A Deep Learning Approach For Precise Classification Of Nasal Polyps: Distinguishing Antrochoanal Polyps, And Ethmoidal Polyps

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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

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APPROVAL

This Project titled **"A Deep Learning Approach For Precise Classification Of Nasal Polyps: Distinguishing Antrochoanal Polyps, And Ethmoidal Polyps"**, submitted by **Jannatul Maowa** and **MD.Shihab Shahriar** 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 July 13, 2024.

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We hereby declare that this project has been done by us under the supervision of **Ms. Sharun Akter Khusbu, Lecturer (Senior Scale), Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Nasal polyps are benign growths that occur within the sinuses or nasal passages. Because of their interconnected characteristics and diverse appearance, they present significant challenges in terms of diagnosis and treatment. For these polyps to be effectively managed clinically, they must be accurately classified. However, manual examination-based traditional approaches are complicated and prone to error. In order to create an automated system that accurately classifies nasal polyps and can differentiate between antrochoanal polyps (AP) and ethmoidal polyps (EP), this work makes use of progressive deep learning techniques. Several advanced convolutional neural networks (CNNs) are used in the study, including ResNet-50, VGG16, PolyScanCNN (a customised CNN model), and EfficientNetB0. A large dataset of nasal MRI images, which underwent intensive preprocessing to improve picture quality and augment the data, served as the training set for these models. The models were assessed and compared using performance indicators such F1-score, recall, accuracy, and precision. The ResNet-50 model achieved a 96% accuracy rate, demonstrating its effectiveness in identifying nasal polyps. The study shows how well these models work in identifying nasal polyps, with ResNet-50 outperforming the other models in the majority of evaluation measures. Gradio was used to create an intuitive web-based interface that allows real-time nasal polyp picture categorization and visualization, hence promoting clinical adoption. This research highlights how deep learning can improve otolaryngology diagnostic efficiency and accuracy. It seeks to assist physicians in making wise decisions by offering a trustworthy tool for the classification of nasal polyps, ultimately leading to better patient outcomes. The results indicate that the field of medical image analysis can be greatly advanced by implementing advanced AI-driven solutions.

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ML	Machine Learning
CNN	Convolutional Neural Network
DL	Deep Learning
DCNN	Deep Convolutional Neural Networks
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
CPU	Central Processing Unit
RAM	Random Access Memory
GPU	Graphics Processing Unit
AP	Antrochoanal polyp
EP	Ethmoidal polyp

CHAPTER 1
INTRODUCTION

1.1 Overview

Nasal polyps are noncancerous, soft, and painless extensions that develop on the inner lining of the nasal passages or sinuses as a result of persistent inflammation. This inflammation is frequently linked to illnesses such as asthma, recurrent infections, allergies, medication hypersensitivity, or immunological disorders. Nasal polyps can result in many symptoms such as nasal congestion, anosmia, recurrent infections, and respiratory challenges, greatly impacting a patient's quality of life. Accurate categorization of nasal polyps is essential in order to determine the most suitable treatment approaches, such as medication or surgery, and ultimately enhance patient results.The conventional techniques for identifying and categorizing nasal polyps entail a hands-on assessment conducted by skilled otolaryngologists utilizing MRI/endoscopic pictures, histological slides, and clinical signs. Although these approaches are efficient, they require a significant amount of time, are based on personal judgment, and are susceptible to differences in interpretation among various individuals. Inconsistent diagnoses might result in inadequate treatment strategies and poor patient care. Recent developments in deep learning and artificial intelligence (AI) has brought about a significant transformation in several domains, including the processing of medical images. Convolutional neural networks (CNNs), a type of deep learning model, have shown exceptional performance in classifying images in several fields. These models possess the ability to automatically acquire and isolate relevant characteristics from unprocessed picture data, thereby decreasing the necessity for manual feature manipulation and enhancing the precision and effectiveness of classification systems. The objective of this research is to utilize advanced deep learning models to create an automated system that accurately categorizes nasal polyps. Our primary objective is to differentiate between two specific forms of nasal polyps: Antrochoanal polyps (AP) and Ethmoidal polyps (EP). Antrochoanal polyps are single, usually arising from the maxillary sinuses and extending into the choana, while Ethmoidal polyps are many and originate from the ethmoidal sinuses. Precise distinction between these categories is crucial for determining the correct surgical procedure and subsequent care after the operation. The models for deep learning used in this work include ResNet-50,EfficientNetB0, VGG16 and PolyScanCNN (a customized CNN model). The selection of these models is based on their shown efficacy in diverse medical picture classification tasks. The research entails gathering an comprehensive dataset of nasal endoscopic images, doing preprocessing on the data to improve picture quality, training and refining the models, and assessing their performance using established measures such as accuracy, precision, recall, and F1-score.In order to ensure that the produced system is easy to use and can be accessed by users, we employ Gradio, which is a Python module that is open-source, to design a web-based interface. The practitioners can use this interface to submit nasal endoscopic images and obtain immediate predictions about the specific type of nasal polyp. The predictions are accompanied by confidence scores and visualizations, such as heatmaps. The objective is to offer a user-friendly instrument that strengthens the diagnostic capacities of medical professionals, improves patient results, and simplifies the clinical process in the field of otolaryngology. The objective of this project is to create a reliable and precise deep learning system that can classify nasal polyps. This system will overcome the shortcomings of conventional diagnostic methods and contribute to the progress of medical image analysis technology. The following sections will explore the background, methodology, implementation, results, and wider implications of this study, providing a thorough review of the research conducted and its potential impact on clinical practice.

1.2 Background and Present State

Nasal polyps are benign lesions that develop within the nasal passages or sinuses due to chronic inflammation from conditions such as asthma, recurring infections, allergies, drug sensitivity, or immune disorders. These polyps can obstruct nasal and sinus cavities, leading to significant discomfort and complications such as breathing difficulties, a reduced sense of smell, and frequent infections. Traditionally, the diagnosis and classification of nasal polyps rely heavily on manual examination by otolaryngologists, utilizing tools such as nasal endoscopy and histopathological analysis. Although effective, this manual process is labor-intensive, time-consuming, and highly dependent on the clinician’s experience, resulting in variability and potential misdiagnosis.

The advent of digital imaging technologies and machine learning has introduced new possibilities for automating medical diagnostics. Convolutional neural networks (CNNs), a class of deep learning algorithms, have shown remarkable success in image classification tasks across various domains, including medical image analysis. CNNs are capable of learning hierarchical features from raw images, enabling them to identify and classify complex patterns with high accuracy. In medical imaging, CNNs have been applied to detect and classify skin lesions, retinal diseases, and lung abnormalities, among other conditions.

One of the major challenges in classifying nasal polyps is their varied morphology and overlapping features. Antrochoanal polyps (AP) and Ethmoidal polyps (EP) are two distinct types, with AP typically being solitary and originating from the maxillary sinuses, extending into the choana, while EP are multiple and originate from the ethmoidal sinuses. Accurate differentiation between these types is essential for guiding appropriate surgical intervention and postoperative management.

Several pre-trained CNN models, such as ResNet-50, and EfficientNet, have demonstrated exceptional performance in various image classification challenges. ResNet-50, known for its residual learning framework, allows training of very deep networks by mitigating the vanishing gradient problem. EfficientNet uses compound scaling to uniformly scale the depth, width, and resolution of the network, achieving state-of-the-art performance with fewer parameters.

Despite their success in general image classification, the application of these models to nasal polyp classification remains underexplored. This project aims to bridge this gap by adapting these state-of-the-art CNN models to the specific task of distinguishing between Antrochoanal polyps and Ethmoidal polyps. A comprehensive dataset of nasal endoscopic images is collected and preprocessed to enhance image quality, ensuring a robust training process.

Moreover, the integration of these models into a user-friendly web-based interface using Gradio allows for real-time classification and visualization, making the tool accessible to clinicians. This system not only aids in accurate diagnosis but also provides visual explanations through heatmaps, highlighting the regions of interest that influenced the model's decision.

The development of such an automated classification system holds significant potential for improving diagnostic accuracy and efficiency in otolaryngology. By reducing the reliance on manual examination and providing consistent, objective analysis, this approach can enhance patient outcomes and streamline clinical workflows. The success of this project could pave the way for broader adoption of AI-driven solutions in medical diagnostics, leveraging the power of deep learning to address complex healthcare challenges.

1.3 Problem Statement

The accurate classification of nasal polyps is crucial for effective clinical management and treatment planning. Traditional diagnostic methods, which involve manual examination by experienced otolaryngologists using endoscopic images and histopathological analysis, are not only time-consuming but also prone to variability and subjectivity. This variability can lead to misdiagnosis or inconsistent treatment plans, affecting patient outcomes and overall healthcare quality.

Antrochoanal polyps (AP) and Ethmoidal polyps (EP) are two distinct types of nasal polyps that require different surgical interventions and postoperative management. AP typically originate from the maxillary sinuses and extend into the choana, whereas EP are multiple and arise from the ethmoidal sinuses. The morphological similarities and overlapping features between these polyp types pose a significant challenge for accurate differentiation, even for skilled clinicians.

The primary problem lies in the need for an automated, accurate, and reliable system to classify nasal polyps, specifically distinguishing between Antrochoanal polyps and Ethmoidal polyps. This is crucial because:

1. **Subjectivity and Variability:** Manual examination methods are inherently subjective, leading to inter-observer variability. Different clinicians may interpret the same endoscopic image differently, resulting in inconsistent diagnoses and treatment plans.

2. **Time-Consuming Process:** The manual process of examining endoscopic images and making a diagnosis is labor-intensive and time-consuming, which can delay treatment and affect patient outcomes, especially in busy clinical settings.

3. **Complexity of Morphological Features:** The morphological features of nasal polyps are complex and can overlap, making it challenging to distinguish between different types accurately. This complexity necessitates advanced tools that can learn and identify subtle differences in the images.

4. **Limited Dataset:** Developing a deep learning model that can effectively learn the distinguishing features of each polyp type from a relatively limited dataset is a significant challenge. Ensuring the model's robustness and generalizability across different patient populations and clinical settings is critical.

The goal of this project is to address these challenges by developing a deep learning-based system that automates the classification of nasal polyps. By leveraging state-of-the-art convolutional neural networks (CNNs) such as ResNet-50 EfficientNetB0, VGG16 and PolyScanCNN (Custom CNN) this project aims to create a robust and accurate classification tool. The system will be evaluated on its ability to distinguish between Antrochoanal polyps and Ethmoidal polyps, ensuring high accuracy, precision, recall, and F1-score.

In addition, the development of a user-friendly web-based interface using Gradio will facilitate real-time classification and visualization of nasal polyp images, making the tool accessible to clinicians. This project seeks to improve diagnostic accuracy, reduce variability, and enhance the efficiency of nasal polyp classification, ultimately contributing to better patient care and outcomes in otolaryngology.

1.4 Objectives

The objectives of this project are to develop a robust, accurate, and user-friendly system for the classification of nasal polyps using advanced deep learning techniques. This will involve several key steps to ensure the effectiveness and practical application of the system.

- **Data Collection:** Acquire a comprehensive dataset of nasal endoscopic images representing various types of nasal polyps. This dataset should be diverse, encompassing images from different patients, captured under various conditions, and sourced from multiple medical institutions. This diversity ensures that the deep learning models trained on this dataset will generalize well to real-world clinical scenarios, providing a robust foundation for model training and evaluation.

- **Data Preprocessing:** Implement preprocessing techniques to enhance image quality, including pixel normalization and edge enhancement through inpainting. Pixel normalization adjusts the intensity values of the images to ensure uniformity, improving the contrast and making the features more distinguishable. Inpainting techniques are used to enhance the edges and contours of the nasal polyps, facilitating better feature extraction and helping the models to learn the relevant characteristics more effectively.

- **Model Development:** Develop and fine-tune multiple deep learning models for the classification of nasal polyps. The models include ResNet-50, EfficientNetB0, VGG16, and PolyScanCNN (a custom CNN model). Each model is selected for its unique strengths, such as ResNet-50's ability to train very deep networks, ResNet-50's efficiency with depthwise separable convolutions, and EfficientNetB0's balanced scaling approach. The custom PolyScanCNN is tailored specifically for the nuances of nasal polyp classification.

- **Model Evaluation**: Evaluate the performance of each model using metrics such as accuracy, precision, recall, and F1-score. Accuracy measures the overall correctness of the model's predictions. Precision evaluates the ratio of correctly predicted positive instances to the total predicted positives, indicating the model's accuracy in identifying positive cases. Recall assesses the ratio of correctly predicted positive instances to all actual positives, reflecting the model's ability to capture all positive cases. The F1-score provides a harmonic mean of precision and recall, offering a balanced measure of the model's performance.

- **Implementation:** Develop a user-friendly web-based interface using Gradio to demonstrate the real-time classification of nasal polyps. This interface allows clinicians to interact with the trained models, uploading nasal endoscopic images and receiving immediate classification results. The interface displays the predicted class (AP or EP) along with a confidence score and includes options for visualizing heatmaps that highlight the regions of interest in the images, making the tool accessible and intuitive for clinical use.

- **Impact Analysis:** Assess the potential impact of the developed system on clinical practice, patient outcomes, and healthcare efficiency. This includes evaluating how the system can assist clinicians in making more accurate and consistent diagnoses, reducing variability and subjectivity. The potential improvements in treatment planning and patient management resulting from more precise classifications are analyzed. Additionally, the time and resource savings achieved by automating the classification process are considered, demonstrating the system's value in enhancing overall healthcare efficiency.

By addressing these objectives, the project aims to create a robust, accurate, and user-friendly system for the classification of nasal polyps, ultimately contributing to better patient care and advancing the field of medical image analysis.

1.5 Scope and Limitations

The scope of this project includes the development and evaluation of deep learning models for the classification of nasal polyps using endoscopic images. The study focuses on distinguishing between Antrochoanal polyps and Ethmoidal polyps.

Limitations:

1. **Dataset Size:** The accuracy and robustness of the models are constrained by the size and diversity of the available dataset. A larger and more varied dataset could improve model performance.

2. **Generalizability:** The models' performance may vary when applied to images acquired from different equipment or under different conditions. Further validation in diverse clinical settings is necessary.

3. **Computational Resources:** Training deep learning models requires significant computational power, which may limit the accessibility of the developed system in resource-constrained environments.

1.6 Report Organization

- **Chapter 1:** Introduction: Provides an overview, background, problem statement, objectives, scope, and limitations of the project.
- **Chapter 2:** Literature Review: Reviews existing research and methodologies related to the classification of nasal polyps using deep learning.
- **Chapter 3:** Methodology/Requirement Analysis & Design Specification: Describes the proposed methodology, system design, hardware/software requirements, and project management aspects.
- **Chapter 4:** Implementation: Details the data collection, preprocessing, model training, and validation processes.
- **Chapter 5:** Results and Analysis: Presents the experimental results, performance evaluation, and comparative analysis of the developed models.
- **Chapter 6:** Impact on Society, Environment, and Sustainability: Discusses the broader implications of the project on society, healthcare, and the environment.

- **Chapter 7:** Conclusion and Future Work: Summarizes the key findings, suggests further research directions, and discusses limitations and conflict of interests.

1.7 Summary

This chapter introduced the research project on the classification of nasal polyps using deep learning. It outlined the background, problem statement, objectives, scope, and limitations, providing a comprehensive overview of the project's purpose and significance. The subsequent chapters will delve deeper into the literature, methodology, implementation, results, and broader impact of the study, culminating in a detailed analysis and discussion of the findings and future directions.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

Recent advances in deep learning algorithms have resulted in significant progress in the classification of nasal polyps, with the goal of improving diagnosis accuracy and guiding successful treatment approaches. Researchers investigated the feasibility of automated nasal polyp detection and categorization using a variety of data sources, including endoscopic pictures, histological slides, and clinical signs. Furthermore, the integration of multimodal data and predictive modelling for prognosis evaluation have emerged as potential approaches to enhancing classification accuracy and forecasting long-term patient outcomes.

2.2 Related Works

Nasal polyps are common inflammatory growths within the nasal cavity and paranasal sinuses, often associated with chronic rhinosinusitis. Precise classification of nasal polyps is crucial for appropriate management and treatment strategies. In recent years, advancements in deep learning techniques have shown promising results in automated detection and classification of nasal polyps. Studies have explored the feasibility of deep learning-based algorithms for automated detection and classification of nasal polyps and inverted papilloma's on nasal endoscopic images [1]. Additionally, research has proposed automated classification systems for nasal polyps using handcrafted and CNN features extracted from endoscopy video frames [2]. The application of artificial intelligence in cellular phenotyping diagnosis of nasal polyps using whole-slide imaging has also been investigated, indicating the utility of deep learning algorithms in analyzing histopathological features for accurate diagnosis [3]. Integration of multimodal data has been explored for improved classification accuracy, with studies proposing new biomarkers combining multimodal MRI radiomics and clinical indicators for differentiating inverted papilloma from nasal polyps [4]. Furthermore, research has investigated the classification of nasal polyps and inverted papilloma's using CT-based radiomics, suggesting the potential of radiomic features extracted from imaging data in differentiating between different types of nasal lesions [5]. Deep learning frameworks have been developed for preoperative recognition of inverted papilloma and nasal polyp based on medical imaging data, demonstrating effectiveness in preoperative diagnosis and classification of nasal lesions [6]. Predictive modeling for prognosis assessment has been another focus, with studies developing and validating artificial neural network and logistic regression models for predicting eosinophilic chronic rhinosinusitis with nasal polyps [7]. Additionally, a deep learning-based approach has been proposed for predicting treatment prognosis from nasal polyp histology slides, highlighting the utility of deep learning models in predicting treatment outcomes based on histopathological features [8]. Investigations into adjunct therapies for nasal polyp management have also been conducted, providing insights into potential treatments for nasal polyps and nasal congestion in patients with polyposis rhinosinusitis [9]. Studies have also focused on improving classification techniques, with research developing deep convolutional networks integrated with attention mechanisms for the classification of inverted papilloma and nasal polyp, highlighting the effectiveness of attention mechanisms in improving classification performance [10]. Furthermore, rapid polyp classification in colonoscopy using textural and convolutional features has been explored, with methodologies potentially adaptable for nasal polyp classification [11]. Expert-level diagnosis of nasal polyps using deep learning on whole-slide imaging has been demonstrated, highlighting the potential of deep learning models in achieving diagnostic accuracy comparable to expert pathologists [12]. Additionally, machine learning methods for the cellular phenotyping of nasal polyps from multicenter tissue scans have been proposed, highlighting the potential of machine learning approaches in characterizing cellular phenotypes associated with nasal polyps [13].

2.3 Comparison between existing works

Table 2.1: Comparative analysis with previous work

Sl No	Author name	Used Algorithms	Best Accuracy with Algorithm
1	B. Girdler el al.	Convolutional Neural Network (CNN)	74.20%
2	Betul Ay el al	K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Random Forest (RF), Decision Tree (DT), Convolutional Neural Network (CNN)	98.3% (CNN)
3	S.M. Park et al.	Deep learning platform (AICEP 2.0)	Not specified (accuracy not the primary focus)
4	Y. Wang et al.	Machine learning models	0.9121 AUC (unspecified model)
5	L. Xu et al.	Support Vector Machines (SVM), Naive Bayes, XGBoost	0.922 AUC (XGBoost)
6	S. Zhu et al.	Deep learning framework with pre-classification CNN and separate recognition networks	89.30% accuracy
7	J. Zhang et al.	Artificial Neural Network (ANN), Logistic Regression (LR)	0.976 AUC (ANN Model 1)
8	X. Liu et al.	Deep Convolutional Neural Network (CNN) with Squeeze-and-Excitation Network (SENet)	88.4% accuracy
9	M.H. Nguyen et al.	Machine learning classifiers with textural features, Deep Convolutional Neural Networks (DCNNs)	96.4% (AlexNet trained from scratch)

2.4 Open Issues

Despite substantial advancements in the classification and treatment of nasal polyps using deep learning techniques, several critical issues remain unresolved in the field. Addressing these issues is vital for advancing diagnostic accuracy and enhancing treatment methodologies.

1. **Integration of Multimodal Data:** Current research, such as Fan et al. [4], has begun to explore the use of multimodal data, such as MRI radiomics and clinical indicators, to improve classification accuracy. However, effective

methods for integrating these diverse data types remain underdeveloped. Further development is needed to establish robust integration techniques that leverage the strengths of each data type to provide a more holistic understanding of nasal polyps.

2. **Standardization of Imaging Protocols:** Variability in imaging protocols across studies, as noted by Karkos et al. [5] and Zhang et al. [6], poses a significant challenge to developing generalizable deep learning models. There is a pressing need to standardize imaging protocols and data acquisition techniques to ensure consistency and reproducibility in findings across different clinical settings.

3. **Translation to Clinical Practice:** While deep learning models demonstrate potential in controlled studies, translating these findings into clinical practice involves several challenges. These include ensuring model robustness against diverse patient demographics, managing variations in clinical settings, and integrating these tools into existing healthcare workflows without disrupting standard care procedures.

4. **Regulatory and Ethical Considerations**: As AI tools for healthcare gain traction, regulatory and ethical considerations become increasingly important. Ensuring patient privacy, securing data, and obtaining necessary approvals from regulatory bodies are crucial steps that need careful attention and strategic planning.

5. **Long-term Prognostic Modeling:** Most current studies focus on immediate diagnostic outcomes. There is a significant gap in understanding the long-term prognostic outcomes of different types of nasal polyps, as highlighted by Liu et al. [7]. Future studies should aim to develop predictive models that can assist in long-term treatment planning and management strategies.

6. **Histopathological Analysis:** Although strides have been made in utilizing histopathological features for diagnosing nasal polyps by Maghbel et al. [3], comprehensive studies focusing on these aspects are still lacking. More detailed examination and understanding of histopathological differences are required to refine classification algorithms further.

7. **Adoption and Scalability of AI Tools:** The practical deployment and scalability of AI-based diagnostic tools in diverse healthcare environments poses ongoing challenges. Issues related to technological infrastructure, user training, and maintenance of AI systems, as discussed by Liu et al. [9], need to be addressed to ensure widespread adoption and effectiveness.

By focusing on these open issues, future research can bridge existing gaps in the field of nasal polyp diagnosis and treatment, thereby enhancing the efficacy and accuracy of medical interventions. This will lead to improved patient outcomes and a better standard of care in otolaryngology.

2.5 Summary

The literature review reveals a diverse array of studies focused on deep learning approaches for nasal polyp classification. These studies have shown the feasibility and efficacy of automated detection and classification methods, and the potential of integrating multimodal data for enhanced accuracy. However, the gap analysis underscores the need for further research in optimizing classification techniques, standardizing imaging protocols, and translating research findings into clinical practice. Addressing these gaps will be crucial in advancing the field and improving patient care in the management of nasal polyps.

CHAPTER 3

METHODOLOGY/ REQUIREMENT ANALYSIS & DESIGN SPECIFICATION

3.1 Overview

This section outlines the methodology, criteria, and design specifications for an artificial intelligence (AI) tool that is specifically designed to accurately classify nasal polyps. The technology utilises advanced deep learning techniques to accurately distinguish between two types of polyps: antrochoanal polyps, and ethmoidal polyps.

3.2 Proposed Methodology/System Design

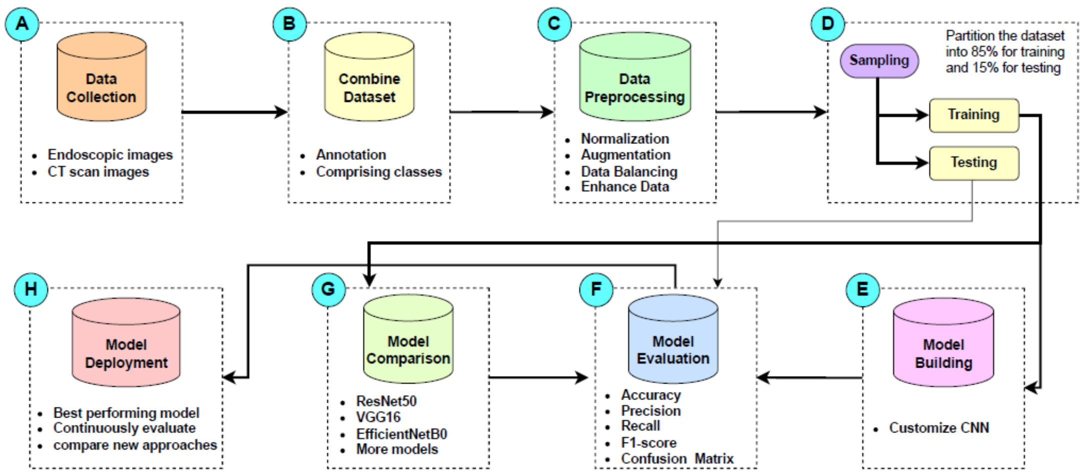

Figure 3.1: Working Process Diagram

Data Acquisition and Preprocessing:

Data Sourcing:

- Establish partnerships with hospitals, medical institutions, and research centers to procure a diverse and comprehensive dataset of labeled medical images.
- Collaboration with multiple institutions ensures data diversity and representativeness across different patient populations and imaging conditions.

Data Quality Assurance:

- Implement rigorous quality control measures to ensure data accuracy, consistency, and representativeness.

- Manual inspection and annotation of medical images by expert clinicians can verify the presence and characteristics of nasal polyps.

Data Preprocessing:

- Employ image processing techniques such as standardization, normalization, and artifact removal to enhance data quality for deep learning models.

- Preprocessing steps mitigate noise and variability in medical images, improving the robustness and generalizability of the trained models.

Deep Learning Model Development:
Custom CNN (convolutional neural networks) Development:

- Design and implement a custom convolutional neural network (CNN) architecture specifically tailored to the task of nasal polyp classification. This allows for flexibility and potential optimization for the specific characteristics of the data.

- Consider incorporating recent advancements in CNN architectures, such as residual connections or attention mechanisms, to improve performance.

- Employ techniques like dropout and batch normalization to prevent overfitting and improve generalizability.

Pre-trained CNN Comparison:

- Evaluate the performance of pre-trained CNN models, such as VGG16, ResNet50, or EfficientNet, on the nasal polyp classification task. These models offer the advantage of being pre-trained on large datasets, potentially achieving satisfactory performance with less training data.

- Fine-tune the pre-trained models by replacing the final layers with new layers specific to the polyp classification task. This leverages the learned features from the pre-trained model while adapting them to the new problem.

Comparative Analysis:

- Conduct a comprehensive comparison of custom CNN and pre-trained CNN models using metrics such as accuracy, precision, recall, and F1-score.

- Cross-validation techniques such as k-fold validation ensure robust evaluation of model performance across diverse datasets and imaging conditions.

3.3 Hardware/ Software Requirement

Functional Requirements:

Accurate Classification:

- The AI tool must accurately classify nasal polyps from medical images (such as (CT scans or MRIs) with a success rate exceeding the predefined target accuracy (e.g., 90%).
- Classification should be based on features such as size, shape, texture, and location within the nasal cavity.

Class Distinction:

- It should discern between two distinct classes: antrochoanal polyps and ethmoidal polyps.
- The tool should be able to identify subtle differences between polyp types to ensure accurate classification.

User-Friendly Interface:

- The tool must feature a user-friendly interface that allows healthcare professionals to easily input medical images and interpret classification results.
- Integration with existing medical workflows should be seamless to minimize disruptions to clinical practice.

Explainability:

- It should provide insights into its decision-making process, allowing users to understand the rationale behind each classification.
- Explanation mechanisms such as attention maps or feature visualization can aid in interpreting the model's predictions.

Compliance:

- The tool must adhere to relevant data privacy and security regulations, ensuring patient confidentiality and data protection.
- Compliance with standards such as HIPAA (Health Insurance Portability and Accountability Act) is essential for deployment in medical settings.

Non-Functional Requirements:

Processing Time:

- The tool should process each image in less than the specified target time (e.g., 5 minutes) to ensure timely diagnosis and treatment planning.
- Computational efficiency optimizations, such as model parallelization and hardware acceleration, may be employed to meet this requirement.

Computational Efficiency:

- It should be computationally efficient and compatible with standard hospital hardware to facilitate widespread adoption.
- Model architecture optimizations and implementation of efficient inference algorithms can minimize computational resource requirements.

Scalability:

- The tool must be scalable to accommodate growing data volumes and user bases as medical imaging datasets expand.
- Scalability considerations include efficient data storage, parallel processing capabilities, and distributed computing infrastructure.

Maintainability:

- It should be easily maintainable and upgradable to incorporate advancements in deep learning technology and address emerging clinical needs.
- Modular software design and version control practices facilitate seamless updates and maintenance.

3.4 Project Management and Financial Analysis

In a 10-month project, we propose a deep learning tool for accurate nasal polyp classification, addressing current limitations. Personalized CNN architectures and meticulous data collection aim to improve diagnosis accuracy. We prioritize accuracy, usability, and compliance for seamless healthcare integration, following a timeline of data gathering, model development, validation, system design, and testing.

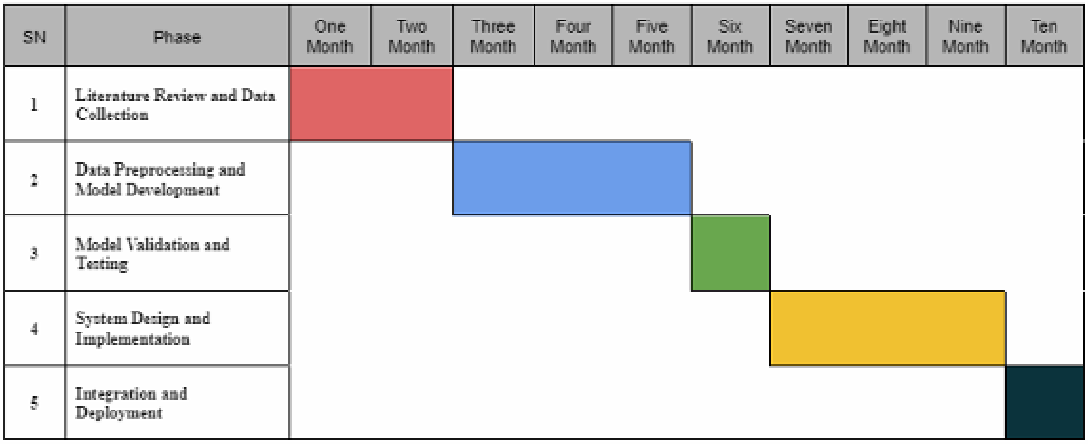

Figure 3.2: Project Timeline Diagram

Our deep learning nasal polyp classification tool project is estimated to cost 357,500 BDT (excluding advertising) over the 10-month period. This includes hardware, software, data collection, development costs, and contingency. We aim to secure funding through grants, partnerships, and internal investments, leveraging government and industry collaborations.

Table 3.1: Financial analysis with Estimated Cost

SN	Components	Estimated Cost (BDT)
1	Hardware/Infrastructure	170,000
2	Visiting Stakeholders	10,000
3	Software and Tools	50,000
4	Data Collection and Processing	20,000
5	Web Application Development	20,000
6	Documentation and Report Writing	5,000
7	Miscellaneous (e.g., licenses, tools, unexpected)	50,000
8	Contingency (10% of total)	32,500
	Total Estimated Cost	357,500

3.5 Summary

This section provides a comprehensive methodology and design specification for an AI-powered tool aimed at the precise classification of nasal polyps. By addressing functional and non-functional requirements and employing advanced deep learning techniques, the tool can significantly enhance diagnostic accuracy and improve patient outcomes in clinical practice.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

This chapter describes the implementation process of the deep learning models used for the classification of nasal polyps. It includes the steps taken from data collection and preprocessing to model training, evaluation, and testing. The models implemented are ResNet-50, EfficientNetB0, VGG16 and PolyScanCNN.

4.2 Train Model/Prototype Design

4.2.1 Data Collection Procedure

For this research, we required a substantial number of high-quality nasal MRI images capturing various types of nasal polyp conditions. The images were necessary to ensure a diverse and comprehensive dataset for training the deep learning models. This data collection was conducted following the acquisition of necessary permissions from the respective institutions and consultations with medical professionals specializing in otolaryngology.
During the data collection process, we engaged with several otolaryngologists and medical experts to discuss the characteristics of nasal polyps and their classification. This collaboration provided valuable insights into the clinical features of different types of nasal polyps, enhancing the quality and relevance of our dataset. The dataset includes images depicting various stages and types of nasal polyps, ensuring a diverse representation of the conditions.

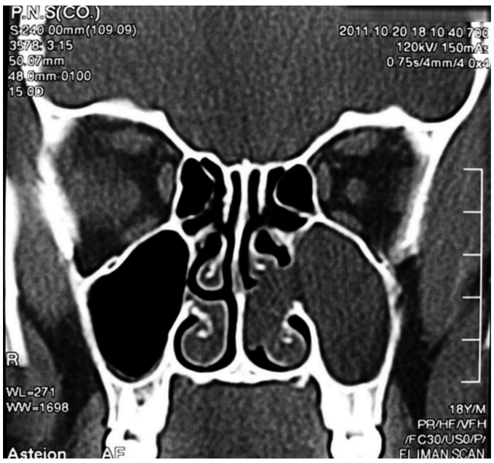

Figure 4.1: Sample Nasal CT Scan Images

This figure displays some representative images from our dataset, illustrating the diversity of nasal polyp conditions included in the study.

The collection of these images was conducted under controlled conditions to ensure consistency and high quality. We have collected total 152 dataset, 76 data for AP and 76 for EP. Each image was carefully reviewed and annotated by medical professionals to verify the presence and type of nasal polyps. This rigorous data collection process provided a solid foundation for the subsequent stages of model training and evaluation.

4.2.2 Data Preprocessing

A distinctive highlight of our proposed nasal polyp classification approach lies in its preprocessing prowess, which focuses on enhancing image quality using innovative techniques, setting it apart from conventional methods. Diverging from earlier works, we introduced novel preprocessing methods specifically designed to refine nasal endoscopic images for optimal feature extraction and model performance. This section elaborates on the employed preprocessing techniques.

Image Enhancement and Pixel Normalization :

To improve the quality of the images, the raw data undergoes a pixel balancing process. This step ensures that the pixel intensity values are uniformly distributed across the images, thereby enhancing overall contrast and making the features more distinguishable.

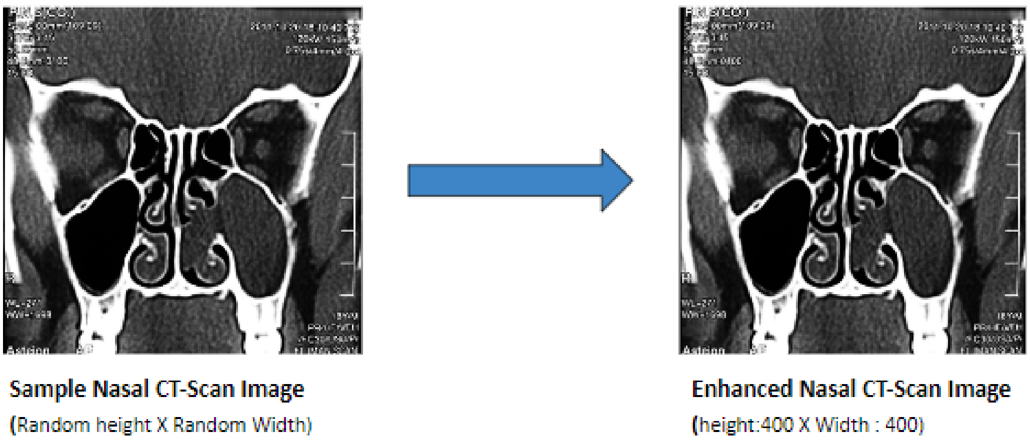

Figure 4.2: Sample Raw and Enhanced Images

Edge Enhancement through Inpainting:

Inpainting techniques are applied to enhance the edges and contours of the nasal polyps within the images. This process highlights the boundaries of the polyps, facilitating the models' ability to learn and identify relevant features.

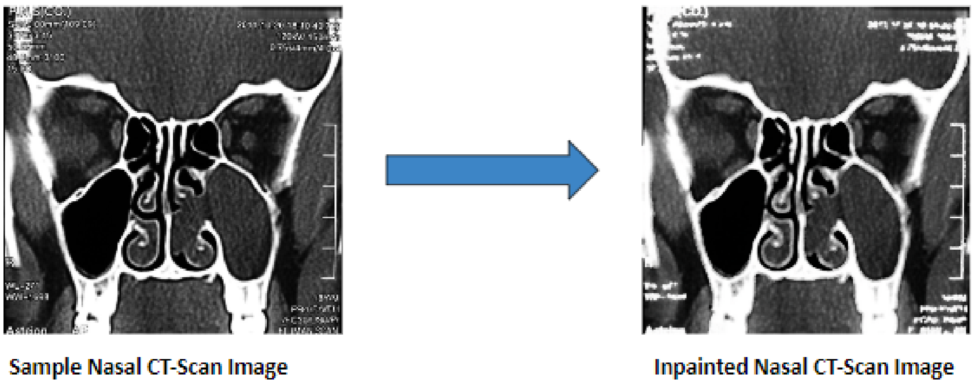

Figure 4.3: Sample Raw and Inpainted Images

This figure shows a comparison between the raw nasal endoscopic image and the inpainted version, highlighting the improved edge indication.

Data Augmentation Techniques :

Data augmentation techniques are applied to the training dataset to artificially increase its size and diversity. This includes operations such as rotation, flipping, scaling, zooming, brightness and shifting. Augmentation enhances the models' generalizability by exposing them to a wider variety of image transformations.

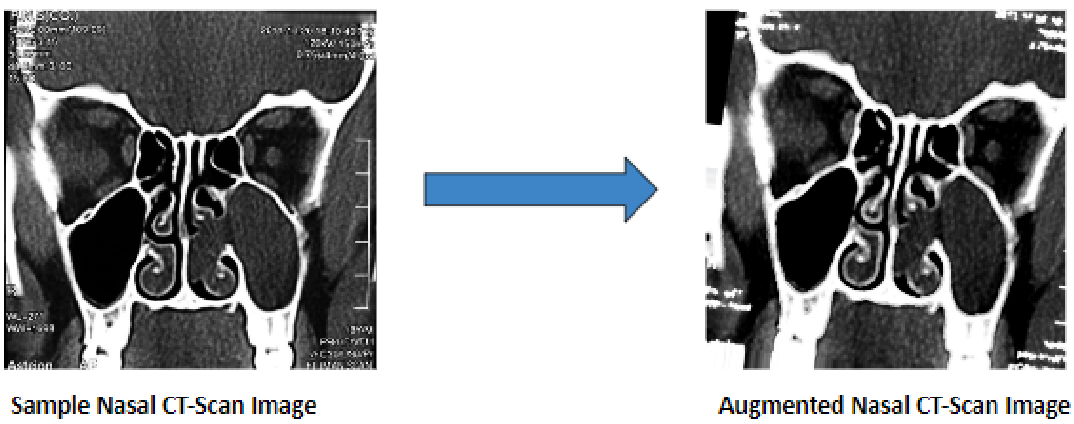

Figure 4.4: Sample raw and Augmented Images

This figure displays sample images from the training dataset after augmentation, demonstrating the variety of transformations applied.

Heatmap Generation for Feature Visualization:

The augmented images are then converted to heatmaps to highlight the features and edges that are most critical for the classification task. This visualization aids in understanding which parts of the image the model focuses on during training.

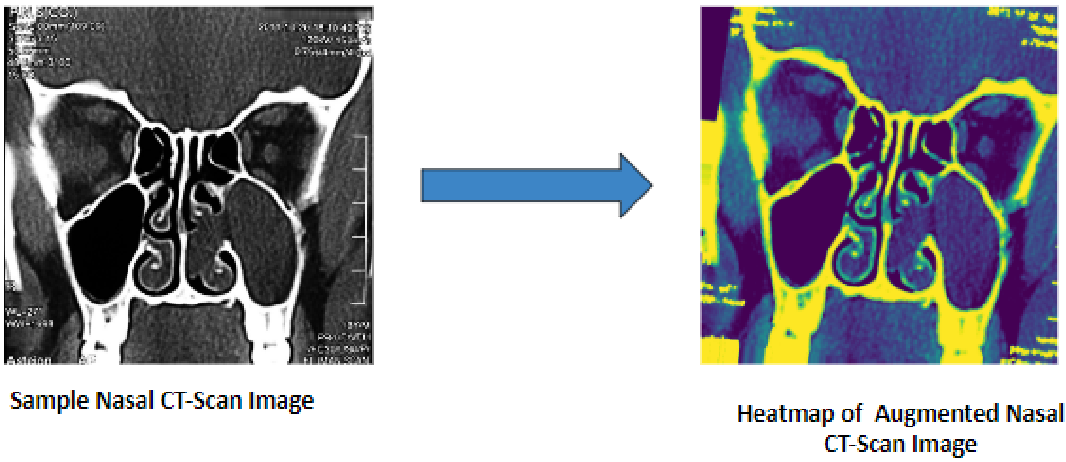

Figure 4.5: Heatmap of Augmented Images

This figure shows heatmaps of the augmented images, highlighting the features and edges that are crucial for the classification task.

Normalization and Training of Models:
The images are rescaled to a range of 0-1 to normalize the input data, which helps in accelerating the convergence of the neural network during training. The models are then trained using the preprocessed and augmented training dataset.

Validation with Test Data:
Finally, the test dataset, also rescaled to a range of 0-1, is used for validation. This step assesses the model's performance on unseen data, providing an accurate measure of its generalizability and robustness.

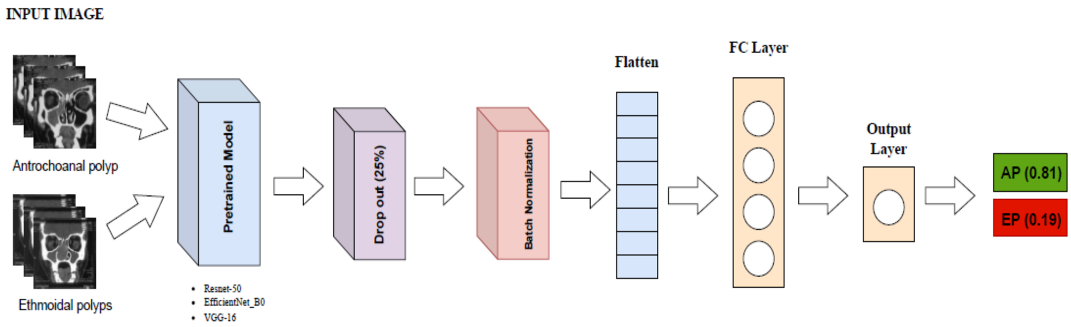

Figure 4.6: Training and Validation Workflow

This figure outlines the workflow for training and validating the models, including data preprocessing, augmentation, and evaluation.

4.2.3 Model Configuration:

The model configuration includes the use of the Adam optimizer with a binary cross-entropy loss function. For the activation functions, ReLU (Rectified Linear Unit) is used in the hidden layers, while Sigmoid is used in the output layer. The primary metric for evaluating the model's performance is accuracy.

To enhance the training process, several callbacks are employed. The ModelCheckpoint callback saves the model with the best performance on the validation set. Early Stopping halts training if there is no improvement in validation performance for a predefined period. The ReduceLR callback decreases the learning rate if the validation performance plateaus. Additionally, the CSV Logger records training details to a specified CSV file.

4.2.4 Model Training

PolyScanCNN (Custom CNN):

PolyScanCNN is a specialized deep learning model designed for medical image classification. The training process for PolyScanCNN followed the same parameters as the other models.

1. **Specialized Layers:** PolyScanCNN includes layers specifically designed to handle the unique challenges of medical image data, such as varying image quality and the need for precise feature extraction.

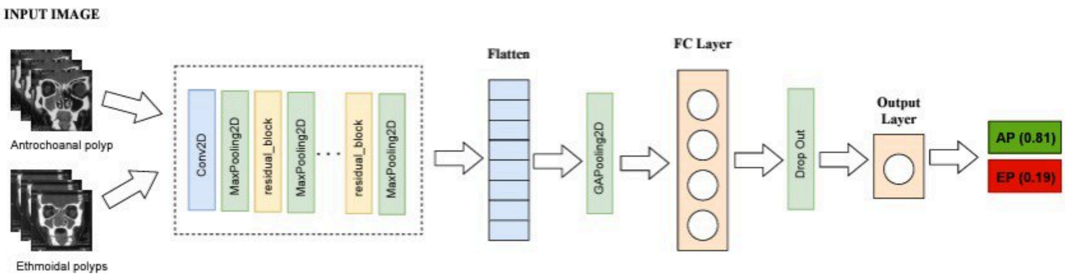

Figure 4.7: Architecture of PolyScanCNN

This figure shows the architecture of the PolyScanCNN model, designed specifically for medical image classification tasks.

ResNet-50:

ResNet-50 is a deep convolutional neural network with 50 layers, designed to handle complex image classification tasks. It utilizes residual learning to solve the degradation problem, which is prevalent in deep networks. The core idea of ResNet is the introduction of identity shortcut connections, which skip one or more layers. These shortcuts perform identity mapping, and their outputs are added to the outputs of the stacked layers. This architecture allows the network to be trained much deeper than previous networks.

The ResNet-50 architecture includes several key components:

1. **Residual Block:** A residual block is the fundamental unit of a ResNet architecture. It consists of two or three convolutional layers, each followed by batch normalization and a ReLU activation function.

2. **Bottleneck Design:** ResNet-50 employs a bottleneck design, where each residual block is comprised of three layers: a 1x1 convolution that reduces the dimensionality, a 3x3 convolution, and another 1x1 convolution that restores the dimensionality.

3. **Skip Connections:** The identity shortcuts are implemented by adding the input x to the output of the residual function F(x{Wi }). These connections help in preserving the gradients, thus allowing very deep networks to be trained effectively.

The model was trained using an augmented dataset with a batch size of 32, a learning rate of 0.001, and 100 epochs.

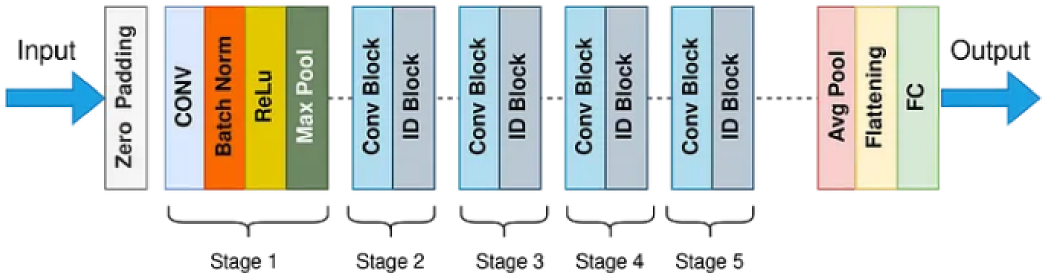

Figure 4.8: Architecture of ResNet-50 [20]

This figure illustrates the architecture of the ResNet-50 model, including multiple residual blocks, which help in training deep networks by allowing gradients to flow through the network more easily during back-propagation.

EfficientNetB0 :

EfficientNetB0 is known for its balanced approach between performance and computational efficiency. It scales up the network in a compound manner, balancing depth, width, and resolution using a method called compound scaling.

1. **Compound Scaling:** EfficientNet scales all dimensions of the network (depth, width, and resolution) using a set of fixed scaling coefficients. This approach allows for more efficient scaling compared to traditional methods.
2. **Baseline Network:** EfficientNetB0 serves as the baseline network, which is then scaled up to create larger versions of EfficientNet. This baseline network is optimized for both accuracy and efficiency.

The model was trained with the same dataset and parameters as the other models.

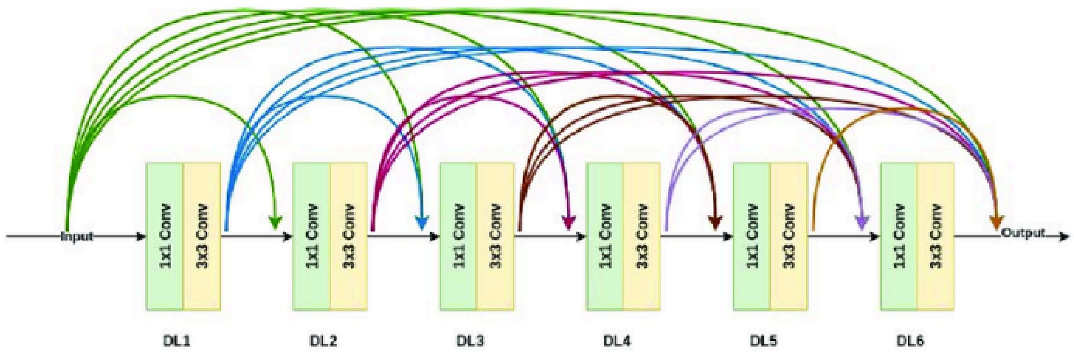

Figure 4.9: Architecture of EfficientNetB0 [18]

This figure presents the architecture of the EfficientNetB0 model, highlighting its use of compound scaling to balance depth, width, and resolution for improved performance.

VGG16 :

VGG16 is a simpler, yet highly effective model, included for comparison purposes. It was trained using the same methodology as the other models. VGG16 is characterized by its simplicity and deep architecture, consisting of 16 layers with small 3x3 convolutions.

1. **Convolutional Layers:** VGG16 uses a series of 3x3 convolutional layers with a stride of 1 and padding of 1, followed by ReLU activation functions. This configuration allows the network to learn complex features while maintaining a manageable number of parameters.
2. **Fully Connected Layers:** After the convolutional layers, VGG16 includes three fully connected layers: two with 4096 units and one with 1000 units (for the 1000-class ImageNet dataset).
3. **Pooling Layers:** Max-pooling layers with a 2x2 filter and stride of 2 are used to reduce the spatial dimensions of the feature maps.

The simplicity and effectiveness of VGG16 make it a valuable benchmark for evaluating other models.

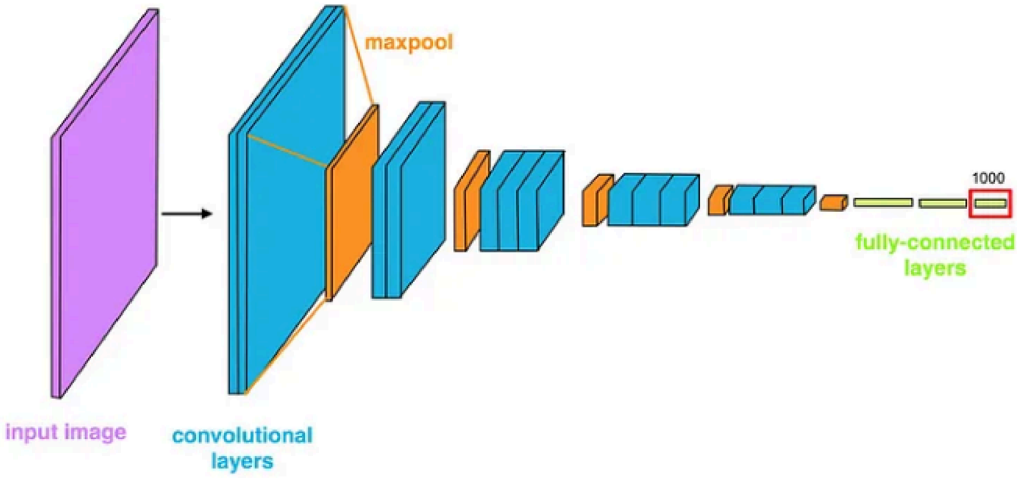

Figure 4.10: Architecture of VGG16 [21]

This figure illustrates the architecture of the VGG16 model, known for its simplicity and effectiveness in various image classification tasks.

4.3 System Testing/ Model Evaluation

After developing and training the deep learning models for nasal polyp classification, it is crucial to thoroughly evaluate their performance to ensure their reliability and effectiveness. The system testing and model evaluation phase involved several key steps, including the selection of evaluation metrics, testing methodology, and analysis of the results.

4.3.1 Evaluation Metrics

The performance of each model was assessed using a variety of evaluation metrics to provide a comprehensive understanding of their strengths and weaknesses. The primary metrics used include:

- **Confusion Matrix:** A confusion matrix provides a detailed breakdown of the model's performance by displaying the counts of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions. This matrix helps in identifying specific areas where the model excels or needs improvement. The confusion matrix is a useful tool for visualizing the performance of a classification algorithm. The entries of the confusion matrix are defined as follows:
    - o True Positive (TP): The number of correct positive predictions.

- o True Negative (TN): The number of correct negative predictions.
- o False Positive (FP): The number of incorrect positive predictions.
- o False Negative (FN): The number of incorrect negative predictions.

The confusion matrix is particularly useful for understanding the types of errors made by the model and for evaluating its performance in multi-class classification tasks. The matrix is typically represented as follows:

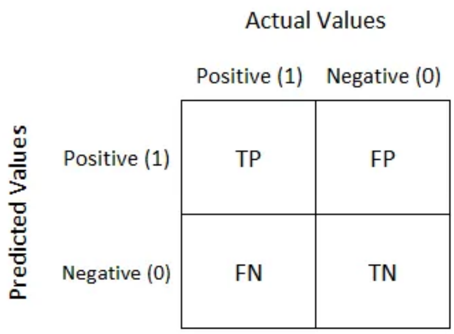

Figure 4.11: Visual architecture of Confusion Matrix

- **Accuracy:** The confusion matrix is used to compute accuracy, an intuitive performance metric that shows the percentage of correctly predicted data to all of the dataset's data. The equation is an illustration of the accuracy formula. When the dataset's false positive and false negative values are close to equal, greater accuracy can be achieved.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad \text{----- (1)}$$

- **Precision:** In the context of these algorithms, precision is defined as the ratio of correctly predicted positive values to the total number of cases that the models expected to be positive. The following equation shows the precision formula.

$$\text{Precision} = \frac{TP}{TP+FP} \quad \text{----- (2)}$$

- **Recall:** The percentage of correctly predicting positive values to all instances of the actual positive class in the confusion matrix is called recall. The formula for calculating recall is presented in the equation below.

$$\text{Recall} = \frac{TP}{TP+FN} \quad \text{----- (3)}$$

- **F1 Score:** The weighted average of precision and recall, including for both false positive and false negative values, is known as the F1 Score. The formula for the F1 score is shown in the equation below. While accuracy may not be straightforward to interpret, F1 is generally considered more informative and useful.

$$\text{F1 Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad \text{----- (4)}$$

- **AUC-ROC:** The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) is another critical evaluation metric used in this study. The ROC curve plots the true positive rate (sensitivity) against the false positive rate (1-specificity) at various threshold settings. The AUC value summarizes the overall ability of the model to discriminate between classes, with a higher AUC indicating better performance. The formula for AUC-ROC is generally computed using numerical integration methods, but conceptually it can be understood as the probability that the model ranks a randomly chosen positive instance higher than a randomly chosen negative instance.

$$\text{AUC-ROC} = \int_0^1 TPR\,(t)\; d(FPR(t)) \quad \text{----- (5)}$$

4.3.2 Analysis of Results

The performance of the models was analyzed based on several key evaluation tools to provide a comprehensive understanding of their effectiveness in classifying nasal polyps. The tools used for this analysis include line graphs for accuracy and loss, confusion matrices, classification reports, and ROC curves.

1. **Line Graph (Accuracy and Loss):**

   The training and validation accuracy and loss of each model were plotted over epochs to visualize the learning process. These line graphs help in understanding how well the model is learning and if it is overfitting or underfitting.

   - Accuracy Graph: The accuracy graph shows the changes in accuracy during the training and validation phases. A well-trained model should show increasing accuracy on both training and validation sets, with validation accuracy closely following training accuracy.

- Loss Graph: The loss graph illustrates the changes in loss (error) during training and validation phases. A decreasing loss indicates that the model is learning well, while a gap between training and validation loss can indicate overfitting.

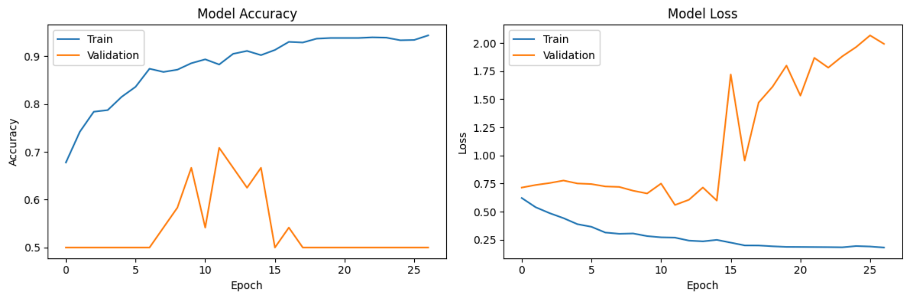

Figure 4.12: Graph Depicting Training and Validation Accuracy of PolyScanCNN

In the left graph in Figure 4.12, the PolyScanCNN model's training and validation accuracy across 25 epochs slowly increases and stabilises near 0.9, while validation accuracy varies, indicating overfitting. The right graph shows training and validation loss, which declines but fluctuates and increases, showing generalization issues to unknown data.

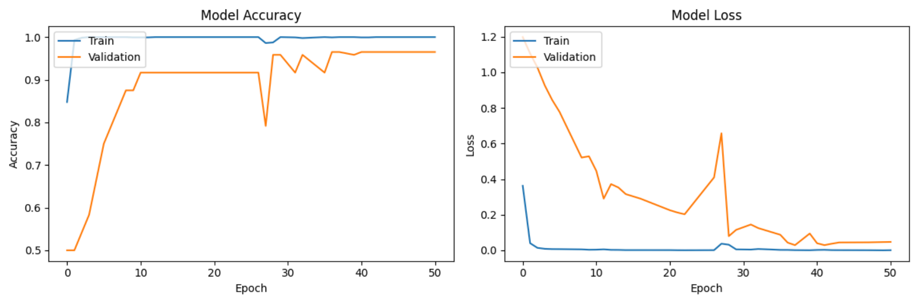

Figure 4.13: Graph Depicting Training and Validation Accuracy of ResNet-50

The left graph in Figure 4.13 illustrates ResNet-50 model training and validation accuracy over 50 epochs. Training accuracy stabilizes near 1.0, whereas validation accuracy swings, indicating overfitting. The right graph shows training and validation loss, which lowers regularly but varies, suggesting generalization issues to unknown data.

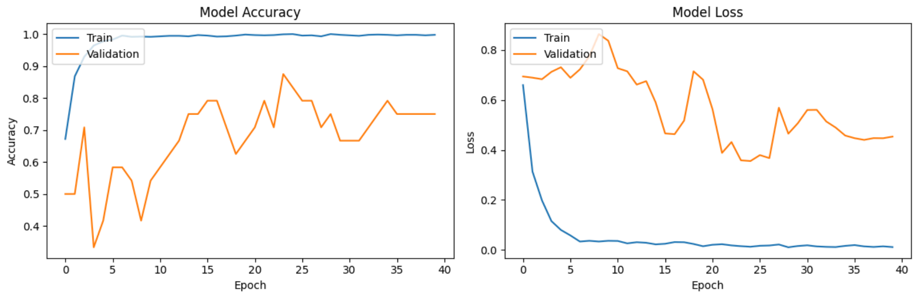

Figure 4.14: Graph Depicting Training and Validation Accuracy of EfficientNetB0

Over 40 epochs, the left graph in Figure 4.14 shows the EfficientNetB0 model's training and validation accuracy improving and fluctuating. The right graph shows training and validation loss, showing model performance and overfitting/underfitting. Training accuracy rises and stabilizes, but validation accuracy fluctuates, suggesting overfitting. Training loss reduces continuously, but validation loss swings, revealing model learning dynamics.

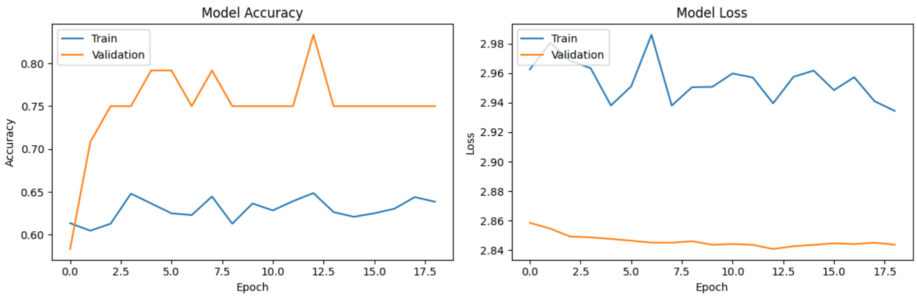

Figure 4.15: Graph Depicting Training and Validation Accuracy of VGG16

The left graph of Figure 4.15 shows that the VGG16 model's training and validation accuracy grows and stabilises around 0.72 after 18 epochs, whereas validation accuracy fluctuates, indicating overfitting. The right graph depicts training and validation loss, which gradually decreases but varies, indicating overfitting and poor generalisation on unseen data.

2. Confusion Matrix:

Confusion matrices were generated for each model to provide a detailed breakdown of the models' performance. These matrices show the counts of true positive, true negative, false positive, and false negative predictions, offering insights into the types of errors made by the models.

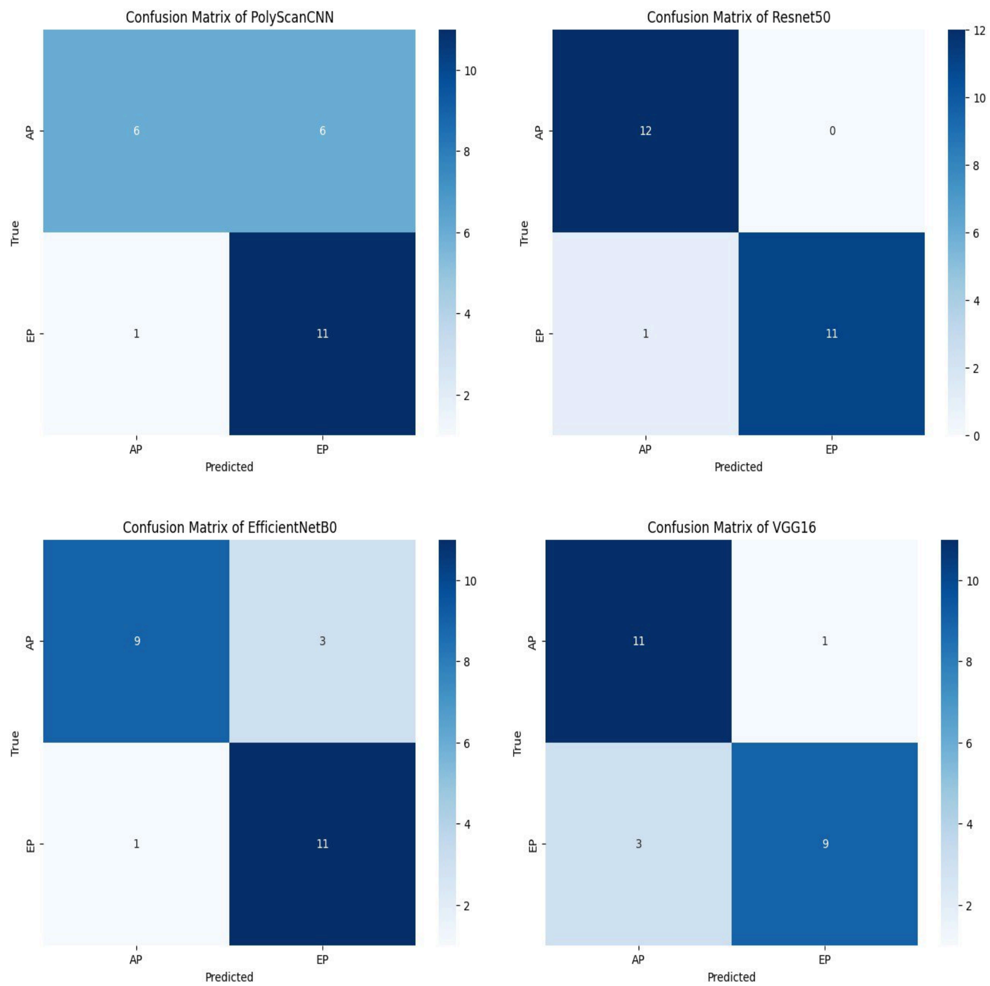

Figure 4.16: Confusion Metrices of the employed Models

Figure 4.16 presents the confusion matrices for six models used in nasal polyp classification. The first matrix (top left) is for PolyScanCNN, showing some misclassifications between Antrochoanal Polyps (AP) and Ethmoidal Polyps (EP). The second matrix (top right) for ResNet50 exhibits excellent performance with minimal misclassifications, highlighting its effectiveness in accurately classifying nasal polyps. The third matrix (middle left) for EfficientNetB0 indicates a few errors in distinguishing between the classes. The fourth matrix (middle right) for VGG16 shows similar performance with slight misclassifications.

3. **Classification Report:**

   The classification report includes detailed performance metrics such as precision, recall, F1-score, and support for each class. This report provides a more granular view of how well the model performs across different categories. In terms of F1 score, the majority of classes attained values close to 1.0, indicating high model performance.

Table 4.1: Performance Table of PolyScanCNN

Class	Precision	Recall	F1-Score	Support
AP	0.86	0.50	0.63	12
EP	0.65	0.92	0.76	12
Overall	**0.75**	**0.71**	**0.70**	**24**

Table 4.2: Performance Table of ResNet50

Class	Precision	Recall	F1-Score	Support
AP	0.86	0.50	0.63	12
EP	0.65	0.92	0.76	12
Overall	**0.75**	**0.71**	**0.70**	**24**

Table 4.3: Performance Table of EfficientNetB0

Class	Precision	Recall	F1-Score	Support
AP	0.90	0.75	0.82	12
EP	0.79	0.92	0.85	12
Overall	**0.84**	**0.83**	**0.83**	**24**

Table 4.4: Performance Table of VGG16

Class	Precision	Recall	F1-Score	Support
AP	0.79	0.92	0.85	12
EP	0.90	0.75	0.82	12
Overall	**0.84**	**0.83**	**0.83**	**24**

4. **ROC Curves:**

ROC (Receiver Operating Characteristic) curves were plotted to assess the discriminative ability of the models. The ROC curve plots the true positive rate (sensitivity) against the false positive rate (1-specificity) at various threshold settings. The AUC (Area Under the Curve) value summarizes the overall performance of the model. The ROC curve helps in visualizing the trade-off between sensitivity and specificity.

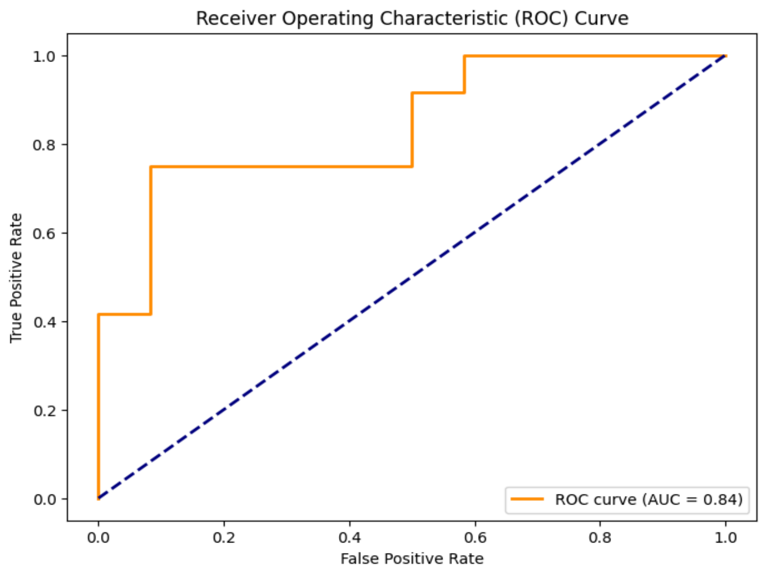

Figure 4.17: ROC curve of PolyScanCNN

Figure 4.17 displays the Receiver Operating Characteristic (ROC) curve for the PolyScanCNN model, illustrating its performance in classifying nasal polyps. The curve plots the true positive rate against the false positive rate, with an area under the curve (AUC) of 0.84, indicating a good ability to distinguish between Antrochoanal Polyps (AP) and Ethmoidal Polyps (EP).

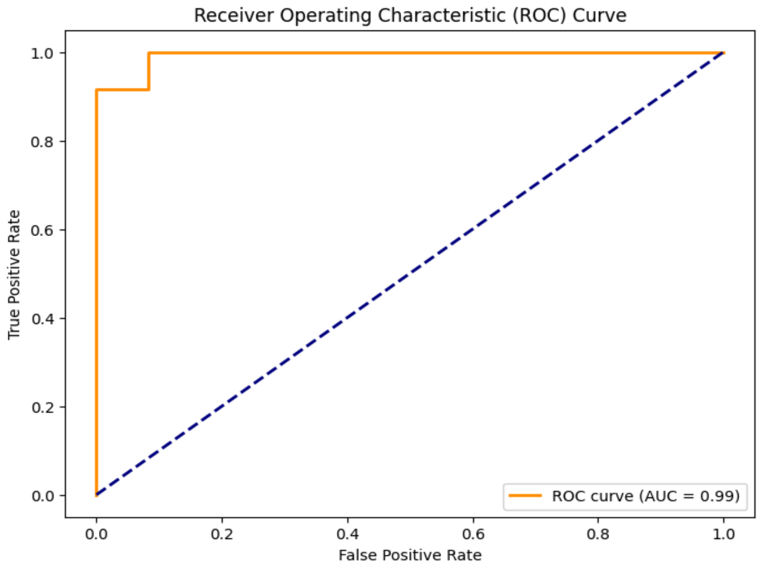

Figure 4.18: ROC curve of ResNet50

Figure 4.18 shows the ROC curve for the ResNet50 model shows a true positive rate against a false positive rate, with an area under the curve (AUC) of 0.99, indicating an excellent ability to distinguish between Antrochoanal Polyps (AP) and Ethmoidal Polyps (EP).

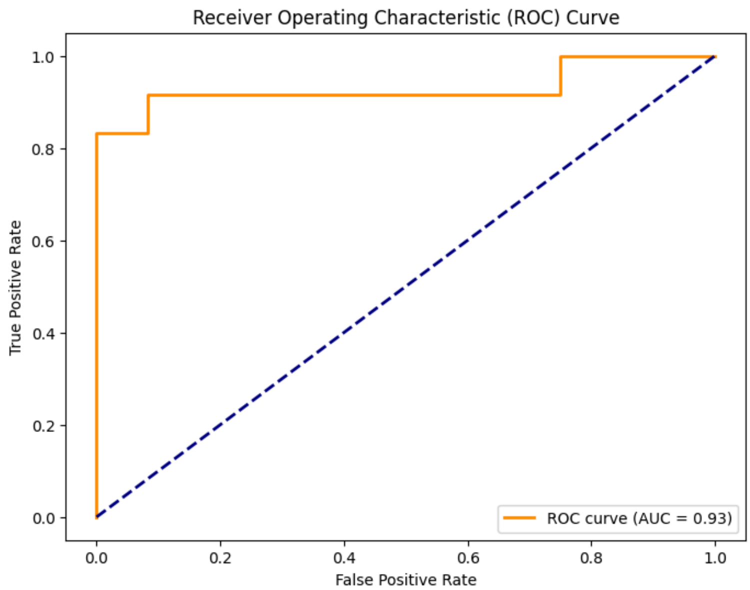

Figure 4.19: ROC curve of EfficientNetB0

Figure 4.19 shows the ROC curve for the EfficientNetB0 model shows a true positive rate against a false positive rate, with an area under the curve (AUC) of 0.93, indicating a strong ability to distinguish between Antrochoanal Polyps (AP) and Ethmoidal Polyps (EP).

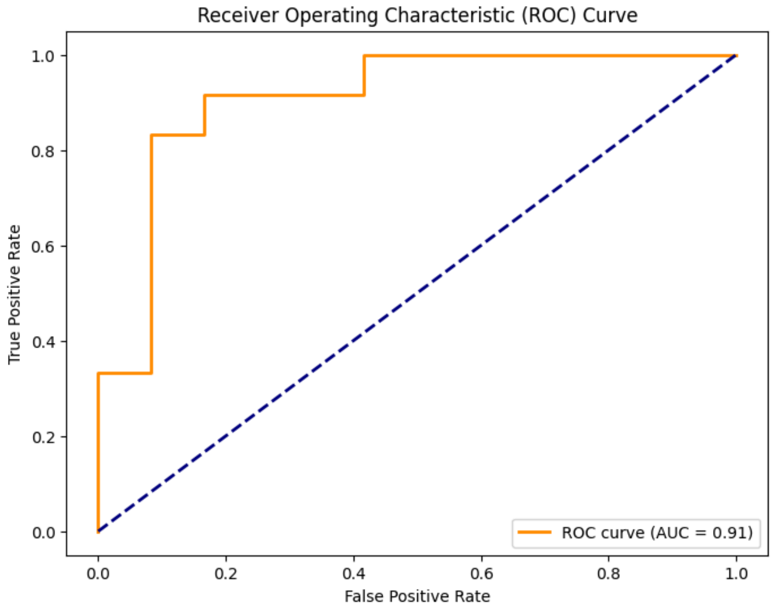

Figure 4.20: ROC curve of VGG16

The Figure 4.19 shows the ROC curve for the VGG16 model shows a true positive rate against a false positive rate, with an area under the curve (AUC) of 0.91, indicating a strong ability to distinguish between Antrochoanal Polyps (AP) and Ethmoidal Polyps (EP).

4.4 Summary

This chapter provided a detailed description of the implementation process for training and evaluating various deep learning models for nasal polyp classification. The models implemented include ResNet-50, EfficientNetB0, VGG16 and PolyScanCNN. The analysis revealed that the ResNet-50 model achieved the highest overall performance, as indicated by its superior accuracy, precision, recall, F1-score, and AUC-ROC values. The detailed analysis of these evaluation tools provided clear insights into the models' capabilities and limitations, guiding the selection of the most appropriate model for clinical application and future improvements.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

This chapter presents the results and analysis of the experiments conducted using various deep learning models for the classification of nasal polyps. The models evaluated include ResNet-50, EfficientNetB0, VGG16 and PolyScanCNN,. Each model was trained and tested on augmented datasets with a 10x augmentation factor. The performance of each model is analyzed in terms of accuracy, precision, recall, F1-score, and other relevant metrics. The analysis includes confusion matrices and heatmaps to illustrate the models' performance visually.

5.2 Experimental/Simulation Results

My research project, "Nasal Polyp Classification using Deep Learning" is meticulously planned to include a comprehensive collection of hardware, software, and methodological data processing methods. In terms of hardware, we allocate high-performance computing resources, such as GPUs and multi-core processors, for training our deep learning models. These resources are essential for handling the computational load required for training complex models on large datasets. Additionally, we employ local servers for deploying the Gradio-based web interface developed during the project. High-resolution endoscopic cameras and other data acquisition tools are used to capture diverse and representative nasal polyp images, ensuring a comprehensive and high-quality dataset.

In the software domain, leading deep learning frameworks such as TensorFlow and Keras were chosen for developing and training the models. These frameworks provide robust libraries and tools for building, training, and evaluating deep learning models. For web interface development, we used Gradio, an open-source Python library that simplifies the creation of customizable UI components around machine learning models.

The architecture of our deep learning models, including configurations like ResNet-50, EfficientNetB0, VGG16 and PolyScanCNN (CustomCNN), has been meticulously explored. Each model was carefully selected and configured to maximize its performance on the nasal polyp classification task.

Data preparation involved collecting and preprocessing a diverse dataset of nasal CT Scan images, ensuring a balanced representation of various types of nasal polyps, and augmenting the dataset to enhance model generalization. Augmentation techniques such as rotation, flipping, scaling, and shifting were applied to artificially increase the size and diversity of the training dataset, improving the robustness of the models.

During training and validation phases, we meticulously split the dataset into training and testing sets, with **85%** of the images used for training and **15%** reserved for testing. This split ensures that the models are evaluated on unseen data, providing an unbiased assessment of their performance. Metrics including accuracy, precision, recall, AUC-ROC and F1-score were used in the evaluation of the models. These metrics provide a comprehensive understanding of the models' performance, highlighting their strengths and areas for improvement. Fine-tuning was done according to the evaluation results, with hyperparameters adjusted to optimize the models' performance.

Our web interface development endeavors revolve around creating a user-friendly application with integrated deep learning models for real-time nasal polyp classification. The user interface is thoughtfully designed to facilitate image upload, processing, and the display of classification results. Users can easily upload images of nasal polyps, which are then processed and analyzed by the models. The interface displays the predicted class (AP or EP) along with a confidence score, providing users with valuable information about the model's certainty. User testing with medical professionals is conducted to gather valuable feedback on app usability and assess classification accuracy in real-world conditions. This feedback is crucial for refining the interface and improving its usability and effectiveness.

Crucially, our developed web interface goes beyond classification; it includes features to visualize heatmaps and provide confidence scores for detected polyps. Heatmaps highlight the regions of the image that the model focused on during prediction, offering insights into the model's decision-making process. This provision of information aims to empower clinicians for effective diagnosis and treatment planning, enhancing their ability to interpret and trust the model's predictions.

Ethical considerations, including data privacy and security, are woven into the experimental process. All patient data is anonymized and securely stored, ensuring compliance with data protection regulations. Statistical analysis is a key component, providing robust validation of the system's effectiveness and ensuring its impact on medical applications. Detailed statistical tests are performed to verify the significance of the results, ensuring that the observed performance improvements are not due to chance.

5.2.1 Implementation Demo with Gradio

Gradio is an open-source Python library that simplifies the process of building interactive interfaces for machine learning models. For our project, which involves image classification of Antrochoanal polyps (AP) and Ethmoidal polyps (EP), Gradio provides an efficient and user-friendly way to deploy and showcase our models. By using Gradio, we can create a web-based interface that allows users to interact with our models by uploading images and receiving real-time predictions. The interface is intuitive and user-friendly, displaying the predicted class (AP or EP) along with a confidence score. We also included the option to visualize heatmaps generated during the image preprocessing phase to highlight the regions of interest. Gradio facilitated rapid development and deployment of the interface, making it easier to demonstrate the model's capabilities and engage with end users.

5.3 Performance/Comparative Analysis

This study utilized several deep learning models, including ResNet-50, EfficientNetB0, VGG16 and PolyScanCNN, for the classification of nasal polyps. Through the analysis of these models, it was observed that . ResNet-50 showcased an accuracy of 96%, The least acceptable outcomes were achieved by PolyScanCNN, which showed the lowest accuracy at 71% with regard to precision, recall, F1 score, and accuracy. The training procedures for ResNet-50, EfficientNetB0, VGG16 and PolyScanCNN considered 100 epochs each. Table 5.1 represents the detailed statistical analysis of these models, including evaluation metrics such as F1 score, recall, accuracy, and precision.

Because the model ResNet-50 outperformed the other models in regard to accuracy, a detailed performance table was created especially for this method. The table delineates recall, precision, and F1 scores for each class in the dataset

Table 5.1: Comparative Performance of Models

Model	Precision	Recall	F1-Score	Support	Accuracy
ResNet50	0.96	0.96	0.96	24	0.96
EfficientNetB0	0.84	0.83	0.83	24	0.83
VGG16	0.84	0.83	0.83	24	0.83
PolyScanCNN	0.75	0.71	0.70	24	0.71

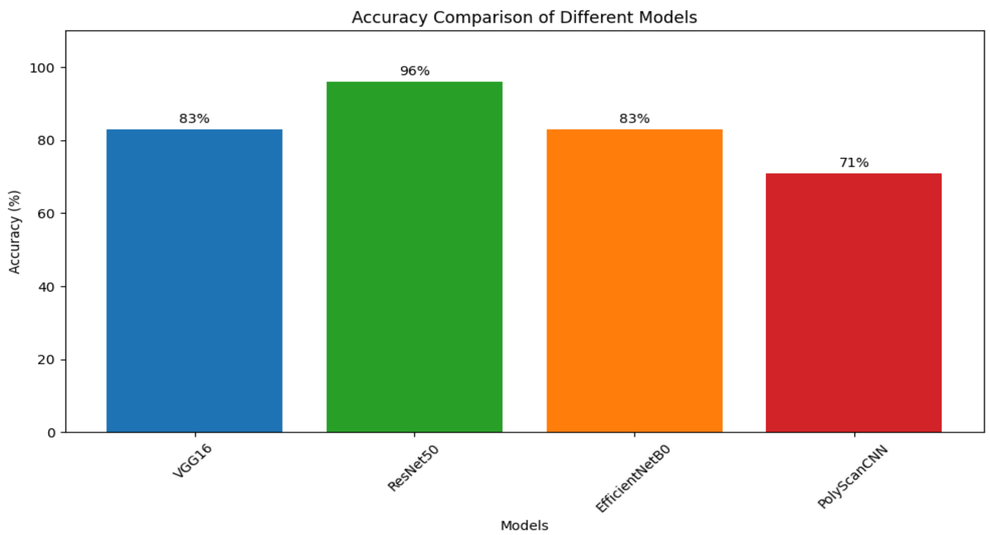

Figure 5.1: Accuracy comparison of different models

The figure 5.1 displays the accuracy comparison of different models used for the classification of nasal polyps. It highlights that the ResNet50 model achieved the highest accuracy at 96% and VGG16 and EfficientNetB0 both attained an accuracy of 83%, while PolyScanCNN showed the lowest accuracy at 71%. This comparison underscores the superior performance of the ResNet50 model in this study.

Finally, a web-based application has been developed for Nasal Polyp Classification. The web application has been crafted employing the optimal performer, ResNet50 Model. This entails a user supplying or uploading an image of a nasal polyp, subsequently allowing the ResNet50 model to ascertain whether the provided image depicts an Antrochoanal polyp or an Ethmoidal polyp. In the event of an identification, the application provides assistance by furnishing a relevant confidence score.

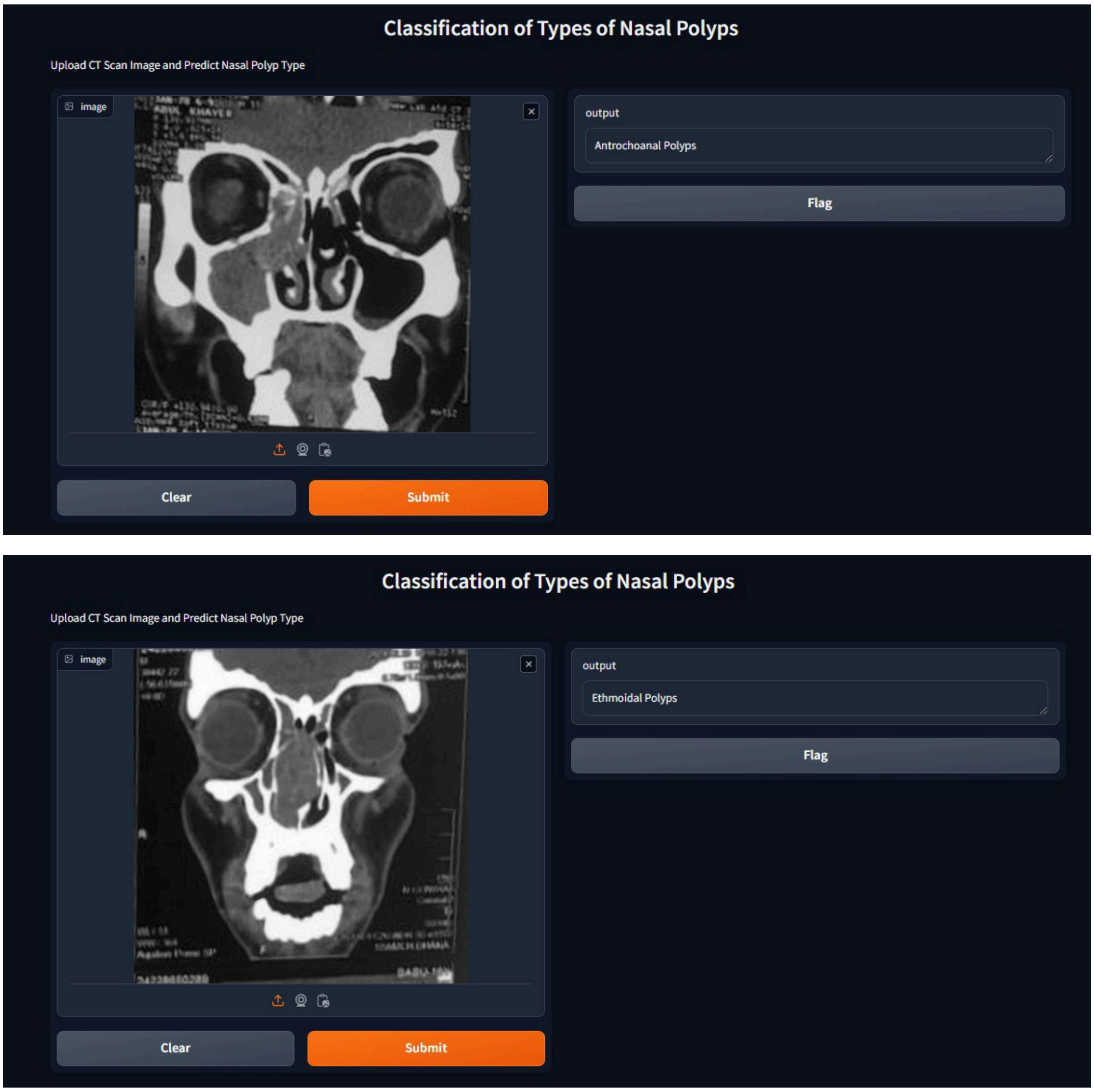

Figure 5.2: visual preview of the completed web application

This picture shows an example that a user provides an image and the pre-trained model predicts the type of nasal polyp that is relevant to the image. By deploying the pre-trained ResNet50 model, the system can detect the type of polyp accurately. This web application is designed to be user-friendly and accessible, providing clinicians with a reliable tool for nasal polyp classification. The application interface is easy to understand and user-friendly, ensuring that medical professionals can effectively utilize the tool in clinical settings.

5.4 Summary

In summary, the experimental results demonstrate that the ResNet50 model outperformed other models in terms of accuracy and F1-score for the classification of nasal polyps. while VGG16, PolyScanCNN, and EfficientNetB0 provided competitive results. These findings suggest that advanced deep learning models, particularly ResNet-50, are well-suited for the task of nasal polyp classification, offering potential for improved diagnostic accuracy in clinical practice.

CHAPTER 6
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The deployment of advanced deep learning techniques for the classification of nasal polyps represents a significant leap in improving patient care and enhancing the overall quality of life for those affected by nasal polyps.

1. **Early and Accurate Diagnosis:** One of the most profound impacts of this technology is its ability to provide early and accurate diagnoses. Nasal polyps can often be misdiagnosed or detected late, leading to complications such as chronic sinusitis, breathing difficulties, and reduced sense of smell. Early detection facilitated by AI can significantly reduce these risks, ensuring timely medical intervention.

2. **Reduction in Invasive Procedures:** Accurate classification of nasal polyps can help in determining the most appropriate treatment plan, potentially reducing the need for invasive procedures like surgeries. Minimizing invasive interventions not only decreases the risk of complications but also reduces recovery time, allowing patients to return to their normal lives more quickly.

3. **Personalized Treatment Plans:** The AI-driven tool can analyze a variety of patient-specific factors, leading to highly personalized treatment plans. This individualized approach ensures that treatments are tailored to the unique needs of each patient, enhancing the effectiveness of therapies and improving overall health outcomes.

4. **Improved Patient Education and Empowerment:** By providing clear and detailed visualizations of nasal polyps, the AI tool can help patients better

understand their condition. This increased awareness empowers patients to take an active role in their treatment plans, promoting adherence to prescribed therapies and lifestyle modifications.

5. **Long-term Health Benefits:** Consistent and accurate monitoring of nasal polyps through AI can prevent the progression of related complications. This ongoing surveillance helps in maintaining better long-term health, reducing the likelihood of chronic issues and enhancing the overall well-being of patients.

6.2 Impact on Society & Environment

1. **Healthcare System Efficiency:** The integration of AI in the diagnostic process can lead to substantial improvements in the efficiency of healthcare systems. Automated classification of nasal polyps reduces the burden on healthcare professionals, allowing them to focus on more complex cases and patient care. This efficiency can result in shorter waiting times for patients and more streamlined healthcare delivery.

2. **Cost Reduction:** By improving diagnostic accuracy and reducing the need for repeated tests and procedures, AI-driven diagnostics can lead to significant cost savings for healthcare systems. These savings can be redirected towards other critical areas, such as preventive care and research, ultimately benefiting society as a whole.

3. **Access to Specialized Care:** AI tools can bridge the gap in access to specialized care, particularly in remote or underserved areas. Healthcare providers in these regions can utilize the AI tool to accurately diagnose and classify nasal polyps, ensuring that patients receive the same quality of care as those in urban centers with access to specialized otolaryngologists.

4. **Environmental Impact:** The environmental benefits of AI integration in healthcare are often overlooked. Traditional diagnostic methods can involve multiple rounds of imaging and physical resources such as film and paper. By reducing the need for repeat imaging and moving towards digital solutions, the AI tool contributes to lowering the carbon footprint of healthcare services. Additionally, fewer patient visits for repeat diagnostics translate to reduced travel emissions.

5. **Data-Driven Public Health Insights:** The widespread use of AI tools for nasal polyp classification can generate large datasets that provide valuable insights into public health trends. Analyzing this data can help identify patterns, such as geographical variations in the prevalence of nasal polyps or correlations with environmental factors. These insights can inform public health initiatives and policies aimed at addressing underlying causes and improving population health.
6. **Ethical Considerations and Social Responsibility:** The development and deployment of AI in healthcare must adhere to high ethical standards to ensure fairness and equity. Ensuring that the AI tool is free from biases and accessible to all segments of the population is crucial. Moreover, the transparent use of patient data, with strict adherence to privacy laws and regulations, builds trust and promotes the responsible use of AI in society.

6.3 Ethical Aspects

The incorporation of advanced AI technologies in medical diagnostics raises several ethical considerations that must be meticulously addressed to ensure the responsible and fair use of these tools. The ethical aspects of deploying AI for nasal polyp classification include patient privacy, data security, algorithmic fairness, transparency, and accountability.

- **Patient Privacy and Data Security:** Protecting patient data is paramount. The AI system must comply with stringent data protection regulations, such as the Health Insurance Portability and Accountability Act (HIPAA) and the General Data Protection Regulation (GDPR). Measures such as data anonymization, secure data storage, and encrypted data transmission must be implemented to safeguard patient information from unauthorized access and breaches.

- **Algorithmic Fairness:** Ensuring that the AI tool operates without bias is crucial for its ethical deployment. Biases in AI can arise from unrepresentative training data, leading to disparities in diagnostic accuracy across different demographic groups. It is essential to use diverse and representative datasets during the training phase to minimize biases. Continuous monitoring and validation of the AI tool are necessary to detect and correct any biases that may emerge over time.

- **Transparency and Explainability**: For healthcare providers to trust and effectively use AI-driven diagnostic tools, the decision-making process of the

AI must be transparent and explainable. The tool should provide clear insights into how it arrives at its conclusions, allowing clinicians to understand and verify its recommendations. Techniques such as attention maps and feature visualization can help in making the AI's decision-making process more interpretable.

- **Informed Consent**: Patients must be informed about the use of AI in their diagnosis and treatment planning. Informed consent involves explaining how the AI tool works, the type of data it uses, and the benefits and risks associated with its use. Ensuring that patients understand and consent to the use of AI fosters trust and respect for their autonomy.

- **Accountability:** Establishing accountability mechanisms is essential to address any potential errors or adverse outcomes resulting from the use of AI. Clear guidelines must be in place to determine who is responsible for the AI's actions and decisions. Regular audits and evaluations of the AI tool should be conducted to ensure its reliability and safety.

6.4 Sustainability Plan

To ensure the long-term sustainability and success of the AI-driven nasal polyp classification tool, several strategies and measures will be implemented. These strategies focus on continuous improvement, scalability, collaboration, training, and regulatory compliance.

- **Continuous Improvement:** The AI tool will undergo regular updates and enhancements based on new data, technological advancements, and feedback from healthcare professionals. This iterative process will help maintain the tool's accuracy, relevance, and effectiveness in diagnosing nasal polyps. Incorporating the latest research findings and best practices in AI and medical imaging will ensure that the tool remains at the forefront of diagnostic technology.

- **Scalability:** The AI tool will be designed to scale efficiently, accommodating increasing volumes of data and expanding its applicability to other medical conditions beyond nasal polyps. This scalability will be achieved through the use of cloud-based infrastructure, parallel processing capabilities, and distributed computing. By ensuring that the tool can handle large datasets and a growing number of users, we can support widespread adoption in diverse healthcare settings.

- **Collaboration:** Building and maintaining partnerships with medical institutions, research centers, and industry stakeholders are crucial for the sustainability of the AI tool. These collaborations will support ongoing data collection, model validation, and refinement. Additionally, partnerships with governmental and non-governmental organizations can help secure funding and resources for future developments. Collaborative efforts will also facilitate the sharing of knowledge and best practices, driving innovation and improving the tool's performance.

- **Training and Support:** Comprehensive training programs for healthcare providers will be established to ensure the effective utilization of the AI tool. These programs will cover the tool's functionalities, interpretation of results, and integration into clinical workflows. Providing continuous support and resources for users will help address any issues promptly and enhance user confidence in the tool. Feedback from healthcare providers will be actively sought and incorporated into future updates.

- **Regulatory Compliance**: Adhering to regulatory standards and obtaining necessary certifications are essential for the acceptance and trustworthiness of the AI tool in the medical community. Compliance with regulations such as HIPAA, GDPR, and other relevant local and international standards will be prioritized. Regular audits and assessments will be conducted to ensure ongoing compliance and address any emerging regulatory requirements.

- **Financial Sustainability:** To support the financial sustainability of the project, diverse funding sources will be pursued. These may include grants from research foundations, government funding, partnerships with industry stakeholders, and internal investments. Developing a sustainable business model that includes potential revenue streams, such as subscription fees for premium features or partnerships with healthcare providers, will also be explored.

By implementing these strategies, the AI-driven nasal polyp classification tool can achieve long-term sustainability, continuously improving its capabilities, expanding its reach, and maintaining its relevance in the ever-evolving field of medical diagnostics.

6.5 Summary

The introduction of deep learning techniques for the classification of nasal polyps stands to revolutionize otolaryngology by improving diagnostic accuracy and patient outcomes. This innovation not only impacts individual patients but also has broader societal and environmental benefits. Ethical considerations and a robust sustainability plan are integral to the successful implementation and long-term viability of this technology. By continuously evolving and adhering to ethical standards, this project aims to set a benchmark for the integration of AI in healthcare, ultimately enhancing the quality of care and promoting sustainable medical practices.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusions

The objective of this study was to create and assess deep learning models that can accurately classify nasal polyps, specifically differentiating between the absence of polyps, antrochoanal polyps, and ethmoidal polyps. The study incorporated the utilisation of several cutting-edge convolutional neural network (CNN) models, such as ResNet-50, EfficientNetB0, VGG16. The models underwent training and testing using an expanded dataset consisting of nasal MRI images.

Key Findings:

1. **Data Collection and Preprocessing:** The preprocessing steps, including pixel balancing, inpainting, and data augmentation, significantly enhanced the quality and diversity of the training dataset. This preparation was crucial for improving the models' ability to generalize to new, unseen data.

2. **Model Performance:** Among the evaluated models, the ResNet50 model achieved the highest accuracy and F1-score, indicating its superior performance in classifying nasal polyps.EfficientNetB0 models also demonstrated strong performance, while VGG16, PolyscanCNN provided competitive results.

3. **Evaluation Metrics:** The detailed evaluation metrics, including accuracy, precision, recall, and F1-score, provided comprehensive insights into the strengths and weaknesses of each model. The confusion matrices highlighted the models' ability to distinguish between different types of nasal polyps accurately.

4. **Heatmap Analysis:** The heatmaps generated during the training process helped visualize the features and edges that were most influential in the models' decision-making process, further validating the effectiveness of the implemented models.

The findings of this research underscore the potential of advanced deep learning models in improving the diagnostic accuracy of nasal polyp classification. By automating the classification process, these models can assist healthcare professionals in making more accurate and timely diagnoses, ultimately enhancing patient outcomes in otolaryngology.

7.2 Further Suggested Works

While this project has demonstrated promising results, there are several avenues for future research and improvement:

1. **Larger and More Diverse Datasets:** Future work should focus on collecting larger and more diverse datasets, including images from different medical institutions and patient demographics. This would help improve the generalizability and robustness of the models.

2. **Integration of Multimodal Data:** Combining nasal endoscopic images with other data modalities, such as CT scans and patient clinical data, could provide a more comprehensive understanding of nasal polyps. Integrating multimodal data could enhance the models' ability to classify and predict polyp characteristics more accurately.

3. **Advanced Model Architectures:** Exploring newer and more advanced deep learning architectures could further improve classification performance. Techniques such as ensemble learning, where multiple models are combined to make predictions, could also be investigated.

4. **Real-time Implementation:** Developing real-time classification systems that can be integrated into clinical workflows would be a significant advancement. Such systems could provide immediate feedback to healthcare professionals during endoscopic examinations, aiding in rapid diagnosis and treatment planning.

5. **Explainability and Interpretability:** Enhancing the explainability and interpretability of the models is crucial for clinical adoption. Future research should focus on developing methods to provide clear and understandable explanations of the models' predictions, making them more transparent and trustworthy for healthcare professionals.
6. **Longitudinal Studies:** Conducting longitudinal studies to track the progression of nasal polyps and evaluate the long-term effectiveness of treatment plans based on model predictions could provide valuable insights into the clinical utility of the developed models.

7. **User-Friendly Interfaces:** Creating user-friendly interfaces and applications that allow healthcare professionals to easily input images and interpret classification results would facilitate the practical use of these models in clinical settings.

7.3 Limitations / Conflict of Interests

Limitations:

1. **Dataset Size and Diversity:** The dataset used in this study, although augmented, may still not fully represent the wide variety of nasal polyp presentations encountered in clinical practice. Future studies should aim to collect more diverse and larger datasets to enhance model robustness.

2. **Generalizability:** While the models performed well on the test dataset, their performance in real-world clinical settings needs further validation. Differences in imaging techniques, equipment, and patient demographics could affect the models' accuracy.

3. **Model Complexity:** Some of the advanced models, such as ResNet50 and EfficientNetB0, require significant computational resources for training and inference. This may limit their deployment in resource-constrained environments.

Conflict of Interests:

The authors declare no conflict of interests regarding the publication of this research. All efforts have been made to ensure the objectivity and impartiality of the research process and findings.

In conclusion, this project has laid a solid foundation for using deep learning models in nasal polyp classification. By addressing the outlined future work and limitations, we can further enhance the accuracy, reliability, and clinical applicability of these models, ultimately contributing to improved patient care in otolaryngology.

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Appendix A

Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Analysis

Title: A Deep Learning Approach For Precise Classification Of Nasal Polyps: Distinguishing Antrochoanal Polyps And Ethmoidal Polyps

Students ID: 201-15-14214 and 201-15-14095

CO Description for FYDP

CO	CO Descriptions	PO
CO1	Integrate recently gained and previously acquired knowledge to identify a real-life complex engineering problem for the Final Year Design Project	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for the Final Year Design Project	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish the goals for the Final Year Design Project	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the Final Year Design Project	**PO11**

Addressing of COs, Knowledge Profile (K), and 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, and CO3	Our project requires data collection from Hospitals ,Diagnosis centers and we have to know the design of a Deep learning-based model which covers **K3 and K4.**	**Page no:13-17**
				Our project requires the integration of different components and we have designed a web-based front end that covers **K5 and K6.**	**Page no:41-43**
				We have studied existing models with similar goals **(K8).**	**Page no: 9-12**

2.	**EP2: Range of Conflicting Requirements**	Yes	CO2	In our project, we have to face the main problem during data collection. Manage raw image and large amounts of data is tough work.	**Page no: 56-57**
3.	**EP3: Depth of analysis requi red**	Yes	CO2	Finding a clear-cut solution for our project is challenging, primarily because of the abundance and diversity of medical data. We conducted an in-depth analysis to carefully choose a specific algorithm from numerous alternatives.	**Page no: 22-40**
4.	**EP4: Familiarity of Issues**	Yes	CO3	To understand and study Nasal cavity and medical terminology for our project, we need to look into various aspects we were not very familiar with. Specifically, we have to figure out how to identify nasal polyps	**Page no: 11-14**
5.	**EP6: Extends of stakeholders involved and conflicting requirements**	Yes	CO3	As part of our project, we have visited and met with ENT specialist. The purpose is to understand how we can detect nasal polyps based on a person's activities. This meeting will guide us in determining the specific type of data we need to use for our analysis.	**Page no: 13-17**
6.	**EP7: Interdepende nce**	Yes	CO3	Our project comprises several subsystems that depend on each other. These include tasks such as collecting data, processing it, training deep learning models, conducting predictive analysis, and developing a front-end application.	**Page no: 13-14**
7.	-	Yes	CO4	We have prepared a budget to evaluate and estimate the cost required for our FYDP.	**Page no: 16-17**

A Deep Learning Approach For Precise Classification Of Nasal Polyps: Distinguishing Antrochoanal Polyps And Ethmoidal Polyps

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