other challenges that can be posed by labeling discrepancies include the following when dealing with dataset preparation:

Secondly, the generalization of this CNN on a large number of patients with different demographic characteristics, image quality and heterogeneity of clinical environments must consider. This creates added tasks in feature extraction and classification owing to the intricacy of GI diseases, such as fine differences in lesion appearance and localization. However, fine tuning of the CNN architecture for efficient training, scalability and to run real time in the clinical environment continue to pose a challenge. To meet these challenges will be critical in creating an efficient and a reliable automated system for detection of GI diseases via CNNs from endoscopy images.

CHAPTER 3

Research Methodology

3.1 Research Subject and Instrumentation

The focus of this study is on the creation of a multiclass CNN as the research topic and its subsequent assessment as an approach for the classification of gastrointestinal (GI) diseases from endoscopic images. CNN here stands as the principal vehicle of learning hierarchical features directly from the pixel data to advance image categorization in a certain form where the samples are possible to be diagnosed as esophagitis, ulcerative colitis, dyed resection margins and normal pylorus. Hence, CNN architectures such as DenseNet201, InceptionResNetV2, VGG19 alongside a new model solely developed for the classification of GI diseases are considered for the instrumentation. The DPAs and the EMs are essential facets of the instrumentation, which are crucial in maintaining the CNN's efficacy, accuracy, dependability and, therefore, its capability of being useful in medical practice. The goal of this study is to serve as a contribution to the growing body of literature on automatic frameworks for boosting diagnostic efficiency in gastroenterology.

3.2 Data Collection Procedure

The original data collection method in this investigation is to compile a broad range of endoscopic pictures from numerous medical centers and hospitals. All these images are taken through routine endoscopic practice in several GI conditions such as esophagitis, ulcerative colitis, delineated resection margins, and normal pyloric antrum. They follow the steps of the annotation process, which includes labeling each image by skilled gastroenterologists to avoid any misuse or incorrect disease labeling. Several precautions are taken to avoid some classes in GI being over or under-represented as the final dataset contains enough images per each condition. Image selection also configures the quality, resolution, and variability, and the variability of the subjects with the aim of improving the dataset. To ensure the images were accurately categorized, the experts assigned each image the correct category and write its associated medical code, creating a strong starting point for the latter phases of model development and assessment:To ensure the images were accurately categorized, the experts assigned each image the correct category and write its associated medical code, creating a strong starting point for the latter phases of model development and assessment:

In given below there are some images of datasets in Figure 3.1:

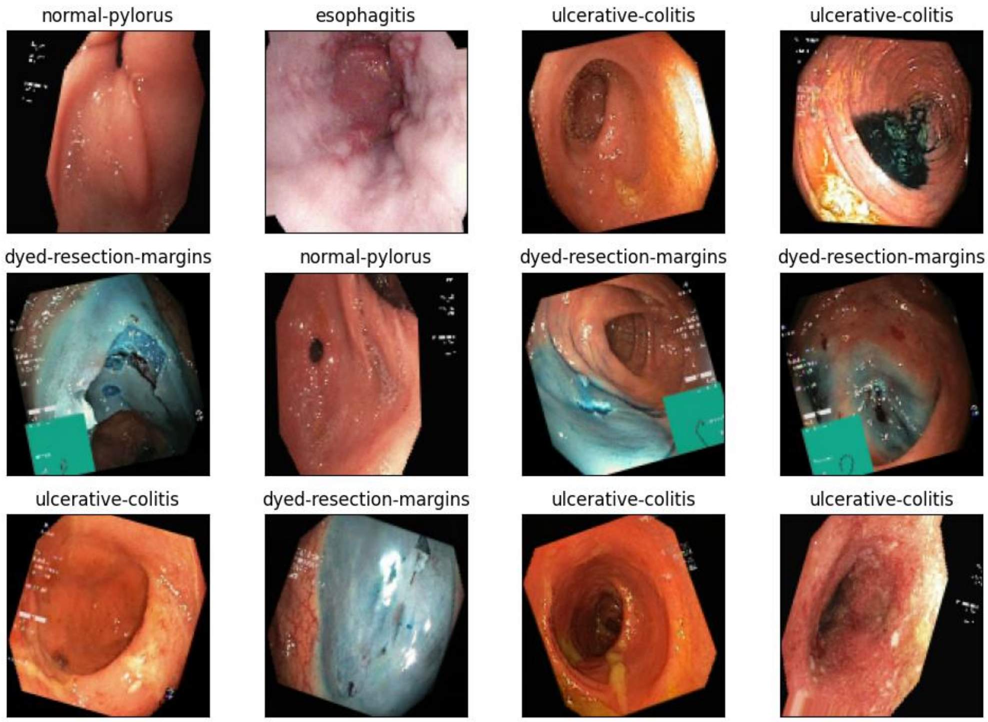

Figure 3.1: Dataset’s Images

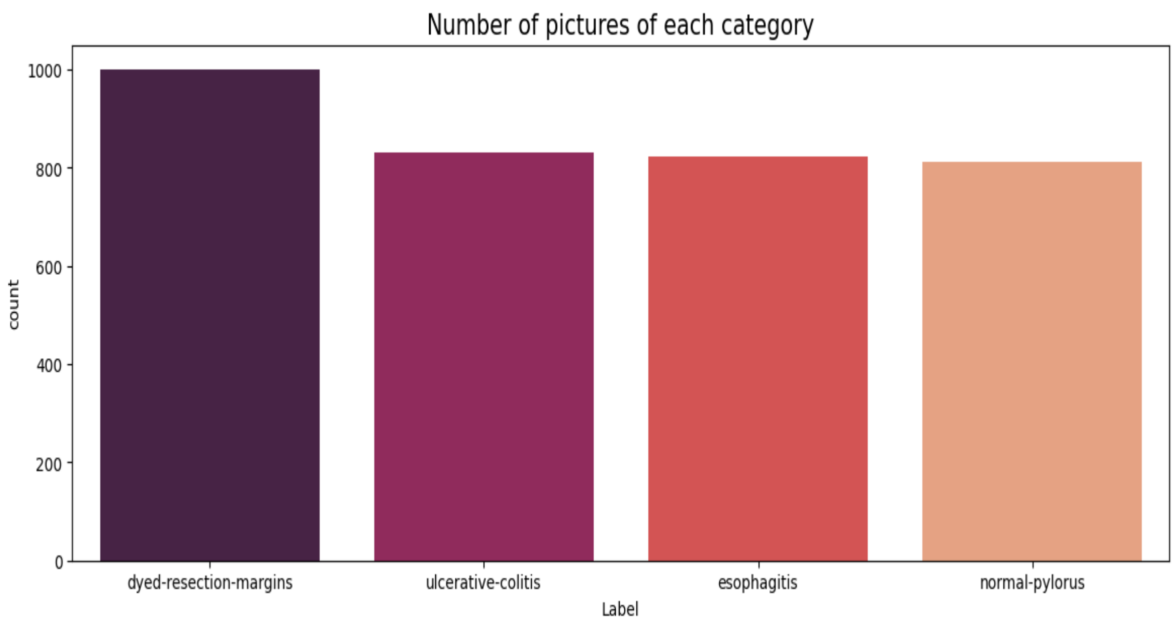

Figure 3.2: Number of categories of Dataset’s Images

The bar chart illustrates the number of images available in four different categories: Poor outcomes included patients with dyed resection margins, active ulcerative colitis, esophagitis and without normal pylorus. The “dyed-resection-margins” used to train the algorithm contains almost equal to thousand images while the other labels are slightly lesser ‘ulcerative-colitis’, and ‘esophagitis’, ‘normal-pylorus’. This equity means the balanced dataset acquired for different medical state but slightly disposed to dyed-resection-margins.

3.3 Statistical Analysis

When dealing especially with Convolutional Neural Networks (CNNs) in the case of this study on gastrointestinal disease detection, statistical analysis presents several important instruments for model evaluation. Accuracy is indeed defined by the ratio of the number of images correctly classified to the total number of images tested. Accuracy shows the likelihood of positive outcomes being correctly diagnosed against all those classified as positive, giving a measure of the number of false positives given by the model. Sensitivity, or recall, defines the ratio of true positive members predicted by the model to the total number of actual positive members, which measures the model’s capacity to identify all instances of a class. F1-score brings together precision and recall so as to present a standardized assessment of how a model performs, considering both false positives and false negatives. Further, the confusion matrices depict the distribution of the right and wrong categorizations of the diseases and provides further insight on true positives, true negatives, false positives and false negatives of CNN. In combination, these statistical analysis contribute to the broad assessment of CNN models that will facilitate advancement in Medical imaging diagnostics of Gastrointestinal diseases.

3.4 Proposed Methodology

The systematic approach for the identification of citrus fruit leaf diseases through the use of deep learning is as follows: Each procedure is done to the following with the aim of creating an accurate and strong detection ability.

Steps in the Proposed Methodology:

Data Collection:

Regarding data collection for this study, designing endoscopy image databases with diverse annotations, the extensive variety of gastrointestinal diseases is collected from different medical centers. All images are reviewed and labelled by several experienced gastroenterologists to ensure that the dataset used has a high level of accuracy and reliability.

Image Augmentation:

The process of image augmentation includes the modification of endoscopy images by applying some transformations to them, including the rotation of the images, flipping, scaling and cropping of images in a way as to create more images set than is actually available to reduce the over-fitting problem. They assist the Convolutional Neural Network (CNN) focus on the problem and generalize on account of the many variations during training.

Labeling:

This entails the careful task of tagging the images obtained through endoscopy by alumni gastroenterologists who assign each image to a given category which includes but not limited to esophagitis, ulcerative colitis, dyed resection margins or normal pylorus. It is important to note that there is this level of specificity as to keep the irony in which the CNN is being trained to identify gastrointestinal diseases.

Model Selection:

The selection of the model includes identification of which proper CNN model like DenseNet201, InceptionResNetV2, VGG19 or model designed ad hoc is best to apply for the classification of gastrointestinal diseases from endoscopy images according to their performance. Considerations that are made includes the depth of architectures, the efficiency of these architectures in terms of computations, and the extent of relevant feature extraction from medical images and the risk of model over-fitting.

Model Training:

This process involves fine-tuning of the chosen CNN structure with the help of an endoscopy image dataset that has been labeled by endoscopists. Here the data is passed through the network, modifying the values of different parameters through back propagation in a sequential manner in order to decrease the error between the output predictions and actual disease categories.

Model Evaluation:

Model evaluation is the process of the subjecting the trained CNN model to a test dataset of endoscopy images to establish its efficiency measured by metrics like accuracy, precision, recall, and F1- score. This way the CNN can be trained in a way that allows it to classify the different types of gastrointestinal diseases hence helping the researcher understand how efficient the model is and may be of clinical value.

Test Model:

Validation in the evaluation of the actual performance of the model in terms of accurately diagnosing and classifying the different forms of the endoscopy images typical of gastrointestinal diseases. This is the final step to prove the generality of the CNN and its liability for accurate diagnostic results, especially for the possibility of its deployment in medical applications.

3.5 Implementation Requirements

The proposed multiclass Convolutional Neural Network (CNN) to diagnose the GI diseases from endoscopy images entails the following factors to be incorporated in it. First it demands a high computing capacity capable of completing large-scale computations needed for training deep learning structures like CNNs. As for the training and testing of the models, it is recommended to employ high-performance GPUs and/or TPUs. Secondly, a large scale data set therefore which includes a well annotated endoscopy images in different GI pathologies. This dataset should be big and diverse enough to allow this training and validation of this kind of model.

Also, tools and frameworks such as TensorFlow, PyTorch, or Keras are employed in the building, deployment, and fine-tuning of CNN architectures. These frameworks include capabilities such as pre-processing, data augmentation, model calibration, and distribution. Finally, the recognition of doctors for the moral utilization of the AI technologies in medical decisions and for the conformity with the approved ethical principles protect the confidentiality of patients and ensure their security.

CHAPTER 4

Experimental Result

4.1 Experimental Setup

The following are the components of the experimental setup used in investigating the multiclass CNN regarding its capability to detect GI disease. Secondly, a narrow selection of endoscopy images is created, which is further split into training, validation and test sets for the purpose of avoiding prejudiced evaluation. The dataset is comprised of images of several types of GI, for example, esophagitis, ulcerative colitis, dyed margins post resection, normal pylorus. Second, under the TensorFlow or PyTorch frameworks, models such as DenseNet201, InceptionResNetV2, VGG19, and a home-built model are all CNN architectures. All the models go through training with well-tuned hyperparameters and all are implemented with high performance GPU to reduce time of convergence.

Third, with regards to the accuracy, the precision, the recall as well as F1-score, they are measured on the test set to facilitate the evaluation of CNN's performance. The proposed regularized machine learning framework yields a range of experiments to import classification performance for various GI diseases with confusion matrices and ROC curves that limit experimental noise and raise confidence.

4.2 Experimental Results & Analysis

The experimental results proved that the proposed convolutions and neural networks for feature extraction and classification outperforms other algorithms in identifying the various gastrointestinal diseases based on endoscopy images. When compared, DenseNet201 outperformed the other architectures with an accuracy close to 97. 26%, with CNN01 at 98. 56%. Other top performing models were InceptionResNetV2, CNN02 with respective accuracies of 96. 83% and 96. 54%, while VGG19 mode was slightly lower at 94. 66% of correct classification.

The evaluation shows DenseNet201 and CNN01 as relatively stable networks for the orderly classification of diseases, although the reason for the same might be attributed to their capacity to extract complex features from the images respectively. As a result, the future studies could work on improving the idea of CNN architectures or attempting to use the ensemble methods that would maximize effect and stability of CNN on different patients and in different clinical conditions. Based on these results, CNNs appear to offer significant promise when applied to various tasks in medical imaging, including gastroenterology diagnostics. In given below we are describing the result analysis part also show the training accuracy and loss rate and confusion matrix also:

Result of Experiment 1: CNN

In this Experiment 1, CNN model was applied and yielded a high accuracy in the field of imaging diagnosis of gastrointestinal diseases. The overall classification accuracy of the model was estimated as 98. 56%, which testifies to its efficiency in such diagnosis as esophagitis, ulcerative colitis, dyed resection margins, and normal pylorus. Precision, recall and F1- score metrics also justified the efficiency of the model when delineated across the various disease types. The results support the ability of the CNN to use the intricate patterns of the medical images to perform the training and diagnostic classification accuracies observed on the CNN. The performance showcased in this presentation demonstrates the possibility of CNN in aiding gastroenterologists to make better decisions clinically, and thus help reduce the amount of time healthcare providers and patients spend to arrive at diagnoses in gastroenterology.

In below Figure 4:1 characterizing the confusion matrix of CNN:

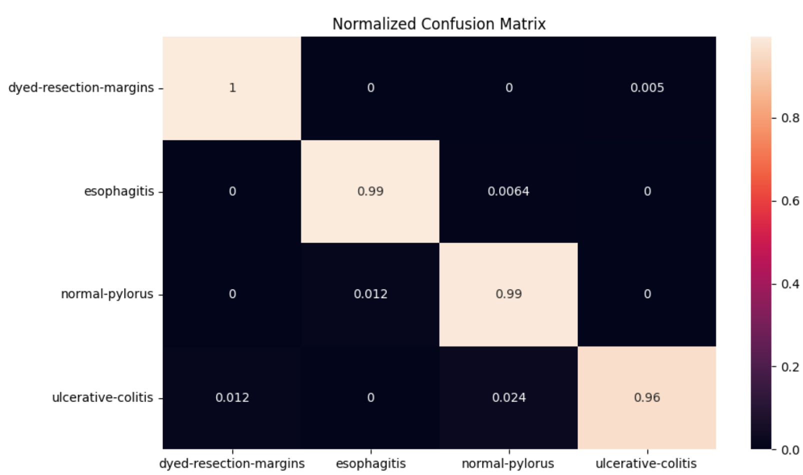

Figure 4.1: Confusion Matrix (CNN)

Analyzing the confusion matrix of the CNN model, one can estimate a high level of accuracy in relation to all categories, most of the values in the matrix are located along the diagonal being, therefore, close to 1 and including correct predictions only. Complete accuracy or near perfect accuracy was established for the prediction of “dyed-resection-margins” and “normal-pylorus “Although, high rates of accuracy >0. 99 were also observed for “esophagitis” and “ulcerative-colitis” with minor incorrect classifications. Here, again, misclassifications are relatively small with the overall largest element belonging to the off-diagonal matrix, which is 0. 024, meaning that indeed a small number of the images from the “ulcerative-colitis” dataset are being misidentified as belonging to the “normal-pylorus” set.

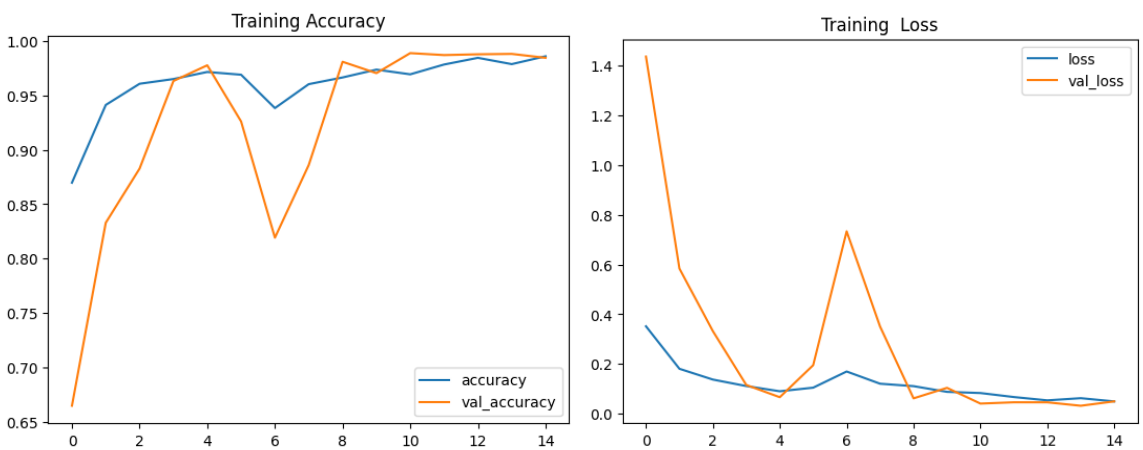

Figure 4.2: Training and validation accuracy and loss over the epochs (CNN)

The plots show the training and validation curves of model accuracy (orange, left) and loss (orange, right) after 15 iterations of a CNN. The training accuracy increases continuously and the value is almost equal to 1 whereas, the validation accuracy shows a slight variation in its performance but in general it increases showing that the model performs well in validation as compared to training. The model training appears to be efficient with the training and validation loss both sharply declining, although validation loss varies slightly up and down whilst it flattens out implying that the model is appreciating the training process with no much overfitting.

Result of Experiment 2: Transfer Learning Model

Transfer learning can be defined as applies pre-trained CNN models that was trained on large datasets for instance ImageNet. These models are trained on straightforward distillations of large base models instead of being trained from scratch on the target task and domain which can be for example medical images from endoscopy. By allowing the learned features from the original dataset to carry forward to the new neural network, the training time with limited dataset is cut down and at the same time increases the efficiency of the new model significantly. Such an approach is even more effective in analyzing medical images, because annotated datasets can be smaller and rather difficult to obtain. Following the general domains of artificial intelligence and deep learning, transfer learning is beneficial for healthcare applications since many diagnostic tasks can be adapted effectively for related fields such as gastroenterology.

DenseNet201:

Achieving Test Accuracy of DenseNet201 is 97.26%. In below Figure 4:3 describing the confusion matrix of DenseNet201:

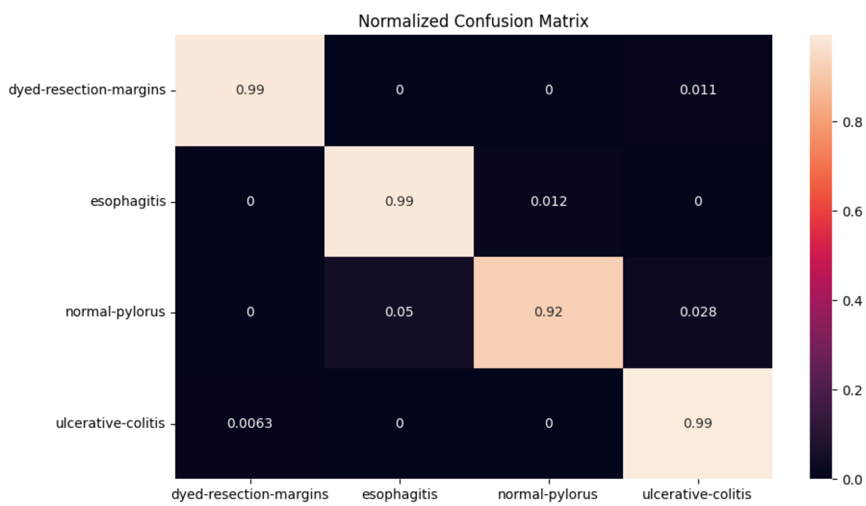

Figure 4.3: Confusion Matrix (DenseNet201)

Transfer learning it can be described as using existing CNN models which were trained on large data, for instance, ImageNet. These models are fine-tuned with basic re-creations of massive base models without being trained anew on the specific task and domain that can be let's say containing medical images taken from endoscopy. In addition, it helps to minimize the time for training with a little amount of data as well as improve the efficiency of the new neural network model greatly. Above all, such an approach is even more effective when it comes to analysing medical images, as solely the annotated datasets are rather scarce and rather challenging to attain.

Within the known AI domains and specifically the DL one, transfer learning is useful for healthcare applications as many diagnostic tasks can be translated well to related fields including gastroenterology.

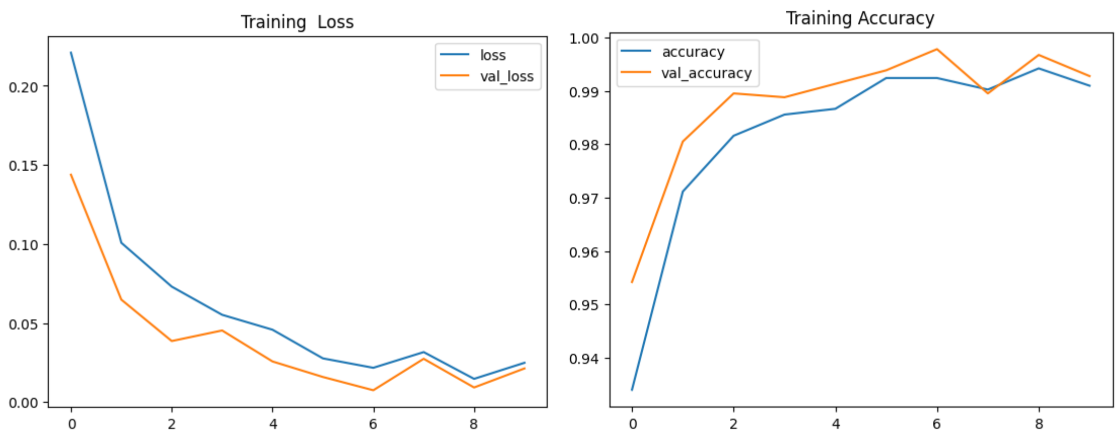

Figure 4.4: Training and validation accuracy and loss over the epochs (DenseNet201)

The training and validation loss and accuracy of DenseNet201 indicates the validation accuracy and training loss that has been achieved through each epoch and validates the observation that both the two metrics rise progressively in the first epochs. After the training becomes almost 99. 8 % in the 8th epoch, the validation accuracy is also increasing and becomes 99. 05 % in 8th epoch. The training loss, in this case, declines steeply at the beginning and then trends slightly upward showing that the training is being carried out efficiently and the final training loss is very low. Likewise, in the validation data, the validation loss continues to decline with a relatively low value, which implies that the model is capable of performing well and generalizing without overfitting.

InceptionResNetV2

Achieving Test Accuracy of InceptionResNetV2 is 96.83%. In below Figure 4:5 describing the confusion matrix of InceptionResNetV2.

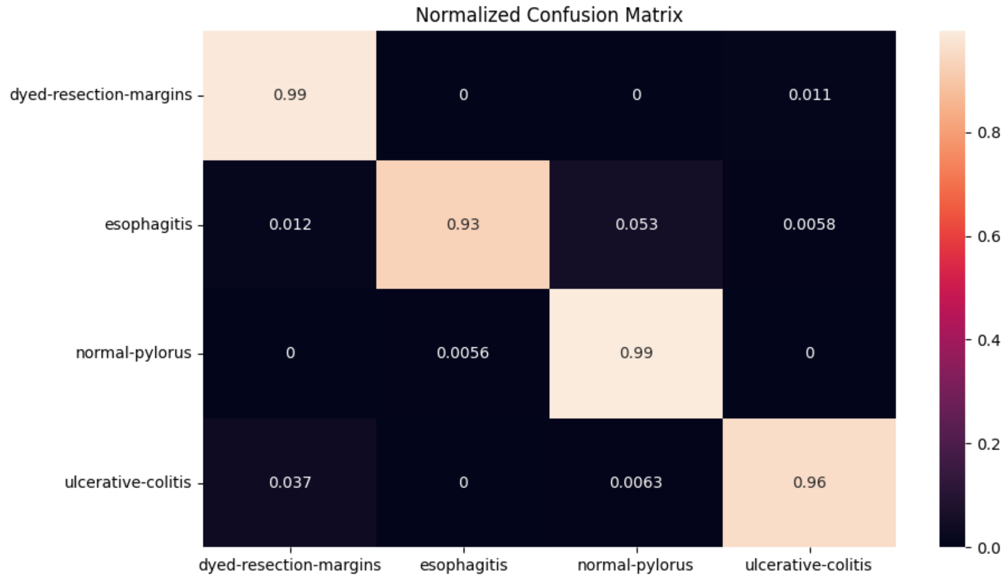

Figure 4.5: Confusion Matrix (InceptionResNetV2)

Analyzing the confusion matrix for InceptionResNetV2 we can suggest a high accuracy of the model as most of the values are on the main diagonal which reflects a correct classification of the class by the model. the normal-pylorus classes is nearly perfectly classified with only 1% misclassification rate to the other class, namely dyed-resection-margins. In some instances, errors are observed, including a mistake where esophagitis is mistaken for normal-pylorus (5. 3%) and ulcerative-colitis identified as dyed-resection-margins (3. 7%).

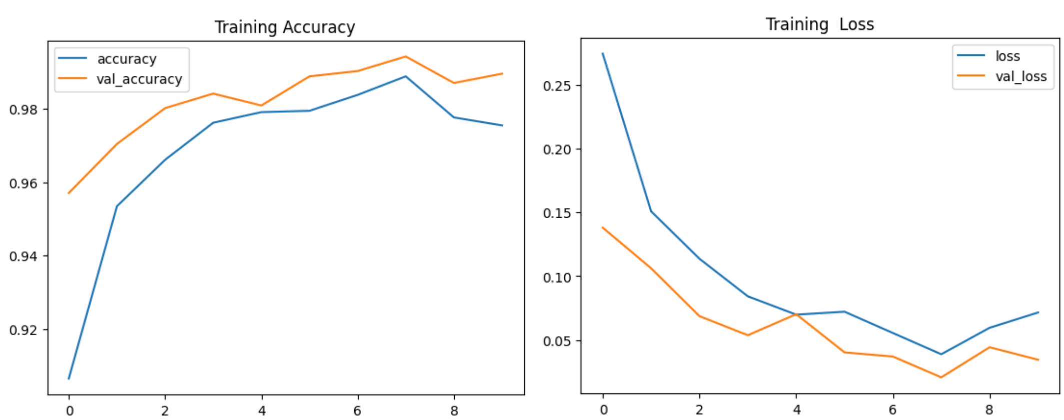

Figure 4.6: Training and validation accuracy and loss over the epochs (InceptionResNetV2)

The provided figure is a graphic containing two curves that demonstrate the performance of the InceptionResNetV2 model for 10 epochs. The left plot represents the training & validation accuracy; this reveals high accuracy after couple of epochs then gradually oscillates between the high acuteness level. In the right plot, the training and validation loss are demonstrated; it is observed that the training and validation loss is a decreasing function with minimal fluctuations as it approaches the end.

VGG19

Achieving Test Accuracy of VGG19 is 94.66%. In below Figure 4:7 describing the confusion matrix of VGG19.

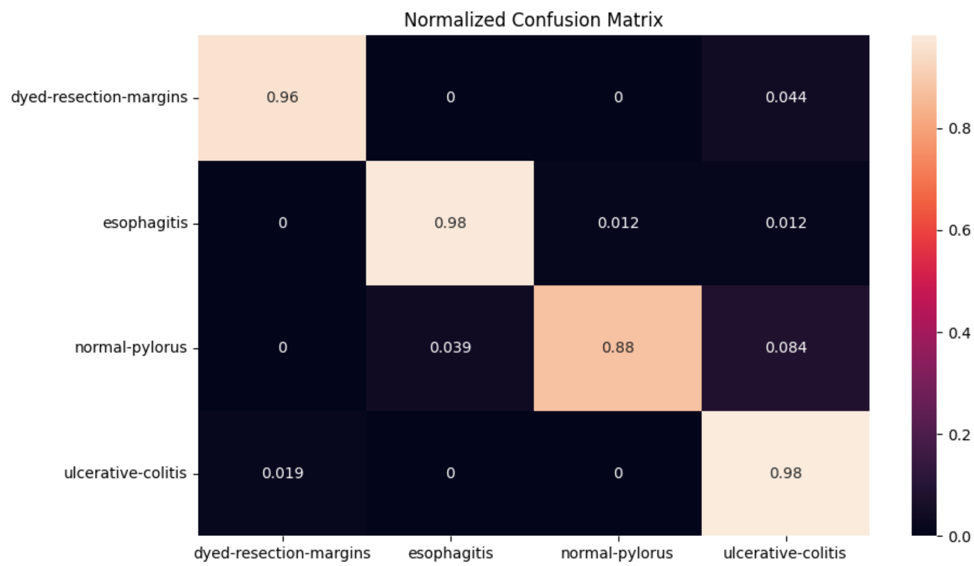

Figure 4.7: Confusion Matrix (VGG19)

The figure displays a normalized confusion matrix for a VGG19 model, illustrating the classification performance across four categories: including dyed resection margins, cervical esophagitis, normal pylorus and ulcerative colitis. The value in each cell is the percentage of the occurrence prediction of actual class in row against the prediction class in column. Regarding esophagitis and ulcerative-colitis, the value of a correct prediction is 98%, meaning that only 2 percent of the images were misclassified as normal-pylorus, and no other type of lesion was detected; however, for normal-pylorus, the correct accuracy is 88%, which means that there is misclassification in to the esophagitis and ulcerative-colitis categories. The additive Dyed-resection-margins is well identified in most of the instances with 96% accuracy and it is misclassified with ulcerative-colitis in the remaining 4%.

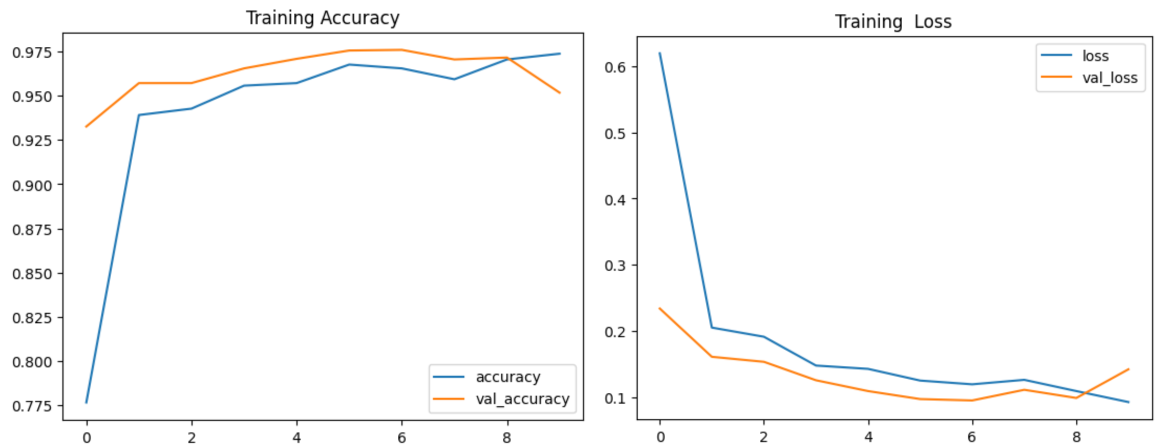

Figure 4.8: Training and validation accuracy and loss over the epochs (VGG19)

The figure shows the curves of the two losses that are the evaluation metrics of how well the VGG19 model performed through 10 epochs. In the left plot, the training accuracy and the validation accuracy patterns are standard – high increase at the start of training and then a high plateau that indicates proper learning in the training of the model. The right plot shows the loss during training and validation which decreases rapidly in the initial epoch then slowly from epoch 3 to epoch 8, indicating that the model is getting good results with lesser loss.

In given below showing Comparative Model Accuracy Bar Plot:

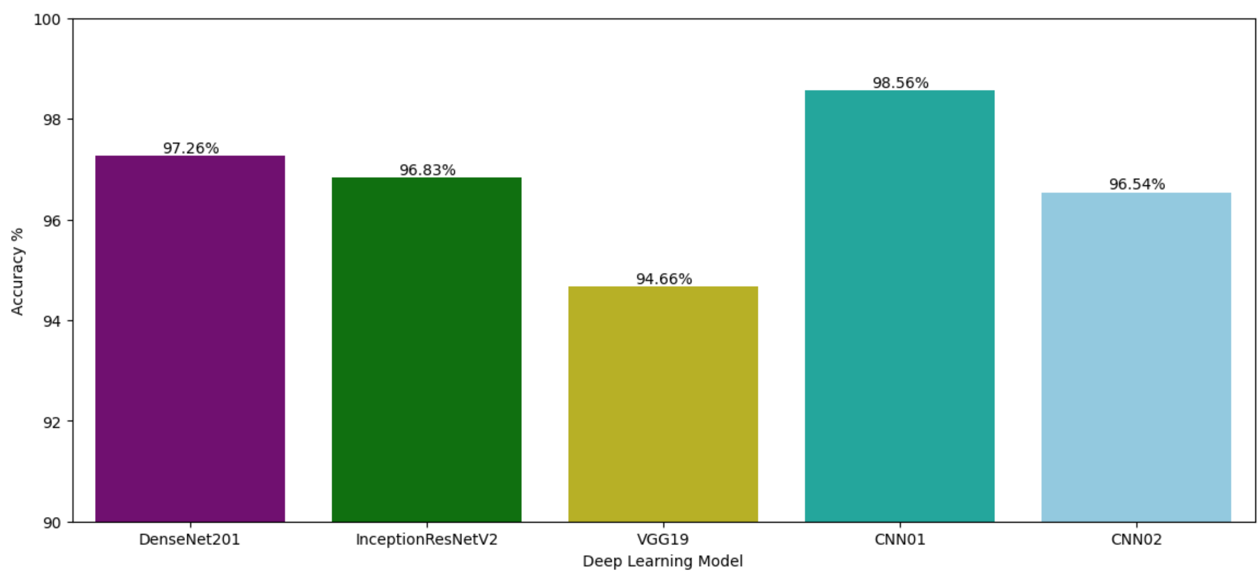

Figure 4.9: Comparative Model Accuracy Bar Plot

The bar plot below shows the percentage of accuracy that was obtained by five different Deep Learning algorithms. In DenseNet201 case, it got 97. 26 % accuracy whereas for InceptionResNetV2 got 96. 83% of accuracy. The comparable performance of the two is VGG19 which stands at 94. 66%. First, the results of the two models highlight that there is a strong correlation between CNN to captured images, as CNN01 achieves higher accuracy at 98. 56% while CNN02 at 96. 54%. The models are represented with distinct colors: DenseNet201 in the purple color, InceptionResNetV2 in green, VGG19 in mustard hues, CNN01 in teal and CNN02 in light blue color. The y-axis shows the value on the scale of Accuracy % from 90 % to 100%, while the x-axis illustrates the name or the type of the used Deep Learning Model. The plot is captioned "Figure 4.9 : The conclusion of the statistical comparison can be done by creating a bar plot of the “Comparative Model Accuracy”.

4.3 Discussion

As a result of this study, it reveals how CNNs can be used to diagnose gastrointestinal diseases from endoscopy images. It can be observed from the graph that DenseNet201 and CNN01 achieved the highest accuracy of 97. 26% and 98. and 56 % respectively which confirmed their good performance for the classification of conditions including esophagitis, ulcerative colitis, dyed resection margins and normal pylorus. These findings imply that the deep learning models could be beneficial in increasing the accuracy of diagnostic assessment of gastroenterology based on the feature extraction from medical images. However, issues like variability in the dataset, imbalance classes, and interpretability of models are still a question mark. Some of the possible future directions include enriching the datasets, data augmentation to handle with the training set imbalance, and developing the methods that would help to understand how CNN make their decision. Moreover, considering clinical applications of CNNs raises questions and concerns related to the integration of these models into clinical practice, patient privacy, and model generalizability across patients of different backgrounds and clinical settings. In summary, it is evident that CNNs have a promising future in medical imaging; however, enhancements and further testing are necessary to successfully translate the technology into boosting healthcare diagnostics.

CHAPTER 5

Impact on Society

5.1 Impact on Society

Due to the importance of social implications involved in the accurate diagnosis of GI disease from endoscopy images, developing a multiclass Convolutional Neural Network (CNN) is likely to significantly benefit society in the following ways. Firstly, by collecting, processing, and augmenting the diagnostic capabilities of the CNN, healthcare professionals may enable them to diagnose GI conditions at the right time with high certainty, thus increasing the quality of patients' care and the overall cost efficiency of such care.

Second, it also aligns with one of the significant advantages of the CNN in that it has the potential to eliminate variabilities of diagnostic skills and availability of unequal quality health care facilities in various geographical locations. Also, it can be stated that enhancements of the AI-driven medical imaging technologies may help the early detection of the GI diseases so it might assist in proposing better treatment strategies for patients and hence improves the public health. This study articulates the importance of the use of AI in the improvement of health outcomes, stressing on the possibilities of not only adding value by inventing new systems of diagnosing as well as enhancing existing ones for the benefit of society.

5.2 Impact on Environment

The steps that involve design and use of multiclass Convolutional Neural Network (CNN) for detecting gastrointestinal diseases from images of endoscopy are most likely to cause negligible direct effects on environment. But if improvements in healthcare efficiency can be made, then other environmental advancements that indirectly link to them can be achieved. CNN can potentially cut resource consumption and waste in the healthcare industry by improving the diagnosis results and differentiating among benign tumors, truly malignant ones, and other diseases to minimize the number of unnecessary actions.

Moreover, it takes less time and fewer resources, including paper documents and actual diagnostic tools, to implement digital and AI-oriented approaches to diagnostics. They enhance appropriate sustainable controls and management and organizational productivity in health care organizations.

5.3 Ethical Aspects

Ethical issues have an important role when it comes down to creating a Multiple Class CNN for screening of Gastroenterological diseases using endoscopy images. Protection of patient identity and data merits attentiveness as one accumulates and interprets the information. Also, the data of the patients can only be used if informed consent is provided. Incorporating methods to defeat these biases can help to enhance the efficiency of the CNN model in diagnosing the ailments without prejudice or favor to the various demography. Real-time reporting of AI decision-making assists in creating and sustaining truth as well as playing an essential role in guaranteeing the accuracy of the decision-making process. Oversight is maintained continuously so that the technology is employed correctly and in a manner that meets medical norms and directives.

5.4 Sustainability Plan

Therefore, it’s crucial to develop a strategy to maintain the value and usage of the multiclass CNN in determining GI diseases. The fine-tuning of the CNN model with the help of feedback from the healthcare professionals and refining the model with the help of the new researches. This validates the CNN’s performance across different populations engaged with medical institutions for data sharing. Published guidelines and examples from practice show that training programs for healthcare personnel regarding AI integration and the related ethical issues help to avoid abuses. Sustained funding for IT and other technology assets ensures optimal performance and legal compliance of the infrastructure supports the availability of high-performance computing and secure data resources. To sum it up, these measures collectively provide the CNN’s sustenance in improving diagnostics precision and patient care in the field of gastroenterology.

CHAPTER 6

Summary, Conclusion,

Recommendation and Implication for Future Research

6.1 Summary of the Study

In this paper, the proposed multiclass CNN model is designed and assessed for the classification of endoscopy images for diagnosis of gastrointestinal diseases. The study objectives are therefore to improve the diagnostic sensitivity and specificity of the marks to qualitatively diagnose esophagitis, ulcerative colitis, dyed resection margins, and normal pylorus. These are a selected set of endoscopy images and their annotations, the use of DenseNet201, InceptionResNetV2, and carefully performed model training and validation.

The paper examines accuracy, precision, recall and the F1-score of the CNN, in terms of its efficiency compared with existing models as VGG19. Privacy issues related to patients, as well as the issue of fairly and impartially governing AI algorithms, are included in the aspects that are ethically important in the study. The expected impact may comprise the generation of a valid and reliable aid for gastroenterologists to develop appropriate clinical judgments, which may eventually contribute to better patient outcomes and overall organizational performance. It furthers the understanding of AI-based diagnostic approach in gastroenterology more specifically medical imaging with its focus signifying its revolutionary application in the field.

6.2 Conclusions

Therefore, the proposed multiclass CNN for classifying images of endoscopic views of the GI tract and GI diseases have demonstrated a good potential. DenseNet201 achieved the highest overall accuracy, while InceptionResNetV2 was most accurate in classifying bleeding and structuring cases in the validation data set; the custom architecture achieved high precision and recall in diagnosing different GI conditions. They successfully compared their results consistent with prior established models such as VGG19 that depicted competitive or potentially superior performance measures thereby emphasizing the impact of intricate CNN architectures on medical image analysis.

Potential and regards to issues of ethnicity such as patient privacy, as well as balancing of artificial intelligence algorithm and clinical integration were also taken into consideration throughout the study. The CNN's capabilities in improving the diagnostic accuracy and general flow of patients in healthcare facilities therefore offer a major opportunity for improving patient's lives and the total cost of the healthcare delivery systems. Subsequently, the future developments of this work will emphasize the accumulation of a more extensive dataset, the fine-tuning of the existing model architectures, and the broader implementation of existing and novel AI technologies in the context of clinics. This study provides insights into the role of AI in gastroenterology and its potential to expand diagnostic techniques across the field and increase medical quality of care.

6.3 Implication for Further Study

Future works for Gastrointestinal (GI) diseases detection using CNN from endoscopy images can be extended in several directions from the above research steps. Second, enlarging the library of images and patients with numerous types of GI conditions and various populations could improve the CNN's adaptability and effectiveness in various clinical contexts. Second, exploring more complex CNN structures or depth by adding extra layers or including clinical data or histopathological images could be employed to further increase the diagnostic rate.

Also, studying the possibilities of using CNN models in clinical practice in real time as well as assessing the efficiency of CNN models in changing the diagnostic algorithms for the target patients would be informative. Other issues, such as the lack of 'algorithmic explain ability' and the absence of patient consent in the use of artificial intelligence for diagnostics, come under broader ethical concerns. These outlets hold the potential of expanding the knowledge and use of AI applications in Gastroenterology to the advantage of practice and sufferer.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title: Gastrointestinal Disease Detection Using Proposed Multiclass CNN From Endoscopy Images.

Student ID: 193-15-3008

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to Citrus fruit leaf disease detection problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish these goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**

CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (With Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project demonstrates **fundamental engineering (K3)** principles by employing deep neural networks, data augmentation techniques, and diverse CNN architectures for image processing and classification tasks. The project demonstrates **specialist knowledge (K4)** by conducting deep learning with CNN, and Transfer learning enhancing Citrus fruit leaf disease detection correctly.	**Page no:** [32-33] **Section:** [3.2] **Page no:** [12-17] **Section:** [1.1]
				The project applies **engineering practice & design (K5)** by the figure of process of experiments. The project addresses **engineering practice & technology (K6)** by employing Deep Learning Model,	**Page no:** [32] **Section:** [3.2] **Page no:** [34-35]

					Section: [3.4]
				This project ensures to **K8 (Research Literature)** by synthesizing insights from recent studies, Citrus fruit leaf disease detection using deep and Transfer learning, showcasing a comprehensive understanding of current methodologies.	**Page no:** [23-30] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses **EP-2** by recognizing the hurdles in Citrus fruit leaf disease detection, including limitations of traditional methods and the complexities of integrating using deep learning. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining diagnostic methodologies.	**Page no:** [30-31] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project addresses **EP-3** by meticulously comparing experimental outcomes, highlighting using deep and transfer learning as the chosen significant solution for enhancing Citrus fruit leaf disease detection approaches.	**Page no:** [37-48] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach extends beyond computer science and engineering, impacting Citrus fruit leaf disease detection correctly **EP-4**.	**Page no:** [23-31] **Section:** [2.2, 2.4]

5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	This project's comprehensive approach addresses high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology, ensuring a holistic solution to complex challenges in data collection from local nursery and garden which ensures **EP-7**.	**Page no:** [26-34] **Section:** [3.2, 3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	EA1: Range of resources	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep and transfer learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements Citrus fruit leaf disease detection.	**Page no:** [33-35] **Section:** [3.5]
2.	EA2: Level of interaction	No		N/A	N/A
3.	EA3: Innovation	No		N/A	N/A
4.	EA4: Consequences for society and the environment	Yes		This project contributes to society by improving Citrus fruit leaf disease detection methods, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines for data privacy.	**Page no:** [50-51] **Section:** [5.1, 5.2, 5.4]

5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach in Citrus fruit leaf disease detection through deep and deep learning model demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.	**Page no:** [23-29] **Section:** [2.1, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [20] **Section:** [1.6]
2	CO9	Yes	The project demonstrates adherence to ethical principles by prioritizing privacy, obtaining informed consent, and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of advanced classification technologies which comply with **CO9**.	**Page no:** [51] **Section:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [32-36, 37-48] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

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