AUTOMATED HISTOPATHOLOGIC ORAL CANCER DETECTION USING DEEP LEARNING FOR EARLY DIAGNOSIS

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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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January 12, 2025

APPROVAL

This Project titled Automated Histopathologic Oral Cancer Detection using Deep Learning for Early Diagnosis submitted by Abid Hasan and Ashis Kumar Karmakar. ID No: 211-15-4030 and 211-15-4035 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 12 January 2025.

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We hereby declare that this project has been done by us under the supervision of **Dr. Sheak Rashed Haider Noori, Professor & Head,** 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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ACKNOWLEDGEMENTS

This work would not have been possible without the support and contributions of many individuals over the past two semesters. We are deeply grateful to everyone who has assisted us in one way or another.

First, we express our heartfelt thanks and gratefulness to the almighty for His divine blessing making it possible for us to complete the **Final Year Design Project (FYDP)** successfully.

We are grateful and wish our profound indebtedness to **Dr. Sheak Rashed Haider Noori, Professor & Head**, Department of Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh. Deep knowledge and keen interest of our supervisor in the field of **Deep learning** to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this project.

We would like to express our heartfelt gratitude to the Head of the Department of Computer Science and Engineering, for his kind help in finishing our project and also to other faculty members and the staff of the Department of Computer Science and Engineering, Daffodil International University.

We would like to thank our entire course-mates at Daffodil International University, who took part in this discussion while completing the coursework.

Finally, we must acknowledge with due respect the constant support and patience of our parents.

ABSTRACT

An Innovative way to solve the very important problem in the world of early diagnosis is to use deep learning to automate the histopathologic discovery of oral cancer. The death rate goes up a lot when oral cancer is found late, which shows how important it is to have quick, accurate, and scalable testing tools. This study aims to use advanced deep-learning techniques on histopathological images to find oral cancer more quickly and accurately. It researched several convolutional neural network (CNN) designs and shows that the EfficientNetB3 with attention mechanism technique model performed better. This model got the accurately tells the difference between cancerous and non-cancerous cells with an impressive 95% accuracy. The suggested method reduces the death rate. Our research will help in timely detection of diseases and reduce mortality. There are issues with the method, such as the rising amount of histopathology data and the small number of trained pathologists available. However, it also makes using AI to diagnose health problems possible. This adaptable and low-cost choice could change how diagnoses are made, especially in places that lack of resources and where it's hard to get specialized care.

Our study results show that EfficientNet-B3 with attention mechanism technique might help find oral cancer early, make the treatment work better, and lower the death rate. We care about people with oral cancer, as shown by our plan to make diagnosis faster and more accurate and lower the number of people who get it around the world. More research is needed into how the model can be used in real healthcare systems and how it can be better for a wider range of clinical cases. This will help patients get better care and save many life's.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Introduction

Oral cancer is the sixth deadliest cancer in the world. According to the Bangladesh World Health Organization (WHO) In the last 5 years around 16,083 oral cases have been found in Bangladesh (Oral Cancer, 2024). There are the top 5 frequent cancers in Bangladesh. Incidence rate (per 100000 population) is 9.5%. Oral cancer is a dangerous disease in the whole world. People can die if oral cancer is not treated properly. Early detection increases the chance of survival. Cancer is one of the main causes of cancer-related fatalities globally, especially in men, according to global cancer statistics. The risk factors are the, such as alcohol, tobacco, or chewing betel nuts, together with poor oral hygiene and restricted access to medical facilities, affects incidence rates.[1] Oral squamous cell carcinoma (OSCC) is the most prevalent, occurring in almost 90% of individuals with head and neck cancer. Squamous cell carcinoma of the oral cavity has historically been considered a disease more common in individuals in their sixth decade of life that is related to cumulative exposure to tobacco, alcohol, and human papillomavirus (HPV) infection [2].Oral squamous cell carcinoma (OSCC) occupies a prominent position among the various malignancies affecting the epithelial cells of the oral cavity. Its worldwide prevalence contributes considerably to the overall burden of cancer-related health problems, resulting in significant morbidity and mortality. It is a highly dead listed disease. The complex development of the OSCC involves a multifaceted interplay of environmental factors is including environmental influences and lifestyle leads. betel nut use, tobacco chewing alcohol consumption human papilloma virus (HPV) infection And it is known that poor oral hygiene significantly increases the susceptibility to developing astrocytes.[3]. The conventional method for negative-margin resection in OSCC entails the random excision of 1 to 1.5 cm of "healthy-appearing" tissue surrounding the tumor to ensure a minimum of 5 mm of microscopically clear margins following histopathologic evaluation [4]. Machine learning (ML) via artificial intelligence (AI) could assist clinicians and oral pathologists in enhancing diagnostic capabilities for potentially malignant lesions, oral cancer, periodontal diseases, salivary gland disorders, oral infectious lesions, oral immune-mediated diseases, and others. AI processing is the capability are providing substantial improvements in critical diagnosis and resolve challenges faced by clinicians, as it detects micro-features undetectable by the human eye, hence enabling solutions in essential diagnostic situations [5]. Machine learning (ML) is equivalent to deep learning (DL), as deep learning is a subset of machine learning, which is itself a subset of artificial intelligence. Deep learning is a fundamental component of artificial intelligence introduced in 2006 by Hinton et al. [6]. A large flow of data insertion is essential for the development of ML/DL programs. A variety of aspects may be employed, including clinical pictures, radiographs, textual data, patient symptoms, histological reports, and auditory elements [7]. In the previous comprehensive investigation, Mahmood et al. evaluated AI-based applications for the diagnosis of head and neck cancer, integrating various imaging modalities along with histological and radiological data. [8]. Other studies utilized clinicopathologic/genomic details. They found that 69% of work were ML methods while 25% of studies were deep learning (DL) methods, and

6% of approaches had a combination of both [9,10]. This demonstrates a growing number of studies on AI/ML in detecting head and neck cancer, employing numerous imaging modalities [8]. For the development of other aspects, engineering approaches are used in place of neurological and physiological approaches. The neural network's capacity for learning allows it to generate fresh data and find new outputs. After observing and generalizing learning examples, the neural network uses the samples to generate a learning rule. Any previously unseen sample can be chosen by the neural networks using the learning principles [11]. Up to the author's knowledge there is limited literature regarding utilization of AI- based programs that could analyze clinical data as well as histopathological findings of oral diseases to provide a reliable differential diagnosis that help doctors during clinical and lab practice as well as in medical education. So, an urgent need for dentists to recognize the conceptualization of AI in the field of oral diagnosis and histopathological reporting and modify the rapidly advancing healthcare protocols [12]. Convolutional Neural Networks (CNNs) are a prevalent deep learning methodology that incorporates convolution operations across numerous artificial neural network layers. Diverse CNN architectures have been created, demonstrating high efficiency in various image classification applications [13,14]. Notable CNN architectures encompass ResNet, EfficientNet, InceptionNet, MobileNet, among others. The primary benefit of these architectures is their proficiency in performing classification tasks, even when the majority of their weights are pre-trained on a different classification job. The concept is referred to as transfer learning and is highly effective for two analogous yet distinct categorization tasks. The primary benefits of the transfer learning model are a decrease in training duration and the ability to perform effectively on limited datasets. [15,16] To enhance the precision of the deep learning models, different strategies are employed, including fine-tuning, feature selection, regularization, optimal parameter selection, and optimization. Conversely, numerous population-based swarm intelligence (SI) optimization methods are extensively employed for optimal parameter identification, weight adjustment, and feature selection in deep learning models to improve accuracy. Swarm Intelligence algorithms are meta-heuristic iterative methods typically inspired by the behaviors and properties of animal swarms. These algorithms are favored in numerous applications primarily because of their minimalism, derivation-free architecture, and capacity to circumvent local optima [17].

1.2 Motivation

Oral cancer constitutes a significant public health concern and is the sixth most lethal malignancy globally. It constitutes a substantial fraction of cancer-associated morbidity and mortality, especially in areas with elevated prevalence rates such as Bangladesh, where more than 16,083 cases have been recorded in the last five years. The gravity of the issue stems not just from its elevated prevalence but also from the protracted diagnosis that typifies the majority of cases. Delayed diagnosis markedly diminishes survival chances and complicates therapeutic interventions, since the illness frequently advances to later stages prior to identification. The postponement in diagnosis is chiefly attributable to the constraints of conventional diagnostic techniques, which predominantly depend on the manual analysis of histopathological specimens. These techniques are laborious, susceptible to human error, and reliant on the presence of highly skilled pathologists, which are frequently deficient in resource-limited environments. This concerning condition highlights the pressing necessity for creative treatments to enhance the early identification and diagnosis of oral cancer. Deep learning, a branch of artificial intelligence (AI), has surfaced as a potential solution capable of tackling these difficulties. Convolutional neural networks (CNNs) have demonstrated significant efficacy in medical imaging applications owing to their capacity to process intricate data and extract salient patterns and characteristics. Modern models like EfficientNet demonstrate significant reliance on computerized economics, which makes them particularly suitable for applications in medical diagnostics where limited availability is available. This research is motivated by two reasons. First, it attempts to use deep learning to address traditional diagnostic methods. The goals of our approach are to increase diagnostic accuracy and reduce variability and to actively identify oral cancer from pathology images and significantly reduce the time required. This automation can reduce the burden on healthcare professionals and allow them to focus on essential decisions and patient care. Our goal of this research is to provide a scalable and usable diagnostic technology for underdeveloped regions that are marginalized, which will play a major role in many global regions, especially in rural areas, where the availability of specialists poses a significant barrier to rapid diagnosis and treatment. This research aims to close the gap by including automated diagnostic tools driven by deep learning, so ensuring that life-saving technology are accessible to those in greatest need. Moreover, the worldwide escalation of cancer cases and the growing intricacy of medical data underscore the imperative for AI-driven advancements in healthcare. Our research aims to illustrate the potential for the use and necessity of de-pluralization by further improving diagnostic methods and establishing a standard for incorporating the use of artificial intelligence into medical practice. This initiative aims to inspire additional innovation and further improve the use of artificial intelligence technologies in healthcare systems worldwide.

Our research should have a practical impact on the use of artificial intelligence in healthcare and the inclusion of important domains. The goal of this work is to increase the comparability of deep learning model applications in medical imaging , thus facilitating proactive diagnosis and prioritization in the future. The principal objective is to preserve lives by the facilitation of earlier and more precise identification of oral cancer, consequently boosting treatment results, diminishing healthcare inequalities, and augmenting the overall efficacy of medical systems. This project aims to significantly enhance world health and promote the utilization of AI in addressing essential medical issues.

1.3 Objectives

Develop an Automated Diagnostic System Skilled in accurately identifying oral cancer from histopathology images with 95% or greater accuracy and building and using a deep learning model.

Optimize Model Performance Explore advanced architectures like Efficient Net and hybrid models to improve diagnostic accuracy while reducing computing complexity.

Enhance Accessibility Develop a scalable and economical diagnostic instrument appropriate for use in resource-constrained environments, guaranteeing fair access to life-saving technology.

Technical Challenges Reduce issues such as class imbalance, dataset constraints, and inconsistencies in imaging circumstances by employing data augmentation, preprocessing, and model optimization strategies.

Contribute to the Field of AI in Healthcare Provide a comprehensive assessment of model efficacy, hybrid structures, and techniques to enhance the research area in artificial intelligence (AI) medical diagnostics.

Support Sustainability Goals Take advantage of energy-efficient layouts such as EfficientNet-B3 with attention mechanism technique to optimize performance while minimizing environmental effect, so separating the research with global environmental goals.

1.4 Methodology

The methodology of our study proposed the application of advanced data preprocessing, augmentation techniques and transfer learning models to the classification of oral histopathology images. All dataset photos are moved to a resolution of 224 × 224 pixels, a common dimension for deep learning models, to maintain consistency and minimize processing requirements. To improve the quality of the data set used in our study class balancing techniques were used to reduce overfitting and to increase the performance of the model. These changes have been shown to change the bias and improve the diagnostic accuracy of the data set. Four pre-trained models EfficientNetB3, ResNet50V2, DenseNet169, InceptionV3 and EfficientNetB3 + attention mechanism were optimized for the oral cancer classification task. Fine-tuning required the use of a batch normalization layer, and a dropout layer, and two dense layers to enhance feature extraction and augment classification accuracy. The models was trained and evaluated with the NDB-UFES dataset, with 10% training data designated for use in implementation.

Model performance was achieved the accuracy and loss metrics. EfficientNetB3 proved to be the most superior model , beating others in classification accuracy and durability.

1.5 Project Outcome

1.5.1 Diagnostic Model

The main goal of our research is to create a state of the art diagnostic model using deep learning specifically the EfficientNet architecture. EfficientNet was chosen for its high processing efficiency and great performance in picture classification tasks. The model is expected to have a diagnosis accuracy of 95% or higher, effectively differentiating between malignant and non-cancerous histology images. The model will be trained and validated on large datasets, with complex preprocessing techniques, augmentation procedures, and optimization approaches used to improve its diagnostic efficacy. This high-accuracy model is intended to help pathologists and clinicians make precise diagnoses.

1.5.2 Hybrid Architectures

Our research will examine the possibility and efficiency of hybrid and depolarizing models that combine features across different clinical architectures such as EfficientNet, DenseNet, and InceptionV3. A comparison analysis will compare hybrid models to standalone structures in terms of accuracy, sensitivity and computational efficiency. These insights will provide a critical understanding of the potential benefits and downsides of hybrid designs allowing for the creation of more complex and integrated diagnostic systems.

1.5.3 Contribution to Research Literature

Our research aims to greatly expand the growing body of AI-driven healthcare knowledge. Our research covers the development and evaluation of proposed models. The acquired methods will release experimental data and visual documentation. This research will be a valuable resource for the future of proactive cancer control. It provides a special process test on CNN architecture, performance on hybrid models and diagnostic processes. It plays a very important role in medical diagnostics, especially in early detection, and is expected to drive further research using deep learning technology in areas such as class association and personalized therapy planning.

1.5.4 Healthcare Challenges

Besides from technological achievements, the study aims to address broader healthcare concerns by demonstrating how deep learning can enhance diagnosis accuracy and efficiency. This study will show how AI has the ability to reduce the burden on healthcare systems relieve pathologists' workloads, and improve patient outcomes. The discovery has the potential to improve global healthcare delivery by reducing the need for manual interpretation and speeding up the diagnosing process.

1.5.5 Educational and Training Resources

The results of this study are anticipated to serve as educational materials for the training of healthcare professionals and students in AI-driven diagnostic tools. This study may promote the integration of AI technologies in medical education and clinical practice by elucidating the functionality of deep learning models and their potential applications in imaging.

1.6 Organization of the Report

In the Chapter 1 Introduction This chapter introduces the research challenge and defines the motivation for performing the investigation. It includes the project's rationale, outlines the research objectives, and specifies the study's scope.

In the Chapter 2: Background This chapter offers a comprehensive examination of the fundamental terminologies, concepts, and related literature in the domain of automated oral cancer diagnosis by deep learning. It evaluates significant progress, highlights difficulties in conventional diagnostic techniques, and recognizes gaps in current research.

In the Chapter 3: Research Methodology This chapter explores the comprehensive methodology employed in the investigation. This outlines the data preprocessing methods, deep learning model architectures, training configurations, and evaluation requirements utilized to achieve the research objectives.

In the Chapter 4: Implementation and Results This chapter describes the implementation of the proposed approaches and then analyzes the experimental outcomes. It examines model performance, contrasts across architectures, and visual representations of essential metrics including accuracy, precision, recall, and F1-score.

In the Chapter 5: Engineering Standards and Design Challenges This chapter analyzes the correspondence of the research with pertinent engineering standards and ethical principles. It also discusses design obstacles faced during the project, such as dataset restrictions, class imbalances, and computing constraints, as well as the strategies implemented to reduce these problems.

In the Chapter 6: Conclusion This chapter summarizes the study's findings, suggests its contributions to the domain of artificial intelligence (AI) oral cancer treatment, and offers recommendations for future study areas.

Chapter 2

Background

2.1 Introduction

The use of deep learning in medical diagnostics is of significant interest due to its ability to handle complex data sets while providing solutions in an accurate and automated manner including Oral Squamous Cell Carcinoma (OSCC) ranks among the most common types of head and neck malignancies, it is causing significant morbidity and mortality worldwide. Although progress in medical technology, early diagnosis continues to be an important challenge because of the dependence on conventional histopathology techniques, which are challenging, subjective, and resource demanding.

Recent studies have investigated the effectiveness of deep learning models, especially convolutional neural networks (CNNs), in improving diagnostic precision and efficiency for the detection of OSCC. These models employ advanced feature extraction techniques to identify between malignant and non-malignant tissues, providing a dependable alternative to traditional methods. Transfer learning models uses pre-trained models to modify them for specific tasks, which means reducing dependency on large data sets and encouraging the development of flexible diagnostic systems.

This section examines significant developments in deep learning applications for the detection of oral cancer. It focuses on multiple techniques, including hybrid models and data augmentation and transfer learning techniques, while facing challenges such as dataset limitations, class imbalances and computing constraints. Our research highlights the utilization of several designs such as EfficientNetB3, ResNet50V2, DenseNet169, InceptionV3 and EfficientNetB3 + attention mechanism which are shown that positive results across many experiments.

The findings from this research highlight the innovative effectiveness of based on artificial intelligence diagnostics in enhancing healthcare outcomes.

2.2 Literature Review

Fati et al. [18] proposed an advanced classification framework for artificial neural networks utilizing hybrid features derived from AlexNet, discrete wavelet transform (DWT), local binary patterns (LBP), feature concatenation histogram (FCH), and gray-level co-occurrence matrix (GLCM). Their model is applied to a dataset of 5,192 histological images of OSCC, which comprises 2,494 normal histopathological images, accounting for 48% of the total, and 2,698 malignant histopathology images of OSCC, representing 52% of the total. A successful predictive model attained an accuracy of 99.3%. Moreover, they aim to extend the suggested systems over many datasets and integrate characteristics extracted from other CNN models.

In another study by Shavlokhova et al. [19] employed convolutional neural networks (CNNs) for the automated categorization of oral squamous cell carcinoma using ex vivo fluorescence cytometry imaging for the first time.The input images, derived from the combined samples of 20 patients, measured 256 × 256 pixels. The MobileNet model, a CNN architecture, is utilized for the diagnosis of squamous cell carcinoma. A CNN model was trained on a restricted dataset of ex vivo FCM pictures, yielding encouraging outcomes in the automated classification of neoplastic tissue. Among the methodologies The MobileNet model, a CNN architecture, attained a sensitivity of 47% and a specificity of 96%.In the future, substantial sample sizes will be necessary to implement this technology in clinical settings.

In order to The provided photos have been categorized by CNN into four classes namely normal tissue, mild dysplastic tissue, moderate dysplastic tissue and severe dysplastic tissue, Gupta et al [20], took 672 tissue images of 52 patients. augmentation on the given dataset, 2688 images were created. Further, these 2688 images were classified into 4 categories with the help of an expert Oral Pathologist. To fix the issue of overfitting, data augmentation and image enhancement were carried out. In general, a successful predictive model requires a large amount of data for sufficient CNN training. After extracting and classifying deep feature maps, the model achieved an accuracy of 89.3%.

Tanriver et al [21], Have Proposed a two-phase deep learning system for identifying and categorizing possibly cancerous conditions of the mouth. They apply their model to the private data photographic images which is conducted in collaboration with the Oncology Institute at Istanbul University. 652 images have 3 classes (Benign, OPMD, Carcinoma). They classified the lesions they found using EfficientNet-b4 and detected lesions using YOLOv5. The EfficientNet-b4 model generated a 0.926 without TTA and 0.929 with TTA, and they gave classification results for several models employed in their studies. They want to achieve their goal of better performing model to a large dataset which will get first detection in the future.

Alhazmi et al [22], presented a Oral cancer detection using an ANN-based prediction model. The model was trained for 10000 interactions. The output of The ANN model is assigned a fractional number between 0 and 1. They used numerical dataset a total of 73 patients met the eligibility criteria. Twenty-two (30.13%) were benign cases, and 51 (69.86%) were malignant cases. Thirty-seven were female, and 36 were male, with a mean age of 63.09 years. They looked at 29 different factors related to patients with mouth cancer. Their prediction accuracy for oral cancer was 78.95%. The lack of data pre-processing and a strong prediction model to enhance oral cancer screening and diagnosis were two of their study's shortcomings, though.

Aubreville et al. [23] they used a deep learning convolutional neural network model was employed to identify oral cancer. A two-fold augmentation was employed, generating two randomly rotated duplicates of each original image, which were then utilized for patch extraction on the 7,894 photos. Four distinct areas in the oral cavity are the upper alveolar ridge, oscc, hard palate, and lower inner labium, with an accuracy of 88.3% achieved. In the future, they will extend the current findings to the more intricate challenge of identifying and distinguishing premalignant lesions in situ, and will apply these findings to additional forms of squamous cell carcinomas in the upper aero-digestive tract.

Bur et al. [24] proposed a machine learning method for predicting nodular malignancy in oral cancer. Algorithms have been assessed utilizing on a dataset of 782 patients with nodular tumors. The National Cancer Database (NCDB) dataset was divided in an 80:20 ratio, with 80% of the cases utilized for training the machine learning algorithm and the remaining 20% reserved for testing. The Delong method of the AUC curve has employed to compare the results of the proposed algorithms with a model predicated on the depth of invasion. The decision set algorithm demonstrated superior performance with a decision forest algorithm AUC of 84%. Moreover, the development of machine learning utilizing high-quality multi-institutional dataset is essential for constructing algorithms applicable in clinical settings, ensuring that the patients with occult nodal disease receive appropriate treatment while preventing the costs and morbidity associated with neck dissection in patients without pathological nodal disease.

Soni et al. [25] introduced an enhanced EfficientNetB0 deep learning convolutional neural network model. They implemented their model on 230 patients and a total of 1,224 photos from the OSCC dataset. Two sets of photos exist, each possessing a distinct resolution. The initial collection comprises 439 OSCC photos at 100x magnification and 89 histopathology images of normal oral cavity epithelium. The second group comprised 495 histopathological photos of OSCC tissue at 400x magnification and 201 photographs of normal oral cavity epithelium. The EfficientNetB0 DL-CNN model has attained the greatest accuracy of 91.1% among the approaches.

Nanditha et al. [26] proposed a comprehensive analysis of the integration of ensemble deep learning convolutional neural network models, namely combining Skip-VGG, VGG-16, and ResNet-50. A dataset comprising enhanced oral lesion photos has been compiled, totaling 332 images, of which 63 are benign lesions and 269 are precancerous lesions, sourced from various colleges and hospitals in Karnataka, India. The accuracy of their ensemble hybrid model was 96.20%.

In another study Fu et al. [27] classified oral squamous cell carcinoma (OSCC) using cascaded deep learning with a dataset of 44,409 biopsy-confirmed OSCC pictures and standard clinical attributes. A total of 5,775 images were randomly selected for the development dataset to create the algorithm, while the remaining 401 photographs constituted the internal validation dataset for validation purposes. The sensitivity of the DL methods was 94.90%.

Das et al. [28] suggested a CNN-based multi-class grading technique for the diagnosis of individuals with OSCC. The CNN model is constructed with multiple analogous micro-structures functioning as convolution filters that can identify features in an image, including forms and textures.The suggested models are CNN architectures (AlexNet, ResNet-50, VGG16, and VGG19) employed in deep learning to categorize oral biopsy images into distinct groups based on Broders' histological grading scheme.The training and validation datasets comprise 5016 and 1301 photos, respectively, while the testing dataset contains 1663 images. Resnet-50 attains the best classification accuracy of 92.15%. A CNN with a classification accuracy of 97.5% was proposed.

Amin et al. [29] introduced three pre-trained deep learning models for oral squamous cell carcinoma detection: VGG16, InceptionV3, and ResNet50. utilize their model dataset including 1,224 oral histopathology pictures (290 non-cancerous and 934 malignant) sourced from 230 patients. Images were obtained at two distinct magnifications (100x and 400x) from Hematoxylin and Eosin (H&E) stained tissue slides utilizing a Leica ICC50 HD microscope. There were 89 photographs of normal epithelium and 439 images of OSCC at 100x magnification, whereas 201 images of normal epithelium and 495 images of OSCC were at 400x magnification. The concatenated model surpassed the individual models, with an accuracy of 96.66%. The individual model attained 89.16% for VGG16, 94.16% for InceptionV3, and 90.83% for ResNet50.

2.3 Gap Analysis

De Lima et al. [30]: Reached a balanced accuracy of 83.24% with the combination of histopathological, demographic, and clinical data utilizing advanced image fusion methods and ResNetV2.

Maia et al. [31]: Shown the capability of implementing clinical and imaging data to get 91.91% accuracy.

Both researches highlighted the importance of applying demographic and clinical data to enhance model effectiveness. This dependence on multi-modal data may limit the capacity and application of the models, especially when only histopathology images are provided. The previous studies employed ResNetV2 but failed to investigate more efficient computational layouts such as EfficientNetB3, which optimize both performance and resource utilization. EfficientNetB3 with attention mechanism technique presents an attractive alternative that achieves superior accuracy while minimizing calculating requirements, hence enhancing its practicality for wide usage. While these studies examined deep learning in CAD systems, neither addressed the creation of practical tools, such as mobile applications, for implementation in clinical settings. The deficiency in converting research discoveries into accessible diagnostic remedies constrains the practical impact of their work.

Focusing on improving the performance of different deep learning architectures EfficientNetB3 with attention mechanism technique to get enhanced diagnostic precision. Proving that strong performance may be attained just through histopathology images, therefore ensuring scalability in environments with limited resources. Creating a mobile application to improve the accessibility and usability of the diagnostic process connecting research with real clinical application. Establishing a foundation for effective and accurate oral cancer diagnosis, so setting a standard for future research aimed at enhancing the capacity and usability of AI-based diagnostic tools.

2.4 Summary

This section analyzed the background and important research on automated oral cancer diagnosis with deep learning, highlighting analogous uses, relevant research, and recognized deficiencies. Previous research, including that of de Lima et al. [30] and Maia et al. [31], illustrated the significance of integrating clinical and histological data to improve diagnostic accuracy, reaching rates of 83.24% and 91.91%, respectively. Although this research highlighted advances in image fusion techniques and CAD systems, their dependence on supplementary data and lack of user-friendly applications posed constraints.

The gap analysis identified critical areas for improvement, such as improving independent deep learning architectures, minimizing dependent on multi-modal data, and transforming research into functional tools like mobile applications. This study resolves these weaknesses by achieving an outstanding accuracy of 95% on EfficientNet-B3 with attention mechanism technique only on histopathology pictures and presenting a mobile application to enhance accessibility and usage.

This section highlights the improvements in the field, defines the limitations, and highlights the innovative contributions of this research to the evolution of automated oral cancer diagnosis.

Chapter 3

Research Methodology

3.1 Methodology

3.1.1 Overview

Our study is the Automated Histopathologic Oral Cancer Detection Using Deep Learning for Early Diagnosis who has focused on the advanced deep learning methodologies to get the better detection and classification of oral cancer through the histopathologic images. Our research employs transfer learning techniques that can fine-tune and identify the most influential openings in the model architecture and integrates evaluation studies to optimize and ensure accurate classification results.

Our research aims to address the challenges and limitations of the real world, such as human and pathology workflows by improving early diagnosis accuracy and addressing current and future practical objectives. Our main objective is to find a reliable, time-efficient and scalable method for diagnosing oral cancer and ultimately improving patient healthcare by advancing medical diagnostics in depth and bridging the gap through their practical application.

3.1.2 Proposed Methodology

One The most problem in medical research is the restricted access to extensive and varied datasets. This difficulty can be alleviated by employing transfer learning (TL), a method that utilizes the knowledge embedded in a pre-trained model and applies it to a new model. This process significantly reduces the dependence on large datasets, thereby providing a strong foundation for feature extraction and classification tasks of pre-trained models.
This research utilized four transfer learning models to categorize oral histopathology images into three different classes. Applying the transfer learning models were EfficientNetB3, ResNet50V2, DenseNet169, InceptionV3 and EfficientNetB3 with attention mechanism. These models were refined to tailor their pre-trained information to the specific demands of the oral cancer detection job, illustrating the effectiveness of transfer learning in overcoming the obstacles posed by restricted medical datasets.

Figure 1 depicts the extensive methodology utilized in this work, which includes data augmentation techniques, the fine-tuning of four transfer learning models, and the identification of the most effective fine-tuned model. Preprocessing measures were implemented on the input photos to reduce noise and rectify data imbalances, hence improving the model's training efficacy for the classification job. To equilibrate the dataset classes, photos were added by vertical and horizontal flipping. The augmented photos were subsequently input into four transfer learning models. Each model was refined by integrating a batch normalization layer, a dropout layer and two dense layers, thereby optimizing the images for feature extraction and future training. The NDB-UFES dataset functioned as both the training and testing dataset. The efficacy of each model was assessed utilizing diverse assessment variables, including accuracy, sensitivity, precision and F1-score. Furthermore, accuracy and loss graphs have been generated to analyze the model's performance.

3.1.2.1 EfficientNetB3

EfficientNet is the propular class of convolutional neural networks (CNNs) designed to achieve state of the art performance while optimizing resource utilization.A variant within this family, EfficientNetB3, determines the depth, width and resolution of the network. This scaling method enables EfficientNetB3 to solve a variety of computer vision problems, including image segmentation, object detection, and image classification. The efficientNetB3 model was fine-tuned to classify images from the Oral cancer dataset. Custom layers, such as batch normalization layer with 1536, dense layer with 256 neurons and a output layer with 3 neurons using softmax activation function added to the pre-trained backbone. The fine-tuned EfficientNetB3 model consists of a total parameter of 11,183,922 and a trainable parameter of 11,093,547.

3.1.2.2 DenseNet169

DenseNet, or Dense Convolutional Network, is renowned for its outstanding efficacy in picture classification applications. DenseNet mitigates the vanishing gradient problem and increases the utilization of specialized products by using dense connections between layers. This architecture has direct connections in a feedforward fashion between each layer and the following layers, promoting efficient information flow and improving propagation.Within the DenseNet family, DenseNet169 has exhibited exceptional performance in numerous image classification evaluations, outpacing many other prominent architectures while preserving a comparatively low parameter count. This study incorporates multiple custom layers within the DenseNet169 design. Includes a batch normalization layer with 1664 units, a dense layer with 256 neurons, a dropout layer, and a final dense output layer with three neurons for the classification task. The fine-tuned DenseNet169 model comprises 13,076,547 parameters, of which 12,914,819 are trainable.

3.1.2.3 InceptionV3

InceptionV3 is a widely used convolutional neural network architecture known for its ability to achieve high performance in image classification tasks while maintaining computational efficiency. This architecture incorporates Inception modules, which utilize a combination of convolutional filters with varying kernel sizes to capture multi-scale spatial features. These modules enable the network to learn rich hierarchical representations of the input data while optimizing resource usage. A key feature of InceptionV3 is its focus on factorized convolutions, which reduce the computational cost by decomposing larger convolutions into smaller, more efficient operations. Additionally, batch normalization is integrated extensively throughout the architecture to improve training stability and convergence. In this study, the fine-tuning process involved adding a batch normalization layer with a size of 2048, a dense layer with 256 neurons, a dropout layer and a final dense output layer for classification. The parameter configuration of the fine-tuned InceptionV3 model: total 22,336,291 and trainable 22,297,763.

3.1.2.4 ResNet50V2

The ResNet family, including ResNet50, introduces a groundbreaking innovation in the form of residual connections or skip connections. These connections enable certain layers to be bypassed, allowing input to propagate directly from one layer to deeper layers. This design helps address the vanishing gradient issue and mitigates the degradation problem commonly associated with deeper neural networks. The core building block of ResNet50 is the residual block which comprises two or three convolutional layers connected via identity shortcut connections. This architecture promotes efficient gradient flow and enhances learning in deep networks. In this study, The fine-tuning process included the addition of a batch normalization layer with a size of 2048, a dense layer with 256 neurons, a dropout layer and a final dense output layer with three neuron for multi-class classification. The total number of parameters in the fine-tuned ResNet50v2 model is 24,098,307, and 24,048,771 trainable.

3.2 Detailed Methodology and Design

Our research proposed a systematic approach to categorize oral histopathology images into three classes: Oral Squamous Cell Carcinoma (OSCC), Leukoplakia with dysplasia and without dysplasia. The procedure commences with patch image preprocessing to diminish noise and enhance quality, succeeded by data augmentation methods, such as vertical and horizontal flipping to rectify class imbalances and enhance generalization. These uses play an important role in the data set for training deep learning models and ensuring the correct performance of the model.

The proposed methodology is divided into two parts shown in Figures 1 and 2.

Figure 1 shows the four pre-trained networks, namely EfficientNetB3, DenseNet169, InceptionV3, and ResNet50V2, are employed for feature extraction. These algorithms, developed using extensive datasets, offer a robust basis for detecting complex patterns in histopathological pictures. Custom layers are incorporated during fine-tuning to customize the models for the oral cancer classification task. Batch normalization layers enhance training stability, dense layers of 256 neurons encapsulate intricate interactions, and dropout layers reduce overfitting. A concluding dense output layer with three neurons use a softmax activation function to classify the images.
The augmented and preprocessed images are fed into these fine-tuned models, which output predictions for the three categories. The models' performance is evaluated using metrics such as accuracy, sensitivity, precision and F1-score ensuring a comprehensive assessment.

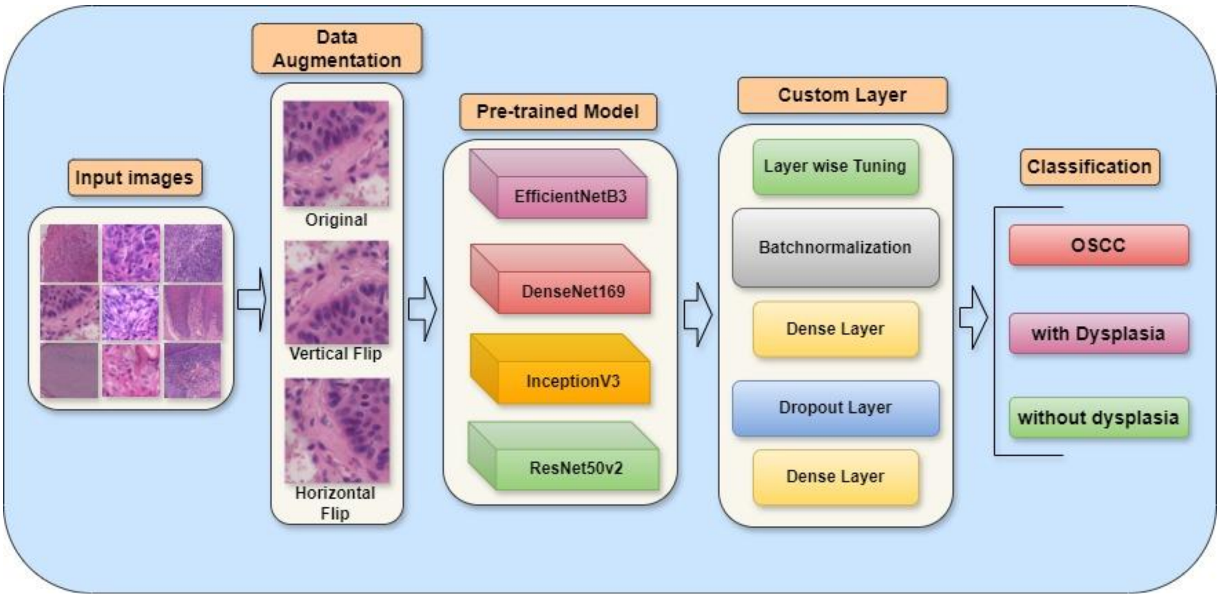


Fig. 1. Applied methodology for best model selection.

Figure 2 shows the selection of best fine-tuned model as EfficientNetB3 and the integration of self-attention mechanisms on the efficientnet backbone.

The integration of attention mechanisms is allowing the model to focus on the relevant regions of the images. The mechanism summarizes context-based information within an input sequence of variable length. In addition, self attention focuses on a single context of data, enabling the model to capture long rang dependencies. The fine-tuned efficientnetb3 model, enhanced with self-attention, splits its feature map into Query, Key, Value. The Query and Key components are first processed using convolution operation to compute attention score. Then normalization applied to the resulting score, normalization process includes the softmax layer to assign probabilistic weights to the data. These attention score are then combined with the value component through convolution, producing a refined feature map. The processed feature map is passed to a fully connected layer (FCL). The final output is used for the classification of oral cancer into three classes through the FCL.

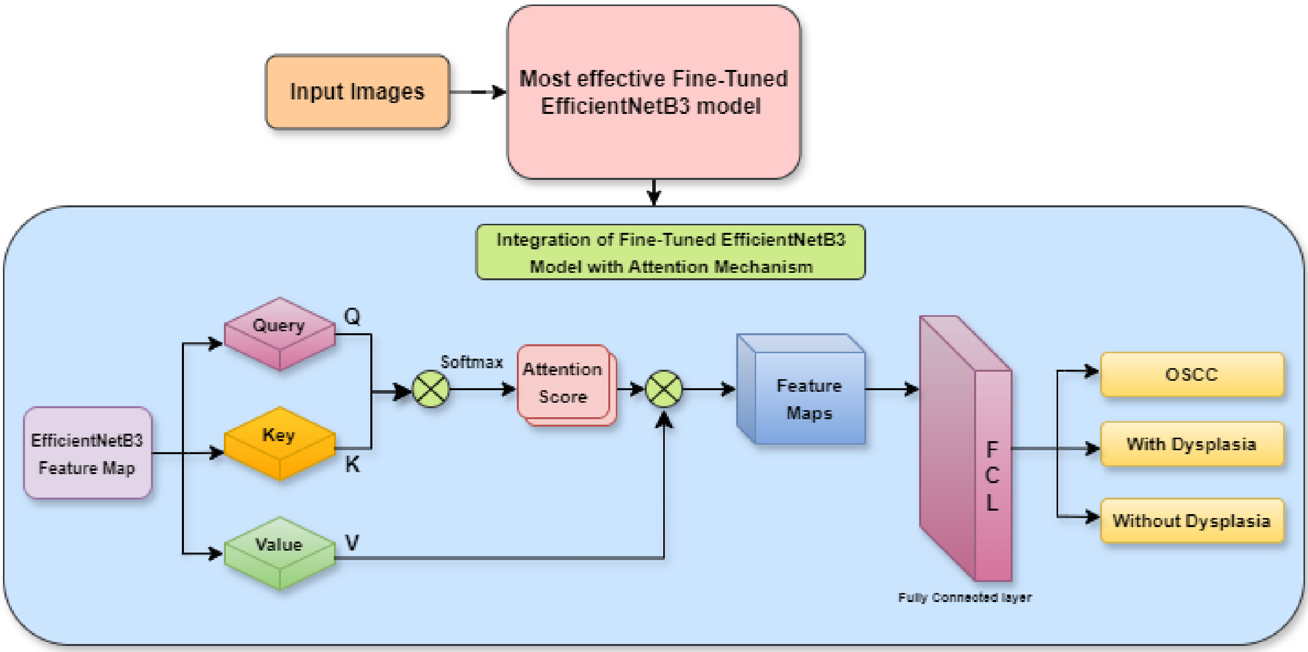


Fig. 2. Proposed fine-tuned EfficientNetB3 model with integration of self-attention mechanisms.

3.3 Project Plan

We have followed a structured approach to successfully carrying out our research studies, which involves a step-by-step approach to ensure that our research is completed with specific objectives and clarity, and measurable progress. We have been successful today through proper planning. This starts with identifying opportunities for work, determining the necessary locations, and setting realistic timelines. Progress is effectively tracked and milestones are quantified. We have read many papers for almost all literature reviews which has given us a proper idea of the paper and it has played a very effective role. We have processed our data set and done preprocessing through which we have been able to filter the right data. This is an important task and we have done this work with a time frame and with skill and determination that has enabled us to do this. Processing and opening the data of a research plays a very important role. If the data preprocessing is not done properly, then it is not possible to do it properly and run the model. As a result, we did this and we proceeded with it in a life-like manner so that we do not have problems later. And we process the data seconds by seconds, we apply different models by applying deep learning and machine learning models, we can reach our goal, we get a good one and our model runs successfully. We can run the model and extract accuracy, precision, recall, F1-score from the model which is very useful for us and will help us make our model more effective in the future. We allocate clear timelines for tasks such as data preparation, model implementation, validation, and results analysis in our research reviews, and we include computer maintenance and software maintenance to maintain data management skills. We make progress and achieve success at every step without delay, and we believe that everything goes according to plan.

3.4 Task Allocation

We effectively distributed the work among team members to ensure that each party's activities were optimized and deadlines met. We did this work in two teams. We had one run the code and the other did the writing, and sometimes both did both the code and the writing. By sharing the work, we were able to present it in a beautiful way. My teammates and I implemented a collaborative approach to maintain clear communication and coordination. We distributed the work among ourselves in a way that promoted efficiency and directed efforts toward successful goals. We reviewed the touch completion and monitoring challenges regularly to ensure alignment with the project goals. Each team member contributed their expertise to successfully achieve their work deliverables within the specified time frame. We processed the data set, we processed the data at speed, we ran different models on them and got better accuracy, through which we can now say that our model is very good, and we did this, we read different papers for writing work, through which we got ideas and we can work through them, and we developed a system, through which it is possible to identify very quickly, and both of us helped each other a lot in writing reports and making presentations, and we completed all the work within the time, through which our work was completed.

Table 3.4: Task Allocation

Tasks	**Weeks**																	
	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Improve an accuracy and F1 score																		
Finalize the model configuration																		
Develop a Mobile application																		
Prepare detailed documentation																		

Estimated Work Period	
Actual Work Period	

3.5 Summary

This study explores the use of advanced deep learning techniques for automated histopathologic oral cancer detection focusing on transfer learning models: EfficientNetB3, ResNet50V2, DenseNet169, InceptionV3 and EfficientNetB3 with attention technique. The methodology involves fine-tuning these models using custom layers and leveraging data augmentation to address class imbalances in the NDB-UFES dataset. Each model was evaluated based on accuracy, sensitivity, precision, and F1-score with performance analyzed through accuracy and loss graphs. The research highlights the efficiency of transfer learning in addressing limited dataset challenges aiming to improve early diagnosis accuracy, reduce pathology workflow errors, and contribute to scalable, reliable cancer detection solutions.

Chapter 4

Implementation and Results

4.1 Environment Setup

4.1.1 Environment Specification

The experimental setup of this study Using a Windows system with specific hardware and software configurations. This system have build an Intel Core i5 12400 CPU operating at 4.10 GHz and is equipped with 16 GB of RAM. All experiments were used the Jupyter Notebook Software. To get the better computational performance, GPU services available on Google Colab and Kaggle were utilized for model training and evaluation. This project employed Python alongside deep learning libraries like Keras and TensorFlow.

4.1.2 Dataset

This study utilized the publicly available NDB-UFES dataset [32] sourced from SAP Buccal and covers cases recorded from January 2010 to December 2021. Patients included in the study were diagnosed with oral leukoplakia or OSCC. Cases without corresponding slides, paraffin-embedded blocks, or insufficient material were excluded.

The dataset includes 237 original histopathological images captured from the most representative areas of the lesion focusing on epithelial dysplasia and OSCC. Due to the limited number of original images, they were divided into smaller patches using the Patch Extractor module in Scikit-Learn. Original images were split into patches of size 512×512, generating a total of 3763 patches shown in Table 4.1.2. Expert pathologists labelled patches into three categories.

Table 4.1.2: Number of images corresponding 3 classes of the NDB-UFES dataset

Class name	Number of images
OSCC	1126
With dysplasia	1930
Without dysplasia	707

4.1.3 Data preprocessing

Data preprocessing plays a crucial role in enhancing model performance and reducing computational time. In the preprocessing stage the dataset images were resized to a resolution of 224 × 224 pixels. This specific resolution was chosen because many images in the dataset already adhered to these dimensions. Furthermore, 224 × 224 is a commonly used input size for popular deep-learning classification models, making it an optimal choice. Resizing images to this standardized dimension accelerates training and minimizes computational demands.

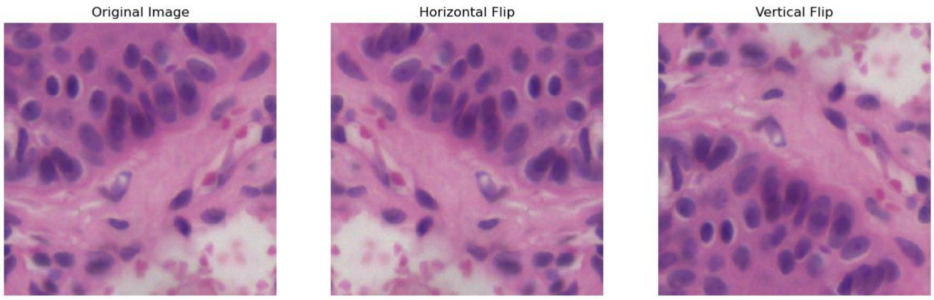


Fig. 3. Sample images after applying data augmentation

The validation dataset was derived by partitioning 10% of the dataset. Various data preparation strategies, including data augmentation, can significantly improve the accuracy of detecting oral cancer. Data augmentation increases model generalization, introduces variability in the data, and mitigates overfitting. To identify the most effective augmentation techniques, ablation studies were conducted. The selected augmentation methods significantly improved model robustness by enriching the dataset with various transformations and generating synthetic data points from the existing data. Figure 1 demonstrates the impact of different data augmentation techniques on a sample image from the dataset. The transformations introduced, such as horizontal flip, vertical flip, make the models more robust and capable of handling complex scenarios.

4.2 Testing and Evaluation/Performance

Evaluation Metrics Various metrics evaluate the performance of machine learning (ML) or deep learning (DL) models. Employing multiple evaluation metrics is essential to assess the effectiveness of a proposed model comprehensively. Metrics such as accuracy, precision, recall and the F1-score are particularly significant, as they provide critical insights into the model's predictive and classification capabilities. These metrics ensure a robust analysis of the model's performance across different aspects.

Accuracy measures the percentage of correctly predicted images out of all predictions. It is calculated as the ratio of the sum of correct predictions (TP + TN) to the total number of predictions (TP + TN + FP + FN) is determined by Eq. (1):

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP+TN}}{\mathbf{TP+TN+FP+FN}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Here, TP, TN, FP, and FN refer to "True Positive", "True Negative", "False Positive" and "False Negative" respectively.

The precision measures the percentage of truly right positive Outcomes is determined by Eq. (2):

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Recall, also known as sensitivity, measures the model's ability to correctly identify positive instances from all the actual positive cases (TP + FN). The following Eq. (3) describe how the recall is stated:

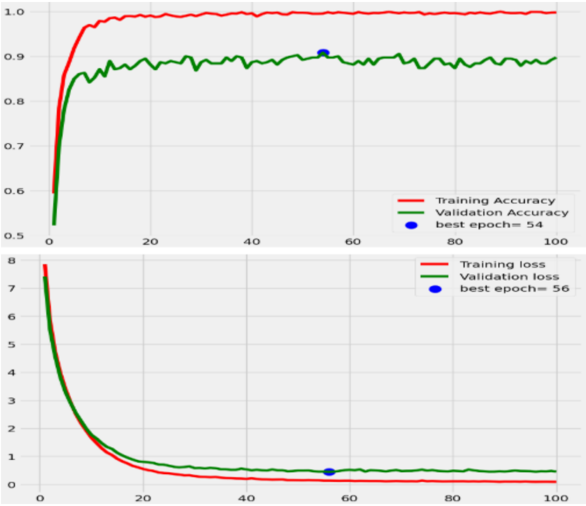
$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

The F1-score provides a harmonic mean of precision and recall it is a technique for enhancing the precision and recall. F1-score defined in the following Eq.(4)

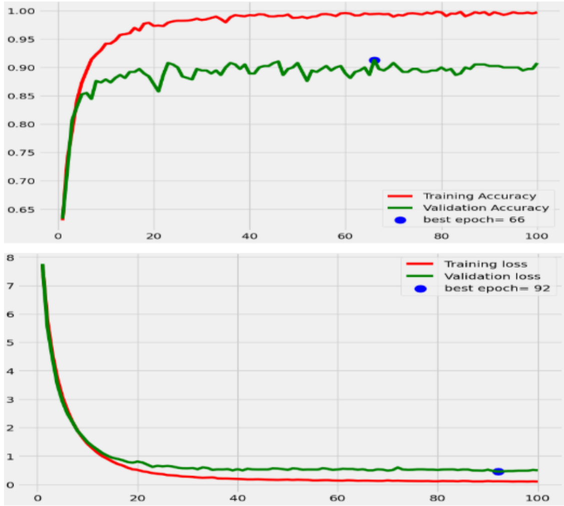
$$\boldsymbol{F1-Score} = \mathbf{2} * \frac{\boldsymbol{Precision*Recall}}{\boldsymbol{Precision+Recall}} \ldots\ldots\ldots\ldots(4)$$

4.3 Results and Discussion

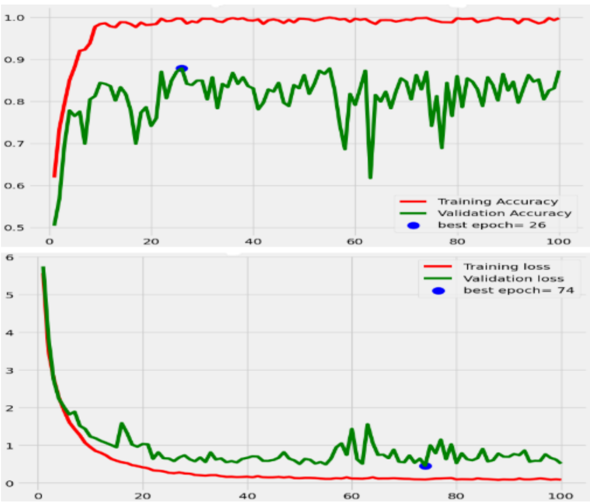
This section describes the performance of various models utilized in the study. The NDB-UFES dataset was used to train four fine-tuned pre-trained models: EfficientNetB3, ResNet50V2, DenseNet169, InceptionV3 and EfficientNetB3 with attention technique. Accuracy and loss graphs are crucial during model training and Validation to understand the model's behavior. Additionally, the ROC-AUC curves for all the implemented models are presented to evaluate their classification performance.



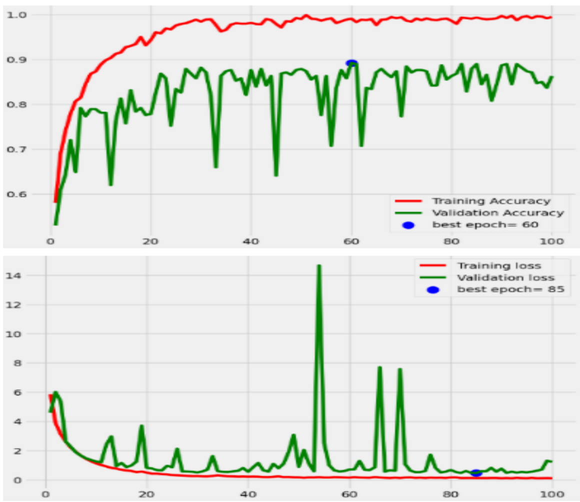
(a) Accuracy, loss vs Epochs for EfficientnetB3



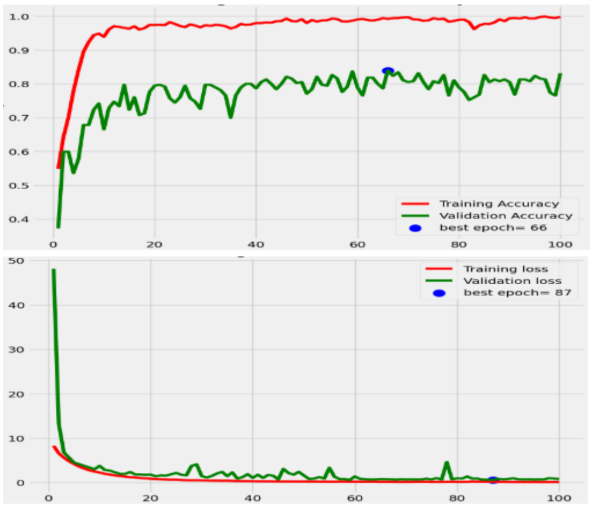
(b) Accuracy, loss vs Epochs for EfficientnetB3 with augmentation



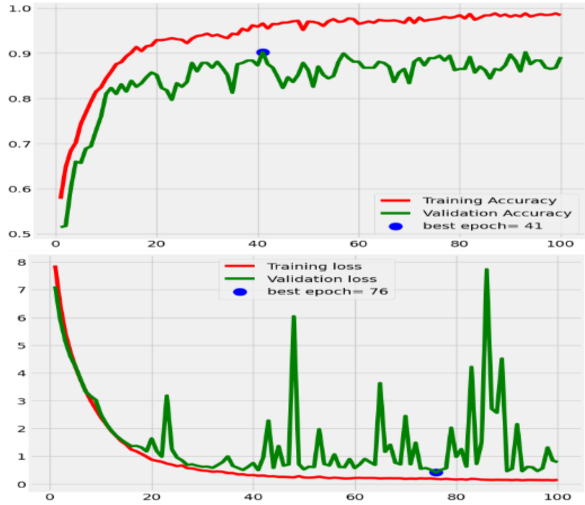
(c) Accuracy, loss vs Epochs for DenseNet169



(d) Accuracy, loss vs Epochs for DenseNet169 with augmentation



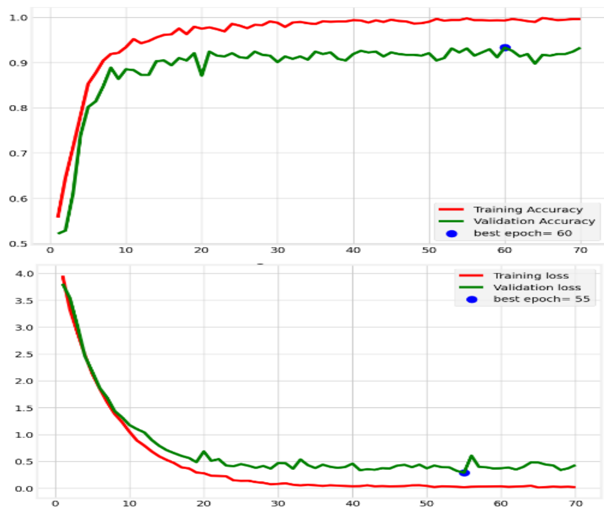
(e) Accuracy, loss vs Epochs for InceptionV3



(f) Accuracy, loss vs Epochs for InceptionV3 with augmentation

(g) Accuracy, loss vs Epochs for ResNet50V2 augmentation

(h) Accuracy, loss vs Epochs for ResNet50V2 with



(i) Accuracy, loss vs Epochs for Efficientnetb3 with integration of attention mechanism with augmentation

Fig. 4. Accuracy and loss curve for EfficientNetB3, DenseNet169, INceptionV3, ResNet50V2 and EfficientNetB3 with attention mechanism, without augmentation and with augmentation.

Figure 4. Presents the accuracy and loss graphs for all four fine-tuned models, both with and without augmentation. The models were trained for 100 epochs, employing the Adamax optimizer with a batch size of 32. The accuracy versus epoch plots illustrates the training and validation accuracy following each epoch iteration. The loss against epoch plots are shown the training and validation losses. The red and green colors signify the training and validation curves, respectively, while the blue color indicates the optimal epochs.

The model utilizing augmentation shows a little difference between the training and validation curves in contrast to the model without augmentation. Figure 3 (b), demonstrates that the accuracy difference between training and validation is modest, suggesting that the model is well-fitted. Furthermore, in the loss against epoch plots, the loss values are significantly lower than the others. The graphs indicate that the EfficientNetB3 model, enhanced by data augmentation, has superior accuracy compared to the other models. Then the attention mechanism integrate with EfficientNetB3, as its outperforming.

Table 4.3.1: Models evaluation metrics performance.

Models		Sensitivity	Precision	F1-score
ResNet50V2	Without Augmentation	0.76	0.80	0.78
ResNet50V2	With Augmentation	0.80	0.89	0.84
DenseNet169	Without Augmentation	0.89	0.92	0.90
DenseNet169	With Augmentation	0.88	0.93	0.90
InceptionV3	Without Augmentation	0.81	0.85	0.82
InceptionV3	With Augmentation	0.91	0.92	0.91
EfficientNetB3	Without Augmentation	0.93	0.93	0.93
EfficientNetB3	With Augmentation	0.94	0.94	0.94
Proposed EfficientNetB3 with attention mechanism	With Augmentation	0.95	0.95	0.95

Different evaluation parameters, including precision, recall (sensitivity), F1-score and accuracy, are employed to assess the performance of the fine-tuned EfficientNetB3 with integration of self-attention in comparison to other transfer learning models. Table 4.3.1 demonstrates that models utilizing augmentation approaches have superior sensitivity values relative to those lacking augmentation. ResNet50V2 without augmentation attained a sensitivity of 76.00%, where are the with augmentation approaches, it achieved 80.00%. In InceptionV3, sensitivity has improved by 10.00%. Nonetheless, the enhancement is minimal in DenseNet169 and EfficientNetB3. The EfficientNetB3 model, utilizing augmentation approaches, has attained the greatest sensitivity value of 94.00% among all applied models. After the integration of self-attention, EfficirntNetB3 provides slightly improve performance in class wise predictions accuracy.

Table 4.3.2: Models training and validation accuracy and loss.

		Accuracy		Loss	
Models	Accuracy	Training	Validation	Training	Validation
ResNet50V2 (Without Augmentation)	80.00%	0.9970	0.8074	0.1137	0.6513
ResNet50V2	86.00%	0.9924	0.8734	0.1331	0.4690
DenseNet169 (Without Augmentation)	91.00%	0.9970	0.8786	0.0918	0.4591
DenseNet169	91.00%	0.9904	0.8918	0.1233	0.4602
InceptionV3 (Without Augmentation)	84.00%	0.9917	0.8391	0.1632	0.5752
InceptionV3	92.00%	0.9661	0.9024	0.1799	0.4112
EfficientNetB3 (Without Augmentation)	94.00%	0.9950	0.9077	0.1341	0.4462
EfficientNetB3	95.00%	0.9940	0.9129	0.1092	0.4130
Proposed EfficientNetB3 with attention mechanism	95.00%	0.9968	0.9326	0.0132	0.2880

Table 4.3.2 compares the accuracy and losses of training and validation with augmentation and without augmentation. The comparison reveals a substantial disparity between the two. The implementation of augmentation approaches has resulted in the applied models attaining superior testing accuracy compared to models lacking such strategies.

The fine-tuned EfficientNetB3 model with attention mechanism, utilizing data augmentation approaches, has performed the best accuracy of 95.00% around the several applied models.

Table 4.3.3: Class-specific Sensitivity, Precision, F1-score of various applied models.

		Without augmentation			With augmentation		
Models	Class Name	Sensitivity	Precision	F1-score	Sensitivity	Precision	F1-score
ResNet50V2	OSCC	0.83	0.78	0.80	0.83	0.95	0.89
	With dysplasia	0.86	0.81	0.83	0.97	0.81	0.88
	Without dysplasia	0.60	0.82	0.69	0.61	0.91	0.74
DenseNet169	OSCC	0.89	0.95	0.92	0.84	0.95	0.89
	With dysplasia	0.95	0.88	0.91	0.96	0.86	0.91
	Without dysplasia	0.81	0.92	0.86	0.83	0.97	0.89
InceptionV3	OSCC	0.90	0.86	0.88	0.91	0.94	0.92
	With dysplasia	0.88	0.83	0.85	0.93	0.91	0.92
	Without dysplasia	0.64	0.87	0.74	0.89	0.90	0.89
EfficientNetB3	OSCC	0.96	0.96	0.96	0.96	0.98	0.97
	With dysplasia	0.94	0.94	0.94	0.95	0.95	0.95
	Without dysplasia	0.90	0.90	0.90	0.91	0.90	0.91
Proposed EfficientNetB3 with attention mechanism	OSCC	0.94	0.95	0.95	0.99	0.93	0.96
	With dysplasia	0.94	0.92	0.93	0.93	0.97	0.95
	Without dysplasia	0.89	0.91	0.90	0.93	0.93	0.93

Table 4.3.3 presents the class-specific evaluation metrics produced by EfficientNetB3, ResNet50V2, DenseNet169, InceptionV3 and EfficientNetB3 with attention technique. In these models the sensitivity value increases with the application of data augmentation strategies. Overall the application of augmentation approaches has been enhanced the performance of all implemented models relative to those are trained without augmentation. The EfficientNetB3 model with attention mechanism with augmentation exhibits the most favorable evaluation metrics, signifying superior performance relative to other models.

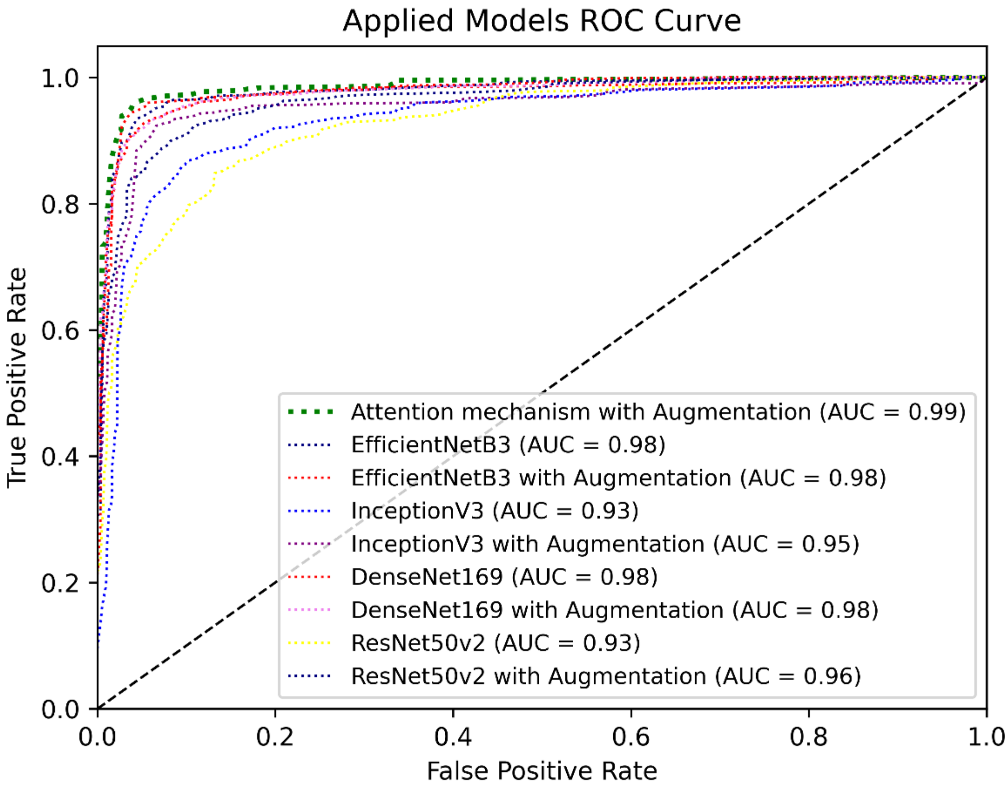


Fig. 5. ROC-AUC Curve of applied models

Fig. 5 shows the ROC-AUC curve of all applied models. The Resnet50v2 and Inception models have lower Auc scores than the other models. However, the EfficientNetB3 and DenseNet169 with augmentation performed better than those without augmentation. Applying data augmentation techniques has led to enhanced performance metrics and favorable ROC curves compared to models trained without augmentation. The EfficientNetB3 model with attention mechanism incorporating augmentation demonstrates the highest AUC score.

4.4 Summary

This chapter details the experimental setup, dataset preparation, and evaluation metrics for the study on oral cancer detection using deep learning models. The NDB-UFES dataset, consisting of 3763 patches across three classes, was preprocessed with resizing and augmented for robustness. Fine-tuned models, EfficientNetB3, ResNet50V2, DenseNet169, InceptionV3 and EfficientNetB3 with attention technique were trained with and without augmentation. Augmentation improved sensitivity, precision, and F1-scores, with EfficientNetB3 with attention mechanism achieving the highest accuracy (95%) and AUC score. Comparative metrics confirmed the significant impact of augmentation on model performance.

Chapter 5

Engineering Standards and Design Challenges

5.1 Compliance with the Standards

5.1.1 Software Standards

Our research used software development best practices to ensure stability, scalability, and usability in a diagnostic system. Extensive documentation was used for the processes. Comprehensive documentation was upheld for processes including data preprocessing, model training, evaluation, and deployment. the development environment comprised technologies such as Python, TensorFlow, and Keras for deep learning, together with libraries for data processing and augmentation. The project implemented a streamlined, bespoke pipeline to harmonize simplicity and functionality, guaranteeing the software's compatibility with both local cpu processing and interaction with Kaggle's gpu infrastructure.

5.1.2 Hardware Standards

Our research hardware used and hardware configuration was primarily CPU-dependent for running diagnostic models and testing while we used more Kaggle or Colab GPUs or Club GPUs for better performance which was used for tasks that required high processing power. This configuration of our used hardware maintains the ability to process large amounts of data and ensures resource efficiency while efficiently training a deep learning model like Efficient Net Rules. Our CPU-centric configuration and the GPU capabilities of Kaggle or Colab were chosen to maximize cost efficiency while meeting the computing requirements of the project, and the hybrid approach provides the flexibility and availability to guarantee that it is feasible for both investigation and implementation in real-world implementations.

5.1.3 Communication Standards

This research utilized a Wi-Fi-enabled system for data and result transfer between the local processing environment, Kaggle, and cloud storage. the wifi configuration allowed continuous connectivity all through dataset uploads, model training, and the retrieval of predictions for deployment in the mobile application. Our research has implemented realistic and effective standards for software development and communication through the use of hardware that is well-structured software Kaggle or Colab GPU coupled with CPU-driven processing and WiFi connectivity resource efficiency and accessibility ensuring excellent performance. These conclusions are consistent with the research objective of developing a measurable and scalable and usable effective diagnostic system for oral cancer diagnosis.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

The main goal of this project is to enhance patient outcomes by facilitating the process of early and accurate identification of oral cancer. Timely diagnosis is essential, since it significantly enhances survival rates, reduces the effectiveness of necessary therapies, and elevates the quality of life for patients. The artificial intelligence (AI) solution reduces diagnosis delays by equipping doctors with an efficient and trusted tool, facilitating quick action. furthermore, the mobile application created in this research improves accessibility, especially for persons in rural or underserved regions with restricted access to specialist healthcare services. Our diagnostic technology is open access and its use ensures that it can be used to identify large numbers of patients, primarily free from geographical or economic constraints. This research has the potential to significantly improve healthcare, especially for marginalized groups. It is beneficial for rural or resource-poor areas. It is common for numerous patients to be diagnosed and treated with adverse outcomes. Our research is being developed through a mobile diagnostic app that will further improve access to healthcare professionals in rural areas, enabling them to screen for oral cancer with the same ease as in urban areas, and it can provide rapid, accurate and reliable diagnosis. The fear of uncertainty can frequently be one of the most troubling facets of disease, especially cancer. The use of this artificial intelligence delivers rapid and precise findings, alleviating patient worry, offering clarity, and empowering informed decisions regarding treatment options. The diagnostic system we have developed using artificial intelligence, which if implemented widely, could improve public health outcomes. Early detection of oral cancer could reduce the incidence of advanced oral cancer, leading to a reduction in cancer-related deaths. The financial benefits of early detection include reduced hospital admissions, reduced need for intensive care, and improved survival rates, which could have a positive impact on the national health care system, which could contribute to the resources of our important areas. Our system will reduce the workload of those who study medicine and those who are doctors in healthcare practice and increase mental well-being through medical prostitutes. It enables a caveat-free approach and is very useful for eliminating complex solutions for specialists and highlights the significant impact of our research on life, its ability to save lives and improve every healthcare experience. Furthermore, automating routine diagnostic processes reduces the workload of healthcare professionals, allowing them to concentrate on intricate and urgent cases. This reduction in workload not only improves the mental health of healthcare professionals but also reduces the probability of errors produced by weariness and overworking. Our application is capable of providing rapid diagnostic results and enabling decision-making that facilitates and empowers patients by providing rapid access to appropriate therapy. The combined impact on the disease treatment professionals and healthcare utilization system demonstrates many benefits in an effort to keep people alive, thereby playing a major role in improving society and leading a healthy life.

5.2.2 Impact on Society & Environment

Our research has a significant impact on society by addressing persistent disparities in quality healthcare delivery and this diagnostic tool, which is developed by the Three Intelligences, makes it possible to use open medical technology and connect it to other technologies with limited space to disseminate it, which increases health care equity. The use of this technology is significantly reducing oral cancer, which is often detected too early due to lack of resources and awareness. The research we have is primarily focused on disease control and preventive care, raising public awareness and using a non-invasive, outcome-based diagnostic tool that ultimately plays a significant role in health care. This technology promotes collaboration among healthcare professionals, policymakers, and researchers. Establishing a collaborative platform for diagnostic innovation enhances the hospital infrastructure, facilitating more effective resource allocation and improved care coordination. The shift to based on artificial intelligence digital diagnostics reduces dependence on physical tests in laboratories, which frequently produce substantial medical waste. Our previous diagnostic systems used disposable chemical reagents that added to the pollution and increased suffering. Our new digital imaging and artificial intelligence that we used in our research established a tradition and promoted sustainable practices in healthcare. However, it may require a large organization to train and deploy the deep learning model, but the system we use is becoming increasingly important. The research utilizes energy efficient topologies such as EfficientNetB3 to enhance computational performance while reducing energy consumption. Moreover, cloud-based computing on platforms such as Kaggle facilitates the efficient use of combined resources, hence reducing the environmental impact. The decrease in medical waste and the focus on energy-efficient artificial intelligence connect the project with global sustainability objectives, guaranteeing that healthcare innovation is not harming environmental health.

5.2.3 Ethical Aspects

Ethical issues are essential and important for the diagnostic tools we use for our research, especially because of their potential impact on patient care. This project, i.e. the research we have, addresses ethical issues. Our research carefully follows data protection requirements to guarantee that all patient data used for training and evaluation are anonymous and securely stored. Nothing is taken illegally and in violation of the law. Robust methods were used for data transcription and retrieval. We used techniques to guarantee that different population groups are treated fairly. The data set was carefully selected to include a variety of patterns, so we were able to innovate by eliminating biases that could be present in diagnostic results. The focus on equity ensures that all patients, irrespective of their background, have precise and dependable diagnoses. Simplicity and Comprehensibility XAI, or explainable artificial intelligence, methodologies were integrated to render the model's decision-making process comprehensible to doctors. Continuous monitoring is essential to maintain the accuracy and ethical integrity of artificial intelligence implemented in real-world healthcare settings. This project incorporates systems for feedback and updates, facilitating regular assessment of the model's efficacy and its effects on patients. The artificial intelligence system is intended to augment human skill, not supplant it. Healthcare workers are equipped with a tool that enhances their diagnostic capabilities, improving productivity and accuracy. The system enhances confidence between healthcare providers and patients by elucidating the diagnostic process, hence assuring ethical accountability. Our own responsibility is to ensure that the system our team and representatives have built adheres to ethical standards and complies with applicable healthcare regulations. The system is systematically validated and implemented to maintain integrity, reliability and ethical degradation. Our research presents itself as a responsible and trustworthy opening in the healthcare industry to address these ethical issues. This project shows significant potential to impact life, society and the environment in a way that adheres to ethical norms and maintains sustainability.

5.2.4 Sustainability Plan

Our research is based on the architecture of the stony image that is being detected by artificial intelligence and deep learning and it includes the best of these models that have worked. We run a large data set using transfer learning and deep learning models such as EfficientNetB3 with attention mechanism technique, which significantly increases the reliability while increasing the system's sensitivity to changes in the environment. This is supported by a comprehensive plan that includes aspects from technical, economic and environmental aspects. The model design of our diagnostic system is scalable and uses detectors that can easily make room for artificial intelligence and deep learning in the future, which can be very important for the use and training of models and reduces the dependence on recharging computers to load the data set, which ensures the effectiveness of resource-constrained environments. We have used CPU to do our main task and for some heavy work we have taken help of GPU which can be done through COLAB or KAGGLE. Our mobile application can be used as an economic or medical or diagnostic tool which is cost effective and environment friendly which requires a lot of energy efficiency. Implementation of Artificial Intelligence model for computational work is very beneficial for the environment. We want to establish a solution for wide adoption and permanent deployment of collaboration with healthcare leaders and decision makers. We need a training program for medical professionals on how to use the tools and permanently increase the efficiency. This eco-friendly strategy allows us to technologically advance the project, economic efficiency and environmental compatibility and to establish the project diagnostic at a rate using time value and subscription value. It is very beneficial for the environment and to establish it as an important part of our system.

5.3 Project Management and Financial Analysis

In this study, we implemented a diagnostic system using artificial intelligence for early diagnosis and detection of oral cancer. Through this, we did not initially consider hardware and software data and operational costs. We took a data set that was publicly available and our work is being used to build a better model. In our project, we use the CPU that is usually available on the computer and run our models, and we run it through Kagle, which is completely free to use. We were able to run our models for free, regardless of the size of our data set, whether it is large or small. This research of ours is not a financial research. We have conducted research to detect oral cancer, for which data is available, a data set of histological images through which we can detect oral cancer. Our data set is publicly available. We have to bear the financial burden of our CPU and the electricity bill. All these are our expenses. In the future, our main source of income through this can be to create a subscription-based model where all the diagnostic systems in the hospital are provided by the health facility. They can be charged a fixed amount per year or per month. Through this model, a system can be created that is reliable and plays an important role in the country and the revenue. Small hospitals that are there will benefit from this and by using it with money, we and the hospital patients can all earn money profitably. We can play a huge role by helping and cooperating with these corporations that are in the health service or pharmaceutical corporations. We can do this by licensing our system. We do not have much source of income outside of this.

Table 5.3: Financial Analysis

SN	Components	Estimated Cost (BDT)
01.	Computer	1,50,000-1,75,000
02.	Tools and Equipment	4,500-5,000
03.	Hardware, Graphics card	40,000-50,000
04.	Documentation and Report Writing	500-1000
Total Estimated Cost		2,25,000-2,67,000

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

Table 5.4.1: Mapping with complex problem solving.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
✓	✓	✓	✓	✓	✓	✓

Mapping with Knowledge Profile for EP1

Table 5.4.2: Mapping with knowledge Profile.

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✓	✓	✓	✓	✓

EP1: Depth of Knowledge

We solve this Engineering Problem 1 we need the Knowledge Profile (**K3-K8**)

K3 (Engineering Fundamentals): This research requires a fundamental knowledge of deep learning concepts and methodologies especially convolutional neural networks (CNNs) image processing, and machine learning.

K4 (Specialist Knowledge): This project requires specialized knowledge in medical image processing specifically with the understanding of histopathology pictures and their complexity.

K5 (Engineering Design): This design of deep learning architecture, including the selection and optimization of models such as EfficientNetB3 with attention mechanism technique necessitates advanced design knowledge.

K6 (Engineering Practice): To ensure that the model works effectively in real-world applications engineering practice knowledge is needed.

K8 (Research Literature): In the end K8 or knowledge of research literature is important for understanding the current record of work and improving it.

EP2: Range of Conflicting Requirements

We solve this Engineering Problem 2 we need the Knowledge Profile (**K3,K5,K6,K8**)

K3 (Engineering Fundamentals): Achieving a balance between computing efficiency and model accuracy requires an established basis in engineering concepts.

K5 (Engineering Design): Designing systems to satisfy performance and resource limitations requires ability in system optimization.

K6 (Engineering Practice): Implementing AI in environments with limited resources requires practical knowledge of its usage.

K8 (Research Literature): Insights of literature promote solutions to challenges in medical AI systems improving performance and efficiency.

EP3: Depth of Analysis

We solve this Engineering Problem 3 we need the Knowledge Profile (**K3,K4,K5,K8**)

K3 (Engineering Fundamentals): Understanding deep learning techniques and data augmentation is necessary for full analysis.

K4 (Specialist Knowledge): Particular knowledge enables an accurate evaluation of model performance in oral cancer detection.

K5 (Engineering Design): Experience in model design and feature extraction improves performance and architectural selections.

K8 (Research Literature): Research findings guide and connect the project with best practices in the field.

EP4: Familiarity of Issues

We solve this Engineering Problem 4 we need the Knowledge Profile (**K4,K5,K6**)

K4 (Specialist Knowledge): Understanding the challenges in oral cancer detection shows the advantages of artificial intelligence for solving diagnostic issues.

K5 (Engineering Design): The design of interfaces and workflows ensures the system's easy integration into the clinical environment.

K6 (Engineering Practice): Understanding healthcare requirements helps the development of solutions that connect with the requirements of doctors and patients.

EP5: Extent of Applicable Codes

We solve this Engineering Problem 5 we need the Knowledge Profile (K5,K6)

K5 (Engineering Design): Implementation with medical standards ensures commitment to rules and regulations.

K6 (Engineering Practice): The realistic deployment of codes facilitates implementation in clinical settings.

EP6: Extent of Stakeholder Involvement

We solve this Engineering Problem 6 we need the Knowledge Profile (K6)

K6 (Engineering Practice): Using people ensures that solutions are clinically relevant and publicly accepted.

EP7: Interdependence

We solve this Engineering Problem 7 we need the Knowledge Profile (K5,K6)

K5 (Engineering Design): Engineering design ensures the efficient connection of all system elements.

K6 (Engineering Practice): Practical knowledge ensures efficient functioning in healthcare environments.

5.4.2 Engineering Activities

Table 5.4.2: Mapping with complex engineering activities.

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✓	✓	✓	✓	

EA1: Range of Resources

This project includes many tools, including computer infrastructure (CPUs and GPUs), histopathology imaging datasets, and deep learning frameworks such as TensorFlow or PyTorch. Effectively managing these resources is necessary for balancing computational capacity with model accuracy.

EA2: Level of Interaction

This system includes multi-tiered interaction among datasets, algorithms, healthcare professionals and end-users. Collaboration with pathologist is necessary for dataset annotation, engineers for artificial intelligence model design and clinicians for integrating systems into diagnostic procedures.

EA3: Innovation

This research applies innovation by utilizing advanced artificial intelligence methodologies such as transformers, CNNs learning to solve issues in oral cancer diagnosis. Furthermore, it supports for the implementation of these solutions in areas with limited resources to address the healthcare connectivity gap.

EA4: Consequences for Society and Environment

This approach aims to improve early diagnosis of oral cancer consequently enhancing patient outcomes and reducing mortality rates. Utilizing accessible models of artificial intelligence can enhance equality in healthcare, especially in rural areas.

5.5 Summary

We have presented in this chapter the specific requirements for the engineering challenge work and the challenges we faced and have created it by combining our research skills, practical skills, and knowledge of the research literature. This study has comprehensively highlighted the engineering challenges we face while maintaining our social and environmental values and we have highlighted them and our research is very beneficial socially and environmentally.

Chapter 6
Conclusion

6.1 Summary

This study was mainly designed at exploring the application of advanced deep learning models for the automatic detection of oral cancer through histopathology pictures. The study revealed that the EfficientNetB3 with attention mechanism technique model was the most effective design attaining an astonishing 95% accuracy thereby establishing it as a dependable option for oral cancer diagnosis. Even after testing several hybrid models none surpassed the performance of the solo EfficientNetB3 with attention mechanism technique model underscoring the importance of choosing optimal models for accurate diagnostics. The research employed rigorous approaches to guarantee the model's superior performance. Methods including data augmentation, image preprocessing and sophisticated assessment measures were employed to increase the dataset, boost model generalization and mitigate the dangers of overfitting. Due to these reasons deep learning models have been able to play a role in the correctness and accuracy of the results. These results have changed the operations of hospitals especially for the identification of hospital patients, which simplifies healthcare and operations, and facilitates the early detection of oral cancer which leads to early detection of patients and reduces mortality. The major goal of this study was the creation of a mobile application which includes the trained deep learning model for application in healthcare environments. The application enables healthcare providers to input histopathology pictures, which are further processed by an artificial intelligence algorithm to identify the existence of oral cancer. This mobile application enhances self esteem of the diagnostic tool and facilitates its use across different hospitals especially in resource constrained environments where advanced diagnostic system may be limited. The mobile application is simple and crafted to aid physicians in expediting informed decision-making, hence enhancing the patient care experience. Despite our good results, our study faces several challenges. One of them is the reliance on a single dataset, which can lead to the model being unable to achieve the same results across multiple populations or scenarios. As a result, the class imbalance of this dataset, which hinders the ability to distinguish specific oral cancer subtypes, hinders the duration of the training process, and hinders the ability to differentiate between specific oral cancer subtypes. The dependence on CPU-based processing for model training led to extended processing durations relative to GPU-based systems, which might have enhanced model efficiency and diminished training time. This study highlights the revolutionary potential of incorporating deep learning models into healthcare systems, particularly in resource-constrained areas. The application of artificial intelligence with a mobile application provides a reliable, efficient and modern solution for the detection of oral cancer in a single platform, which significantly improves early diagnosis and patient prognosis. Despite many obstacles, this new initiative also emphasizes artificial intelligence to transform the healthcare sector in a modern way through improved medical equipment, increased reliability and effectiveness, thus saving lives and improving the quality of healthcare worldwide, and increasing early detection outcomes.

6.2 Limitation

The limitations of our study, which was initially limited to agriculture, are that the model was run on a larger data set. Although the EfficientNetB3 with attention mechanism technique architecture shown performed well with the current dataset, scaling it for larger, more diverse datasets is a significant problem. The dataset utilized in this work was comparatively limited, perhaps constraining the model's capacity to generalize across diverse populations or changes in histopathological pictures. An increased collection with different samples could improve coverage across various populations, cancer stages, and image formats. This constraint may affect the model's efficacy in practical applications, when data from diverse sources and patient characteristics must be analyzed. Extending the model to accommodate larger datasets necessitates further computational resources and modifications to guarantee efficient processing and learning from the augmented data volume. The model's training was performed on CPUs, which, although adequate for smaller datasets, considerably impeded the process with bigger datasets. Using Gpu or online computing power would have improved model training velocities and facilitated the processing of more intricate models or larger datasets within a feasible timeframe. The existing computing limitations presented difficulties, especially when trying to scale the system for practical applications requiring huge data volumes. Despite the model demonstrating strong efficacy of detecting oral cancer, the class imbalance within the dataset may have influenced its performance. Class imbalance, defined as a shortage of specific oral cancer forms relative to others, may result in biases in the model's predictions. While data augmentation techniques were employed to address this issue, a larger and more balanced dataset would have yielded superior results and prevented the model from favoring the class that was dominant. Although the EfficientNetB3 with attention mechanism technique model attained significant accuracy on the current dataset, its capacity to generalize to novel, unknown data particularly from different geographic regions or clinical setting remains weakly evaluated. Expansive and more diverse datasets would facilitate the assessment of the model's ability to sustain its elevated accuracy and robustness across numerous histological pictures and clinical environments. This study's limitations underscore the necessity of augmenting the dataset, enhancing computational resources, and rectifying data imbalance for best model performance in practical applications. Future endeavors must concentrate on addressing these issues by integrating more diverse and extensive datasets, employing superior hardware for expedited processing, and enhancing the model to ensure scalability and durability in healthcare environments.

6.3 Future Work

Our future developments of this research need further investigation and enhancement in many critical areas to increase the performance, scalability, and practical application of the based on artificial intelligence oral cancer detection system. Initially, augmenting the dataset is essential for enhancing the model's capacity to generalize across different patient populations and different imaging conditions. Combining data sets from many large and small countries, including geographical regions in different countries, will experimentally confirm that our model is effective and that it is possible to identify very quickly with this model. A further significant avenue for future research pertains to enhancing the explainability of the AI model. Although deep learning models like our EfficientNetB3 can play an important role and be reliable, it is possible to implement a clean model of Artificial Intelligence. The importance of the model for its future use will be immense and by using this model in hospitals, patients can be identified quickly, which is very beneficial for a sick patient and will play an important role in saving his life. This would enhance communication between the system and human experts, promoting the inclusion of AI tools in diagnostic workflows. additionally enhancing the model's capacity to identify premalignant lesions is essential for the prevention and early intervention of oral cancer. Although the current approach effectively identifies malignant cases, improving its sensitivity to early-stage lesions is crucial for decreasing the prevalence of advanced oral cancer. Prompt diagnosis and intervention for premalignant lesions could significantly enhance patient prognoses and alleviate the total burden of cancer therapy. Providing that the system is simple to use efficient and fits effortlessly into regular operations will be essential for its success. Finally, you all must know that this artificial intelligent system is compatible with the environment and it is very important for the future. It can be identified very easily and the models that are in it are of very high quality and the models that we have are very compatible and it is possible to make it highly effective and it can make it very easy to identify diseases. This will guarantee the implementation of artificial intelligence applications in resource limited environments, where access to robust hardware may be limited, without substantially affecting the environment. although the current initiative has demonstrated encouraging outcomes, there are numerous critical areas for enhancement. Our future work will be to work with this data set more and other data sets that are larger and detect lesions in very detailed ways and to address those problems, our model or artificial intelligence will help them detect oral cancer and increase their naive ability, which will make it possible to detect patients very quickly.

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