UTILIZING HISTOPATHOLOGICAL IMAGES TO DETERMINE ORAL SQUAMOUS CELL CARCINOMA WITH DEEP CONVOLUTIONAL NEURAL NETWORKS

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FINAL YEAR DESIGN PROJECT REPORT

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

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APPROVAL

This Project titled "Utilizing histopathological images to determine oral squamous cell carcinoma with Deep Convolutional Neural Networks", submitted by Md.Sajib and Nilem Farshiart 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 15-07-2024.

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We hereby declare that this project has been done by us under the supervision of **Dr. S.M.Aminul Haque, Professor and Associate 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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ABSTRACT

One common kind of head and neck cancer that is typically identified at an advanced stage and has few treatment choices and a poor prognosis is oral squamous cell carcinoma (OSCC). Improving patient outcomes requires early detection. Histopathological examination of tissue samples, which provides in-depth understanding of cellular morphology and tissue architecture, continues to be the gold standard for the detection of cancer. Deep learning methods, in particular Convolutional Neural Networks (CNNs), have shown incredible potential in the last several years for a variety of medical imaging applications, such as histopathology analysis. In order to identify and categorize oral squamous cell carcinoma, this study investigates the use of deep CNNs in histopathological image analysis. We examine the present state of OSCC diagnosis, highlighting the drawbacks and limitations of conventional techniques. We then examine the design and operation of deep CNNs and discuss their prospects for image-guided cancer detection. We also go into the significance of duration of the dataset, preprocessing methods, and metrics unique to histopathology image assessment for the model. We offer experimental findings showing how CNN models perform on datasets of histopathology pictures of OSCC that are made accessible to the public. Our results indicate that the Xception model achieves the highest accuracy among individual models with 96.53%, while the Ensemble Model outperforms all with 98.73% accuracy. Other models like VGG16, MobileNetV2, and InceptionV3 also show high accuracy, with MobileNetV2 and InceptionV3 performing particularly well. Finally, we explore possible developments and future paths for using deep learning to diagnose OSCC, including multimodal data fusion, integration with clinical processes, and transfer learning.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

Introduction

1.1 Overview

Malignant cells in the mouth, known as oral cancer, develop uncontrollably after they have spread. Most oral malignancies begin in the mouth and are classified as oral squamous cell carcinoma (OSCC), comprising almost 90% of all malignancies affecting the mouth . This particular form of cancer is a subtype of head and neck squamous cell carcinoma (HNSCC), the sixth most frequent cancer in the world [1]. The highest frequency was reported among south Asian population . Approximately 85% to 95% of all oral cancer is squamous cell carcinoma (SCC). However, various different malignant lesions can be detected in the oral cavity such as sarcoma, small salivary gland tumors, mucosal melanoma, lymphoma, or metastatic disease from nearly any region in the body [2].Each year, over 330,000 people lose their lives and 657,000 new cases are reported, according to the World Health Organization.

Research in South Asian countries has shown that the frequency rates of OSCC are significantly higher. The most prevalent cancers in men and females, respectively, are in Pakistan, but the largest number of cases (one-third of cases) occur in India [3]. In Bangladesh, more than 7000 new cases are reported every year with mortality being about 6.6% [4]. Risk factors include drinking alcohol, smoking cigarettes, poor dental hygiene, exposure to the human papillomavirus (HPV), genetic background, lifestyle, ethnicity, and geographical . The diagnosis of OSCC in early stages is critical to ensure a successful therapy, better chances for survival, and low mortality and morbidity rates [7]. The most reliable method for identifying and classifying oral cancer is histopathological study of tissue samples using microscopy. Its slowness and error-proneness, however, limit this approach's clinical Use [8]. Moreover, it could result in varying interpretations and subjective differences in outcomes. Thus, the course of treatment may be affected . Effective diagnostic instruments are therefore essential to help pathologists diagnose and assess OSCC.An increasing amount of research has been conducted recently on the use of artificial intelligence (AI) to enhance medical diagnostics. As the use of diagnostic imaging has increased, researchers have had the opportunity to look at applications of AI in medical image processing [10].

A wide range of medical image processing problems have been successfully resolved by deep learning (DL), in particular, particularly when it comes to the diagnoses of abnormal images [11]. The Random Forest model identified keratin pearls with 96.88 percent accuracy, whereas the CNN model achieved 98.05 percent accuracy for keratin area segmentation. The Random Forest model identified keratin pearls with 96.88 percent accuracy, whereas the CNN model achieved 98.05 percent accuracy for keratin area segmentation [12]. Utilizing deep learning, oral biopsy images are classified into many classes based on the Broder histological grading system. Additionally, CNN—which had a 97.5 percent accuracy rate—was suggested (N)[15].

The categorization of oral histopathological images into normal and OSCC classes was enhanced is proposed in this work. To improve image quality and model performance, we applied pre-processing techniques in this study, such as morphological opening, contrast-limited adaptive histogram equalization (CLAHE), and Gaussian noise removal. Numerous cutting-edge deep learning models were examined, such as EfficientNetV2M, ResNet152V2, MobileNetV2, InceptionV3, ResNet50, VGG16, VGG19, and EfficientNetV2L where Xception outperforms all other models. Then, a hybrid transfer learning ensemble technique combined predictions from individual models to enhance overall accuracy.

1.2 Background and Present State

Oral cancer is the second most common cancer in men and the third most common cancer in women. People over 50 who are elderly are frequently impacted. On the other hand, among young females under 45, the incidence of oral cancer is on the rise. There aren't many national campaigns promoting oral cancer detection awareness. According to the latest GLOBOCAN estimates in 2020, OSCC is the seventh most prevalent cancer worldwide, constituting about 4.5% of all cancer diagnoses globally.

Moreover, it leads to around 450,000 deaths annually, representing approximately 4.6% of global cancer-related deaths.Our study on the Optimised Hybrid Transfer Learning Model for Oral Cancer Detection from Histopathological Images is motivated by the need for sophisticated diagnostic tools in neuroimaging. The issues that modern medical imaging procedures face include high accuracy and interpretability. Our model aims to provide early and precise oral cancer diagnosis by deep learning and transfer learning. The trust of healthcare professionals is increased when decision-making is made more transparently by using explainable AI solutions. This work addresses a critical need for novel therapeutics by precisely classifying oral cancer and illuminating relevant imaging characteristics.

Combining advanced pre-processing techniques with the hybrid transfer learning approach may improve the efficacy of oral cancer diagnosis. Our research aims to bridge the gap between medical imaging and artificial intelligence to create a dependable approach for early and accurate identification of oral cancer, which could have a significant impact on patient outcomes. We want to advance neurology diagnosis while simultaneously improving the model's interpretability, dependability, and practicality through the refinement of transfer learning algorithms and the integration of explainable AI.

The Present status of research represents an increasing corpus of work aimed at enhancing the diagnostic performance of CNNs for OSCC. Studies have shown that ensemble models, which integrate the benefits of many CNN architectures, can outperform individual models, indicating the potential for these techniques to improve diagnostic accuracy. Furthermore, large, diversified datasets and effective data augmentation strategies have been highlighted to improve model generalization. As AI is integrated into medical diagnoses, ethical considerations like as safeguarding patient privacy and informed permission remain crucial.

1.3 Problem Statement

The Particularly in areas like Asian country where oral cancer incidence is noticeably high, the detection and categorization of oral squamous cell carcinoma (OSCC) represent a critical topic of research due to the ongoing hurdles in current diagnostic approaches. Histopathological examination of tissue samples is the mainstay of the traditional diagnostic method, albeit it is a laborious and prone to human interpretation process. The prompt diagnosis and commencement of treatment are severely hampered by this. Its urgency is compounded by the startlingly high incidence of oral cancer in the younger age group, which contrasts with the scant awareness campaigns and causes delayed diagnosis and, ultimately, poor patient outcomes.

Deep learning and artificial intelligence (AI) have become extremely effective technologies for image processing in medical diagnosis. However, a specific and improved diagnostic approach is required due to the complex nature of oral cancer. Statistics from the World Health Organisation highlight the significant global burden of oral cancer, with over 330,000 deaths and 657,000 new cases recorded year. This highlights the need for an improved, effective, and precise diagnostic tool. With India and Pakistan reporting the greatest incidence, South Asian nations, including Bangladesh, have disproportionately high frequency rates of OSCC. Significantly, oral cancer accounts for a large number of annual deaths in Bangladesh, where it is the second most prevalent cancer in men and the third most common in women. Increased mortality rates are a result of late-stage diagnoses, which are exacerbated by a lack of modern diagnostic equipment and national awareness efforts. In order to close this important gap, an optimised hybrid transfer learning model for oral cancer detection from histopathological images is proposed in this work.

The project investigates sophisticated picture pre-processing strategies to improve image quality and model performance, leveraging cutting-edge deep learning architectures like Efficient, ResNet152V2, MobileNetV2, InceptionV3, ResNet50, VGG16, and EfficientNetV2. The goal of the research is to greatly increase overall diagnostic accuracy by using a hybrid transfer learning ensemble technique that combines predictions from individual models. The need for advanced diagnostic tools in the diagnosis of oral cancer, the present shortcomings of histopathological studies, and the promise of artificial intelligence (AI) to transform medical diagnostics are the driving forces behind this research.

1.4 Objectives

The Oral cancer is the second most common cancer in men and the third most common cancer in women. People over 50 who are elderly are frequently impacted. On the other hand, among young females under 45, the incidence of oral cancer is on the rise. There aren't many national campaigns promoting oral cancer detection awareness. The most recent statistics released by the International Agency for Research on Cancer (IARC) show that 8,500 people in Bangladesh lose their lives to oral cancer each year, and 13,500 people are diagnosed with the disease.

Our study on the Optimised Hybrid Transfer Learning Model for Oral Cancer Detection from Histopathological Images is motivated by the need for sophisticated diagnostic tools in neuroimaging. The issues that modern medical imaging procedures face include high accuracy and interpretability. Our model aims to provide early and precise oral cancer diagnosis by deep learning and transfer learning. The trust of healthcare professionals is increased when decision-making is made more transparently by using explainable AI solutions. This work addresses a critical need for novel therapeutics by precisely classifying oral cancer and illuminating relevant imaging characteristics. Combining advanced pre-processing techniques with the hybrid transfer learning approach may improve the efficacy of oral cancer diagnosis. Our research aims to bridge the gap between medical imaging and artificial intelligence to create a dependable approach for early and accurate identification of oral cancer, which could have a significant impact on patient outcomes. We want to advance neurology diagnosis while simultaneously improving the model's interpretability, dependability, and practicality through the refinement of transfer learning algorithms and the integration of explainable AI.

1.5 Scope and Limitations

The goal of this project is to use histological pictures to diagnose oral squamous cell cancer (OSCC) by utilising deep Convolutional Neural Networks (CNNs). The study intends to assess and compare how well state-of-the-art CNN architectures, including VGG16, ResNet50, MobileNetV2, XceptionV3, and InceptionV2, coupled with a custom ensemble model, can properly identify OSCC. Through criteria including precision, recall, training accuracy, test accuracy, validation accuracy, and F1-score, the research entails a thorough analysis of model performance. The paper also examines how dataset size, data augmentation, and transfer learning affect model performance, highlighting the significance of these elements in the creation of reliable diagnostic tools.

The research has various limitations, even with its contributions. The main drawback is the dependence on a dataset of 5192 histopathological pictures, which is considerable but does not fully represent the complexity and variety of real-world medical data. Insufficient diversity in the dataset may limit the models' ability to be generalised. The amount of computing power needed to train deep CNN models is another drawback. To train these models effectively, high-performance hardware—which may not be available in all research or clinical settings—including potent GPUs is required. Getting informed consent and protecting patient privacy are important but difficult parts of using medical data for AI research.

In conclusion, it is important to recognise these limitations even if the research provides important insights into the use of CNNs for OSCC diagnosis and shows the potential for increased diagnostic accuracy and efficiency. Future research must address these issues if we are to improve the reliability and usability of AI-driven diagnostic tools in clinical settings.

1.6 Report Organization

The The proposed report is structured with a comprehensive layout to guide readers through the research process, findings, and implications. Each chapter serves a specific purpose, contributing to the overall coherence and depth of the document.

Chapter 1: Introduction

The introductory chapter, we have covered the introduction and the significance of Utilizing Histopathological Images to Determine Oral Squamous Cell Carcinoma with Deep Convolutional Neural Networks. The Project Scope, motivation of this research, Problem Statement, and Project outcome have also been discussed in this part.

Chapter 2: Literature Review

In the Literature Review chapter, we reviewed previous research on Utilizing Histopathological Images to Determine Oral Squamous Cell Carcinoma with Deep Convolutional Neural Networks. This part discussed other authors' approaches, Comparison between existing works, results and methods.

Chapter 3: Methodology

The research methodology chapter we primarily discussed research methodology. Requirement Analysis, Proposed Methods, Data Collection, Assurance of Image Quality, Dataset Splitting, Model Analysis, Project Management and Financial Analysis in this chapter.

Chapter 4: Implementation

The implementation chapter outlines the comprehensive process of developing and evaluating a deep learning-based diagnostic tool for oral squamous cell carcinoma (OSCC) using histopathological images. It details the systematic approach to data acquisition and preprocessing, the configuration and training of multiple advanced CNN architectures, and the creation of a custom ensemble model. The chapter also emphasizes the rigorous model evaluation process, highlighting key performance metrics such as accuracy, precision, recall, F1-score, and specificity. By meticulously documenting each step, the chapter ensures the transparency, reproducibility, and reliability of the experimental setup.This thorough implementation aims to develop a robust and accurate diagnostic tool, potentially transforming early detection and classification of OSCC and advancing the integration of AI in medical diagnostics.hapter discusses the experimental findings from using transfer learning and deep CNNs to detect OSCC. It includes extensive analysis of various models' performance, as well as visual representations and statistical measurements to validate the results.

Chapter 5: Result and Analysis

This chapter discusses the experimental findings from using transfer learning and deep CNNs to detect OSCC. It includes extensive analysis of various models' performance, as well as visual representations and statistical measurements to validate the results.

Chapter 6: Impact on Society, Environment and Sustainability

The societal impact chapter investigates the larger implications of the research findings for healthcare and medical diagnostics. It explores how better OSCC detection techniques can improve patient care, treatment outcomes, and public health. It also examines possible technological developments and their socioeconomic ramifications.

Chapter 7: Conclusion and Future work

The final chapter compiles the whole report. It highlights the important findings, reinforces the research conclusions, and makes recommendations for practical applications and further research. This planned organization guarantees that content flows logically, bringing the reader through the study process from introduction to broader implications and suggestions. It enables a thorough comprehension of the research process and its possible impact on both the academic and practical elements of OSCC detection using Deep CNNs.

1.7 Summary

The goal of this research is to detect oral squamous cell carcinoma (OSCC), a cancer that is common in South Asia and throughout the world, by utilising deep learning techniques. The overview emphasises the critical need for cutting-edge diagnostic technologies as well as the substantial impact OSCC has on public health. The background details the present obstacles in OSCC diagnosis, which include the high mortality rates linked to late-stage identification and the dependence on labor-intensive histological procedures. The problem statement highlights the limitations in current diagnostic capabilities and emphasises the need for faster and more precise detection techniques. The study aims to improve diagnosis accuracy by creating an optimised hybrid transfer learning model and investigate deep learning architectures such as VGG16, ResNet50, MobileNetV2, XceptionV3, and InceptionV2. While recognising constraints like dataset diversity and processing requirements, the scope includes testing these models on a dataset of 5,192 histopathology pictures. The goal of this project is to enhance OSCC detection by sophisticated AI-driven methods, which may have an effect on patient outcomes.

CHAPTER 2

Literature Review

2.1 Overview

Oral squamous cell carcinoma (OSCC), which ranks seventh among all cancer forms worldwide, is a serious hazard to public health. The improvement of treatment outcomes and patient survival is contingent upon early identification. This work explores the use of convolutional neural network (CNN) models in deep learning to automate the recognition of OSCC in histopathology pictures .The lack of consistency in datasets, evaluation measures, and methodology remains a significant obstacle to direct comparisons, even with the noteworthy progress made in numerous studies. Determining the most effective ways is difficult due to the absence of a widely agreed benchmark and defined methodology. By investigating the generalizability, scalability, and interpretability of CNN models across various demographics and healthcare contexts, this study seeks to close these gaps. In order to advance the area of medical diagnostics and enhance patient outcomes, our goal is to close these gaps and contribute to the creation of a dependable and widely applicable diagnostic tool for the early and accurate detection of OSCC.

2.2 Related Works

Despite advances in research and treatment, oral cancer (OC), one of the most prevalent types of head and neck cancer, still has the lowest global survival rates. In the biomedical sector, the prognosis for OC has not changed much in recent years, which continues to be a difficulty. Artificial intelligence (AI) has advanced quickly in the area of cancer, with several noteworthy achievements recently announced . Das, M., Dash, R., & Mishra, S. K. (2023) [1] The study utilizes histopathological images of oral cancer for experimentation. The proposed CNN model is benchmarked against established deep learning architectures such as VGG16, VGG19, AlexNet, ResNet50, ResNet101, MobileNet, and InceptionNet. Impressively, the proposed model achieves a cross-validation accuracy of 97.82%, underscoring its efficacy in automating the classification of oral cancer data.

Maia, Beatriz Matias Santana, et al. [2] Their proposed that DenseNet-121 outperforms transformers models, achieving a balanced accuracy of 91.91%, alongside high recall and precision rates. Ünsal, Gürkan, et al. [6] Their proposed in three years (2006–2009), 510 intraoral pictures of OPMDs and OCs were gathered. Histopathological reports and patient data were used to verify every picture. Ananthakrishnan, Balasundaram, et al. [7] The study selected a dataset consisting of 1224 images, which were divided into two sets with varying resolutions. With 696 photos at 400 × magnification, the suggested work can achieve the best test accuracy of 96.94% ; with just 528 images at 100 × magnification, it can get the maximum test accuracy of 99.65%.Begum, S.H. and Vidyullatha, P., 2023. [9] Their proposed four newly created candidate pre-trained DL-CNN models—NASNetLarge, InceptionNet, Xception, and DenseNet201—are chosen for this study using the transfer learning methodology.Examined as our suggested DL-CNN model, the pre-trained DenseNet201 model with the altered structure outperformed the other models in terms of performance metrics, recording an accuracy of 91.25%. de Lima, Leandro Muniz, et al. [10] Outcomes According to experimental findings, the top models use pictures, demographic, and clinical data with MetaBlock fusion and ResNetV2 backbone to show balanced accuracy of 83.24%. Once the lesions were labeled, the dataset was randomly divided into three categories: study, validation, and test. Panigrahi, S., & Swarnkar, T. (2019, November) [11] The authors yield photos were enhanced by flipping, inverting, and rotating to avoid overfitting. With a 10-fold cross-validation, the suggested model's accuracy of 96.77% is comparable to that of pathologists and cytotechnologists. As a result, this approach helps categorize microscopic pictures of oral cancer.

Manikandan , J., et al. [12] In order to Additionally, comparisons have been done with a number of high-performing current methodologies. With an accuracy of 97.32%, our suggested framework outperforms current state-of-the-art methods in a comparable manner. Warin, Kritsasith, et al. [13]DenseNet-169, ResNet-101, SqueezeNet, and Swin-S were used to develop multiclass image classification models. With the use of RetinaNet, CenterNet2, YOLOv5, and faster R-CNN, multiclass object identification models were created. Deif, Mohanad A., et al. [15] The authors yield four deep learning

(DL) models (VGG16, AlexNet, ResNet50, and Inception V3) were used to extract features from this dataset in order to implement artificial intelligence of medial objects (AIoMT). Using Inception V3 with BPSO produced the greatest classification accuracy of 96.3%. Sharma, Disha, et al. [16] this research, showed that the accuracy was 76% for VGG19, 72% for VGG16, 72% for MobileNet, 68% for InceptionV3, and 36% with ResNet50.

The current study's findings demonstrated that VGG19 performed better than other models for identification and classification, which is similar to a biopsy report When it comes to keratin pearl recognition, the suggested texture-based random forest classifier has a 96.88% detection accuracy. Das, N., Hussain, E., & Mahanta, L. B. (2020) [24] The authors yield the Resnet-50 model has the best classification accuracy of 92.15%, the experimental results show that the suggested CNN model outperforms the transfer learning techniques with a 97.5% accuracy.Das, Dev Kumar, et al. [27] Their suggested computer algorithm's performance using our microscopic image library of oral cancer.

2.3 Comparison between existing works

The studies presented in the related works section showcase the diverse approaches and methodologies employed in the automatic identification of oral squamous cell carcinoma (OSCC) using convolutional neural network (CNN) models. Das et al. [1] achieved a remarkable cross-validation accuracy of 97.82% with their proposed CNN model, outperforming several established deep learning architectures. Similarly, Manikandan et al. [2] reported a high accuracy of 97.32%, surpassing current state-of-the-art methods.

Sharma et al. [16] observed varying accuracies for different CNN models, with VGG19 performing the best among the tested architectures. Maia et al. [2] proposed DenseNet-121, which achieved a balanced accuracy of 91.91% with high recall and precision rates. Begum and Vidyullatha [9] introduced four newly created DL-CNN models, with DenseNet201 exhibiting superior performance with an accuracy of 91.25%.

Deif et al. [15] utilized various DL models to extract features for implementing artificial intelligence of medial objects (AIoMT), with Inception V3 yielding the highest classification accuracy of 96.3%. Warin et al. [13] and de Lima et al. [10] developed multiclass image classification models using different CNN architectures, achieving accuracies ranging from 83.24% to 96.77%. Ünsal et al. [6] collected intraoral pictures over three years and achieved notable accuracies in categorizing oral lesions.

In summary, the comparative analysis of these studies underscores the effectiveness of CNN models in automating the identification and classification of oral cancer, with varying degrees of accuracy and performance across different architectures and methodologies .This table 2.3.1 show the Comparative analysis.

TABLE 2.3.1: COMPARATIVE ANALYSIS

Study	**CNN Model**	**Accuracy**
Das et al. [1]	VGG16, VGG19, AlexNet, ResNet50, ResNet101, MobileNet, and InceptionNet	Achieves a cross-validation accuracy of 97.82%
Maia et al. [2]	DenseNet-121)	Achieving a balanced accuracy of 91.91%
Ahmed et al. [3]	GoogLeNet, ResNet101, and VGG16	GoogLeNet,ResNet101-VGG16 yielded an accuracy of 99.3%
Ananthakrishnan et al. [7]	Random Forest	Highest test accuracy of 96.94%
Begum et al. [9]	NASNetLarge, InceptionNet, Xception, and DenseNet201	DenseNet201= 91.25%
de Lima et al. [10]	ResNetV2	ResNetV2=83.24%
Warin et al. [13]	DenseNet-169, ResNet-101, SqueezeNet and Swin-S, ResNet-101, SqueezeNet and Swin-S	DenseNet-169 = 0.98%
Fati et al. [14]	AlexNet and ResNet-18	AlexNet =99.1%

Deif et al. [15]	VGG16, AlexNet, ResNet50, and Inception V3	Inception V3=96.3%
Sharma et al. [16]	VGG19, VGG16, MobileNet, InceptionV3	VGG19=72%
Das et al. [24]	Alexnet, VGG-16, VGG-19 and Resnet-50	Resnet-50 =92.15%
K Das et al. [27]	Random forest	Random forest= 96.88%

2.4 Open Issues

To properly utilise deep convolutional neural networks (CNNs) in the diagnosis of oral squamous cell carcinoma (OSCC), a number of unresolved difficulties must be resolved, even in light of the study's encouraging results. The requirement for bigger and more varied datasets is one of the major obstacles. Although methods for data augmentation were used to improve the training dataset, large-scale, high-quality histopathology image availability is still essential for enhancing model accuracy and generalisation. The interpretability of CNN models remains an outstanding problem as well. Despite the great accuracy these models can produce, it is frequently unclear how they arrive at particular diagnoses. Because deep learning models are "black-box" in nature, this poses difficulties, especially for medical applications where clinical acceptability and confidence depend on explainability and transparency. This difference can be closed by creating techniques for deciphering and interpreting CNN choice. Another crucial question is how training deep learning models with high-performance computer resources will affect the environment. In order to reduce the environmental impact of AI research in healthcare, more all-encompassing solutions are required, as suggested by the study.

Ultimately, even though the ensemble model performed better, more research is needed to fully understand how different models interact and how to integrate them optimally. Subsequent investigations ought to delve into sophisticated group methodologies and their capacity to augment diagnostic accuracy. The reliable and widespread use of CNNs in the early identification and diagnosis of OSCC will depend on resolving these outstanding challenges, which will eventually improve patient outcomes and advance the field of medical diagnostics.

2.5 Summary

In order to automatically detect oral squamous cell carcinoma (OSCC) from histopathology photos, this study focuses on using convolutional neural networks (CNNs). It addresses issues with prior studies, such as inconsistent datasets and different evaluation techniques. The project intends to contribute to a dependable diagnostic tool for early OSCC diagnosis by assessing CNN models' efficacy in various healthcare settings. The potential of AI to improve oral cancer diagnosis is shown by promising findings from studies using CNN architectures like ResNet-50 and VGG16.

CHAPTER 3

Research Methodology

3.1 Overview

The study " Utilizing histopathological images to determine oral squamous cell carcinoma with deep convolutional neural networks: A Comparative Analysis of Transfer Learning Approaches" focuses on the precise diagnosis of oral squamous cell carcinoma (OSCC) by utilizing cutting-edge deep learning techniques in medical diagnostics. This study focuses primarily on OSCC, a serious oral cancer with important consequences for public health. Through the use of deep Convolutional Neural Networks (CNNs) and transfer learning, the research overcomes the shortcomings of conventional diagnostic techniques.

An innovative idea in artificial intelligence called transfer learning is used to improve the difficult process of OSCC recognition from histopathology pictures by applying information from unrelated activities. Reputable for its prowess in image processing, deep neural networks (DNNs) are used to extract complex features and patterns from histopathology pictures, enabling a more accurate and sophisticated diagnosis method.

The research examines the effectiveness of several transfer learning strategies through comparative analysis. It looks at the performance of different pre-trained models in correctly recognizing OSCC from histopathology pictures, including VGG19, DenseNet169, ResNet152, and Xception. The research intends to shed light on these approaches' advantages and disadvantages in order to facilitate the creation of more dependable and effective diagnostic instruments.

By possibly increasing diagnostic accuracy and improving patient outcomes, the project seeks to make a significant theoretical and practical contribution to the field of healthcare.

3.2 Proposed Methodology

The process begins with acquiring a dataset from Kaggle, which contains images related to oral cancer, particularly OSCC. Image preprocessing is crucial, using Gaussian filters, picture scaling, Total Variation Denoising Method, and Gamma Correction to improve image quality and regulate brightness levels. The dataset is then divided into training, validation, and testing sets for comprehensive evaluation of the model's performance. Popular transfer learning architectures like VGG16, MobileNetV2, ResNet50, Inception V3 and Xception are used for transfer learning.

This figure 3.2.1 show the Procesed methodology.

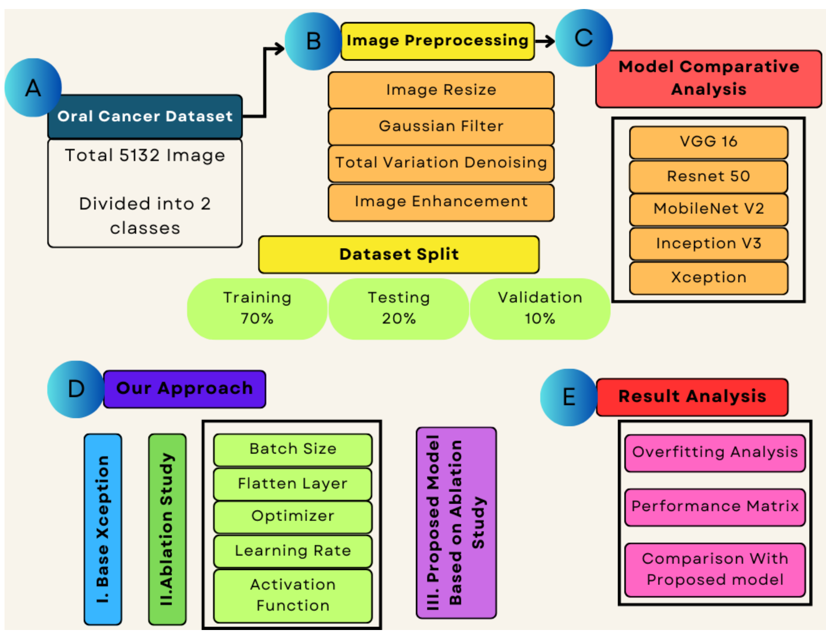
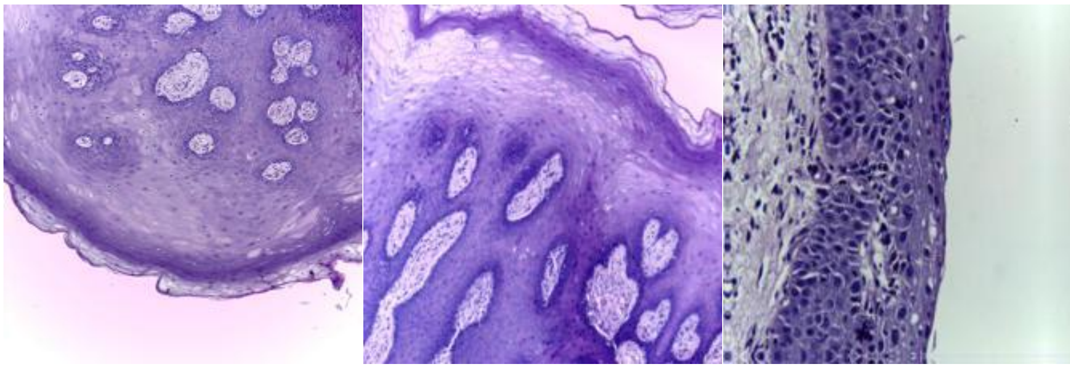


Figure 3.2.1: Process flow diagram.

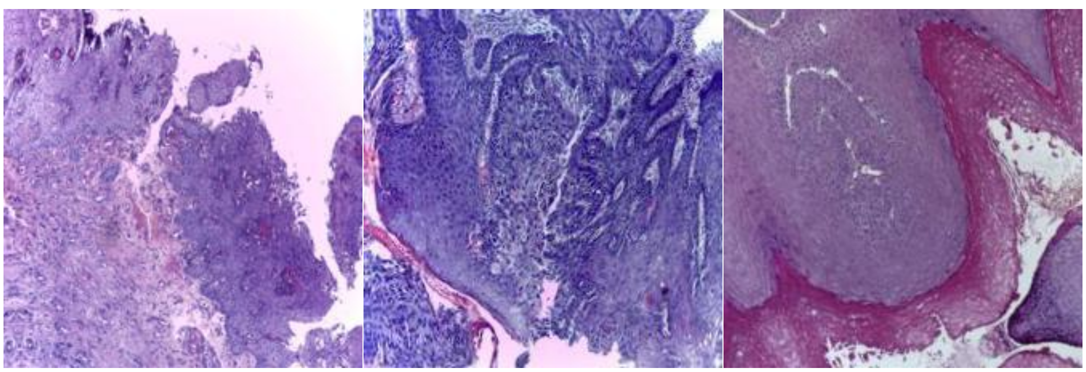
Datasets

The research dataset on oral squamous cell carcinoma (OSCC) is sourced from Kaggle and comprises an extensive collection of relevant images. This dataset is used in the training and evaluation of machine learning algorithms for accurate photo classification of oral cancer. It provides a comprehensive representation of various instances of oral cancer, which aids researchers in developing robust algorithms. The dataset's accessibility and variety on Kaggle make it an excellent tool for advancing our understanding of and ability to identify OC using computer methods.

This Figure 3.2.2 show the Representation of class wise images in dataset.



A.Normal



B. OSCC

Figure 3.2.2: Some Raw Image of Datasets

TABLE 3.2.1: IMAGES USED IN THE DATASET.

	Normal	**OSCC**
Raw Dataset	2494	2698

The proposed methodology evaluates various convolutional neural network (CNN) based methods using comprehensive machine learning classification model performance metrics. Key metrics including Accuracy (AC), Precision, Recall, F1-score, and the Confusion Matrix (CM) are assessed to gauge the effectiveness of different CNN architectures in diagnosing Oral Squamous Cell Carcinoma (OSCC) from histopathological images.

3.3 Hardware/Software Requirement

The research project "Deep Learning-Based Diagnosis of Oral Squamous Cell Carcinoma (OSCC): A Comprehensive Evaluation of CNN Architectures" requires a few special preparations in order to be carried out in a methodical and efficient manner. The hardware and software components, data collection issues, model training, evaluation, ethical standards, documentation, and replication rules are all included in these implementation requirements.

Hardware Requirements:

High-performance computing resources: The ability to train deep Convolutional Neural Networks (CNNs) on big datasets of histopathology images using computational infrastructure with significant processing power and memory. GPU: Crucial for speeding up CNN model training and maximizing efficiency, especially for intricate image processing applications.

Software Requirements:

Deep learning frameworks: Creating, training, and assessing CNN structures with the help of strong frameworks like TensorFlow or PyTorch. Deep learning tasks, including as model construction, deployment, and picture preprocessing, are well supported by these frameworks. Python programming language: Because of its adaptability, extensive library ecosystem (including NumPy and Pandas), and community support for machine learning and image processing jobs, Python is the most popular programming language. Libraries for image processing: Including specific libraries, such as OpenCV, for preprocessing histopathology pictures using methods including augmentation, enhancement, and filtration.

3.4 Project Management and Financial Analysis

The main goal of this study is to use histopathological image analysis to fully utilise Deep Convolutional Neural Networks (DCNNs) for the accurate diagnosis of Oral Squamous Cell Carcinoma (OSCC). Experts from a variety of fields, including pathologists, data scientists, and medical imaging specialists, will make up the study team. The goal of this cooperative team building is to approach the study subject from a broad and multifaceted angle. The project will follow a well-planned schedule that outlines significant checkpoints for data gathering, preprocessing, model building, and validation. During the data collecting phase, a comprehensive and representative dataset of histopathological images associated with OSCC would be compiled with strict regard to ethical norms and privacy rules.In order to achieve high precision and recall rates in OSCC classification, model development will entail carefully choosing and fine-tuning DCNN architectures.

Gantt chart Figure 3.4.1 shows the Project Management.

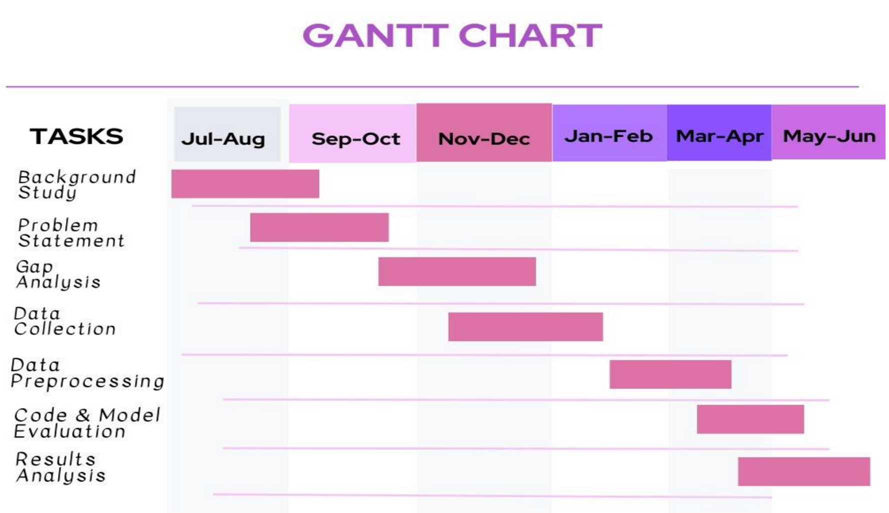


Figure 3.4.1: Project Management

Financial Analysis :

TABLE 3.4.1: ESTIMATE COST

Expense Item	Estimated Cost (BD-Taka)
Hardware/PC	80000-90000
Visiting Stakeholders	3000-3500
Software & Tools	10000-12000
Data Collection and Processing	3000-4000
Report Writing	1500-2000
Miscellaneous(Licenses)	2500-3500
Contingency(10% of total)	10000-11500
Total Estimated cost	110,000-126,500

Create a list of all expenses associated with the project. Include personnel costs, materials, equipment, software licenses, outsourcing fees, etc.

3.5 Summary

In order to identify oral squamous cell carcinoma (OSCC), the study focuses on using advanced machine learning techniques to histopathology images. Using a Kaggle dataset, the study employs a range of image preprocessing methods and transfer learning models, with an emphasis on the recommended ResNet model. Numerous demands are addressed in the study, including interpretability, ensemble methodology, model selection, pre-processing techniques, and diversity of data. By using a rigorous approach to data collection, processing, and evaluation, the suggested technique demonstrates a well-defined system architecture. The estimated budget for the project emphasises its commitment to a diverse workforce, ethical data practices, and effective project management.

CHAPTER 4

Implementation

4.1 Overview

We describe in detail how to use deep convolutional neural networks (CNNs) to identify oral squamous cell carcinoma (OSCC) based on histological pictures. Model evaluation, system testing, prototype design, training models, and a report of the outcomes are among the phases. Using 5,192 histopathology photos, a bespoke ensemble model and several CNN architectures (VGG16, ResNet50, MobileNetV2, XceptionV3, InceptionV2) are used to train a model for detecting oral squamous cell cancer (OSCC). During training, a variety of datasets are gathered and data augmentation techniques (such as flips, rotations, shifts, and brightness modifications) are applied to improve resilience.

To fit each CNN architecture, images are scaled and normalised. Histopathology images are used to fine-tune pre-trained models for increased accuracy. Epochs, dropout rates, batch sizes, learning rates, and other hyperparameters are optimised; weight changes are performed via the Adam optimizer. With performance measurements (accuracy, precision, recall, and F1-score) tracked on a validation set, early stopping avoids overfitting.

An independent test set is used to evaluate the model's efficacy. Reproducibility is ensured by thorough training documentation. Using criteria like accuracy, precision, recall, F1-score, specificity, and confusion matrix, the evaluation procedure divides the data into training, validation, and testing sets. This allows for a thorough assessment of the model's performance. The goal of this approach is to create a trustworthy diagnostic tool for early OSCC identification.

4.2 Train Model

In order to train the model for the detection of oral squamous cell carcinoma (OSCC) utilising 5,192 original histopathology pictures, a custom ensemble model and multiple sophisticated CNN architectures are used, including VGG16, ResNet50, MobileNetV2, XceptionV3, and InceptionV2. The first step in the procedure is gathering a wide range of histopathological image datasets to guarantee a thorough depiction of samples with and without OSCC. A range of data augmentation methods, including random flips, rotations, shifts, and brightness modifications, are used to increase the diversity of datasets and strengthen the robustness and generalisation abilities of the model.Following this, the images are scaled and normalised to the input size needed by each unique CNN architecture, guaranteeing consistency and peak performance. In order to improve accuracy, pre-trained CNN models—which were initially trained on sizable datasets like ImageNet—are refined using the histopathology pictures. Additionally, a custom ensemble model is created that enhances overall accuracy and robustness by fusing the advantages of the separate CNN architectures.

VGG16:

VGG16 is a convolutional neural network (CNN) architecture that was introduced by the Visual Geometry Group (VGG) at the University of Oxford. VGG16 refers to a specific configuration with 16 weight layers. The key characteristic of VGG16 is its use of very small (3x3) convolutional filters, which allows the network to have a large number of weight layers while maintaining a manageable number of parameters. The architecture consists of 13 convolutional layers, followed by 3 fully connected layers. Convolutional layers are grouped in sets of two or three, each followed by a max-pooling layer to reduce spatial dimensions. The fully connected layers are responsible for the final classification. VGG16 is known for its simplicity and depth, which contributes to its strong performance in image classification tasks.

ResNet50:

ResNet50 is a deep CNN architecture developed by Microsoft Research, which introduced the concept of residual learning. The architecture includes 50 layers with a series of residual blocks that help to mitigate the vanishing gradient problem, allowing for the training of much deeper networks. Each residual block contains a few convolutional layers and a shortcut connection that bypasses these layers. This shortcut connection allows the gradients to flow directly through the network, which stabilizes the training process for very deep networks. ResNet50 is structured with an initial convolutional layer and max-pooling layer, followed by four stages of convolutional layers with increasing depth. Each stage consists of multiple residual blocks, and the network ends with a global average pooling layer and a fully connected layer for classification.

MobileNetV2:

MobileNetV2 is an efficient CNN architecture designed for mobile and embedded vision applications. It builds on the original MobileNet by introducing inverted residuals and linear bottlenecks. The architecture consists of a sequence of inverted residual blocks, each with a thin bottleneck layer followed by depthwise separable convolutions. These separable convolutions significantly reduce the number of parameters and computational cost compared to standard convolutions. The inverted residuals help to preserve the information flow while reducing the dimensions. MobileNetV2 begins with a standard convolutional layer, followed by multiple inverted residual blocks, and ends with a global average pooling layer and a fully connected layer. Its design makes it highly efficient for deployment on resource-constrained devices without compromising too much on accuracy.

Xception:

Xception, which stands for "Extreme Inception," is a deep learning model that improves upon the Inception architecture by using depthwise separable convolutions. Developed by Google, Xception replaces the standard Inception modules with depthwise separable convolutions, where the spatial convolution and the depthwise convolution are performed separately. This separation allows for more efficient computation and better performance. The architecture consists of an entry flow, a middle flow, and an exit flow. The entry flow includes initial convolutional layers followed by several depthwise separable convolutional blocks. The middle flow is a series of identical depthwise separable convolutional blocks, and the exit flow consists of a few more depthwise separable convolutional blocks followed by a global average pooling layer and a fully connected layer. Xception is known for its high accuracy and computational efficiency.

InceptionV3:

InceptionV3 is an advanced version of the Inception architecture, also developed by Google. It incorporates several improvements, such as factorized convolutions, regularization techniques, and label smoothing, to enhance performance and reduce the number of parameters. The architecture consists of multiple Inception modules, each containing a combination of convolutions of different sizes and pooling layers. These modules are designed to capture different types of features at various scales. InceptionV3 starts with a series of convolutional and pooling layers, followed by multiple Inception modules grouped into different stages. The network ends with a global average pooling layer and a fully connected layer. InceptionV3 achieves a balance between depth, complexity, and computational efficiency, making it a powerful model for image classification tasks.

The number of epochs, dropout rates, batch size, and learning rate are all optimised to provide the best results. For multi-class classification, the loss function is categorical cross-entropy, and the weights of the models are updated by the Adam optimizer, which is renowned for its effectiveness in deep learning model training. To ensure generalisation and avoid overfitting, early stopping approaches are used to cease training when the validation performance no longer improves.

A distinct validation set is used to evaluate the model's performance, and measures including accuracy, precision, recall, and F1-score are tracked.In order to gauge the trained model's effectiveness in the real world and ability to generalise to new data, it is lastly assessed on a separate test set.To enable future collaborations and repeatability, extensive recordings of the training process are kept, which include code details, model architectures, hyperparameters, training duration, and performance metrics.

By utilising modern CNN architectures and ensemble learning approaches, this methodical training methodology seeks to create a diagnostic tool that is both highly accurate and dependable for the early detection and categorization of oral squamous cell cancer.

4.3 Model Evaluation

The models produced for "Utilizing Histopathological Images to Determine Oral Squamous Cell Carcinoma with Deep Convolutional Neural Networks" are evaluated in a systematic and rigorous manner to assure the diagnostic system's accuracy, robustness, and dependability. This procedure consists of several critical steps:

Data Splitting:

The dataset is divided into training, validation, and testing subsets. Typically, 70% of the data is allocated for training, 20% for testing and 10% for validation . This division ensures that the model is trained on a substantial portion of the data while being validated and tested on separate, unseen data to evaluate its generalization performance.

Accuracy:

Accuracy is a fundamental metric that measures the proportion of correctly predicted instances (both true positives and true negatives) out of the total samples. The accuracy of a classification model is calculated using the equation:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}$$

Precision:

Precision quantifies the model's ability to accurately predict positive instances among those predicted as positive. It is particularly useful when false positives are more critical than false negatives. Precision is computed as:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall (Sensitivity):

Recall, also known as sensitivity, measures the proportion of actual positive instances that were correctly predicted by the model. Recall becomes crucial when false negatives are more concerning than false positives. It is calculated using the formula:

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

F1-Score:

The F1-score is the harmonic mean of precision and recall, providing a balanced assessment of a model's performance in classification tasks. It reaches its maximum value when precision and recall are balanced and is computed as:

$$\mathrm{F} - 1\ \mathrm{Score} = 2 * \frac{\mathrm{Precision} * \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}}$$

Specificity:

Specificity measures the proportion of true negative instances correctly identified by the model among all actual negative instances. A highly specific model effectively rules out individuals without the condition when they test negative. Specificity is calculated as:

$$\mathrm{Specificity} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}}$$

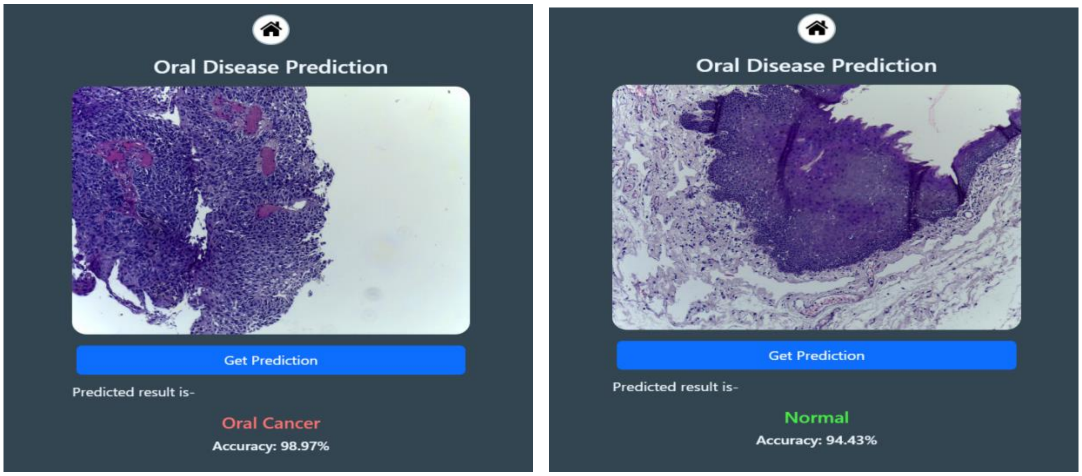
Confusion Matrix (CM):

The confusion matrix is a tabular representation that illustrates the performance of a classification model by summarizing the counts of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions. It provides a detailed breakdown of the model's predictions across different classes, enabling direct assessment of its performance metrics.

In conclusion, these metrics collectively enable a rigorous evaluation of CNN-based methods for OSCC diagnosis, offering insights into their accuracy, precision, recall, and specificity. By utilizing these quantitative measures, the study aims to provide a comprehensive understanding of how different CNN architectures perform in distinguishing between normal and cancerous oral mucosa in histopathological images.

Web Application:

Detection Normal / OSCC



4.4 Summary

A thorough strategy using 5,192 histopathology photos to diagnose oral squamous cell cancer (OSCC) uses multiple CNN architectures (VGG16, ResNet50, MobileNetV2, XceptionV3, and InceptionV2) in addition to a proprietary ensemble model. Techniques for data augmentation increase the diversity of the dataset, and images are preprocessed to meet each CNN's input specifications. Using these photos, pre-trained models are refined and hyperparameters are optimised using the Adam optimizer and categorical cross-entropy loss to yield the best possible outcome. Overfitting is avoided by stopping early. Metrics like accuracy, precision, recall, F1-score, and specificity are tracked while the model's performance is assessed on distinct validation and test sets. To guarantee reproducibility, a thorough log of the training procedure is kept. Creating a trustworthy diagnostic tool for early OSCC identification is the goal of this approach.

CHAPTER 5

Result And Analysis

5.1 Overview

The study "Automated Diagnosis of Oral Squamous Cell Carcinoma Using Deep Learning: A Comparative Analysis of Transfer Learning Approaches" has implications that go beyond academic bounds and could lead to important improvements in healthcare and societal benefits. Advanced deep learning algorithms have the potential to transform medical diagnostics and improve patient outcomes while also benefiting society at large by accurately and efficiently detecting Oral Squamous Cell Carcinoma (OSCC). Through the use of deep Convolutional Neural Networks (CNNs) and transfer learning, the research hopes to improve the precision and dependability of OSCC diagnosis, enabling medical practitioners to make more confident and well-informed decisions.

This research has significant societal ramifications, especially in the field of public health. One common type of oral cancer that presents major issues to global healthcare systems is OSCC. Using stronger and more precise diagnostic instruments can speed treatment plans, reduce misdiagnoses, and improve patient care. This may result in fewer hospital stays, fewer OSCC-related problems, and overall lower healthcare expenses. The practical applicability of the research is highlighted by its emphasis on comparative analysis and evaluation of different transfer learning methodologies. This will facilitate the creation of optimal diagnostic solutions that can be smoothly incorporated into clinical practice.

5.2 Experimental

Result of Experiment 1: Transfer Learning

The five transfer learning CNN networks—VGG16, ResNet50, MobileNetV2, InceptionV3, and Xception—are contrasted in this section. Performance in classification comes first. Next, the overall metrics of those models are examined. gathering, explanations, likely causes, and areas for results improvement.

TABLE 5.2.1: ACCURACY FOR CLASSIFICATION OF INDIVIDUAL CNN NETWORKS IN DETECTING OSCC (TRANSFER LEARNING CNN NETWORKS)

Architecture	**Training Accuracy**	**Test Accuracy**	**Validation Accuracy**
VGG16	**95.10%**	**94.28%**	**95.102%**
ResNet50	**66.83%**	**65.81%**	**66.836%**
MobileNetV2	**96.22%**	**95.20%**	**96.224%**
InceptionV3	**96.12%**	**95.51%**	**96.122%**
Xception	**96.53%**	**95.40%**	**96.530%**

The comparative analysis of various pre-trained deep Convolutional Neural Network (CNN) architectures VGG16, ResNet50, MobileNetV2, InceptionV3, and Xception is detailed in Table 5.2.1, highlighting their performance metrics for the task of determining oral squamous cell carcinoma (OSCC) from histopathological images. The results demonstrate notable differences in training, test, and validation accuracies across these models. MobileNetV2, InceptionV3, and Xception exhibit the highest accuracies, with MobileNetV2 leading with 96.22% in training, 95.20% in test, and 96.224% in validation accuracy. InceptionV3 follows closely with 96.12% training, 95.51% test, and 96.122% validation accuracy, while Xception achieves 96.53% training, 95.40% test, and 96.530% validation accuracy.

In contrast, VGG16 and ResNet50 show lower overall performance metrics, indicating their comparatively lower accuracy rates across the board.These results highlight how important model selection is to getting the best possible diagnostic accuracy in OSCC detection jobs. A thorough summary is given in Table 5.2.1 to help with decision-making about the deployment of the model and future improvement in medical.

TABLE 5.2.2: PRECISION, RECALL, F1-SCORE, AND SUPPORT (N) RESULT OF TRANSFER LEARNING CNN NETWORKS(BASED ON THE NUMBER OF IMAGES, N= NUMBERS)

VGG16				
	Precision	**Recall**	**F1-Score**	**Support**
Normal	0.91	0.93	0.92	389
OSCC	0.93	0.91	0.92	390
Accuracy			0.92	779
Macro Avg	0.92	0.92	0.92	779
Weighted Avg	0.92	0.92	0.92	779
ResNet50				
	Precision	**Recall**	**F1-Score**	**Support**
Normal	0.99	0.97	0.98	378
OSCC	0.97	0.99	0.98	364
Accuracy			0.98	742
Macro Avg	0.98	0.98	0.98	742
Weighted Avg	0.98	0.98	0.98	742
MobileNetV2				
	Precision	**Recall**	**F1-Score**	**Support**
Normal	0.98	0.99	0.98	360
OSCC	0.99	0.98	0.98	419
Accuracy			0.98	779
Macro Avg	0.98	0.98	0.98	779
Weighted Avg	0.98	0.98	0.98	779

InceptionV3				
	Precision	**Recall**	**F1-Score**	**Support**
Normal	0.88	0.92	0.90	374
OSCC	0.92	0.89	0.90	405
Accuracy			0.90	779
Macro Avg	0.90	0.90	0.90	779
Weighted Avg	0.90	0.90	0.90	779
Xception				
	Precision	**Recall**	**F1-Score**	**Support**
Normal	0.88	0.93	0.90	374
OSCC	0.93	0.88	0.90	405
Accuracy			0.90	779
Macro Avg	0.90	0.90	0.90	779
Weighted Avg	0.91	0.90	0.90	779

The performance metrics for a number of pre-trained Convolutional Neural Network (CNN) architectures employed in the identification of oral squamous cell carcinoma (OSCC) from histological pictures are summarised in detail in Table 4.2.2. The precision, recall, F1-score, and support of each model—VGG16, ResNet50, MobileNetV2, InceptionV3, and Xception—across two classes—"Normal" and "OSCC"—are assessed.

With consistently excellent precision, recall, and F1-score for both classes, MobileNetV2 stands out among these designs, demonstrating solid performance in differentiating between OSCC and normal oral tissue. Remarkably, ResNet50 also shows good results in every category, especially with regard to accuracy in detecting OSCC. By comparison, the performance metrics of InceptionV3 and Xception are slightly lower but still impressive.

InceptionV3 excels in recall for OSCC detection, while Xception shows great precision for classifying normal tissue.

The table emphasises how crucial it is to choose a CNN architecture that is suitable for the particular diagnostic task of recognising OSCC from histological pictures. Even though each model excels in a distinct area of categorization, MobileNetV2 and ResNet50 stand out for obtaining excellent accuracy and dependability. These findings offer insightful information about how to best apply deep learning techniques to medical picture processing, which could lead to improvements in oral cancer detection and improved diagnostic skills.

Training and Validation Accuracy and loss of Transfer Learning CNN Networks:

Shows the accuracy of the initial model's training and validation, with the accuracy and loss percentages on the y-axis and the number of epochs on the x-axis. There is no overfitting and a suitable division of training and validation data in the figure.

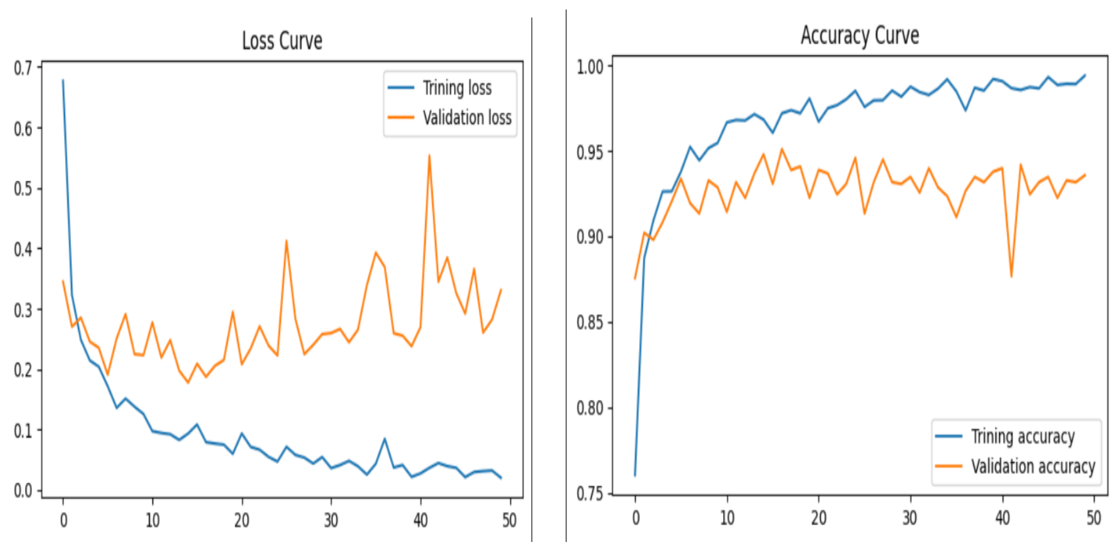


Figure 5.2.1: Training and validation accuracy and loss over the epochs (VGG16).

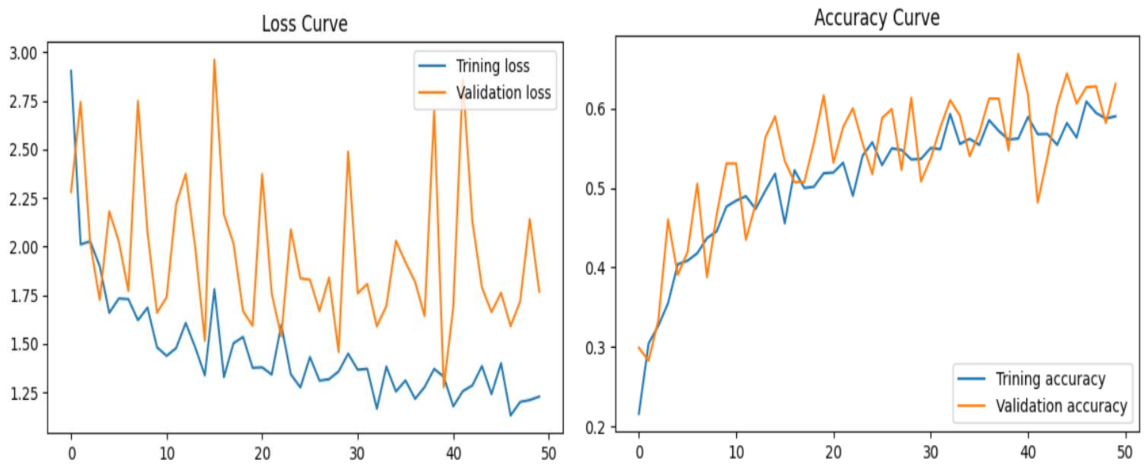


Figure 5.2.2: Training and validation accuracy and loss over the epochs (ResNet50).

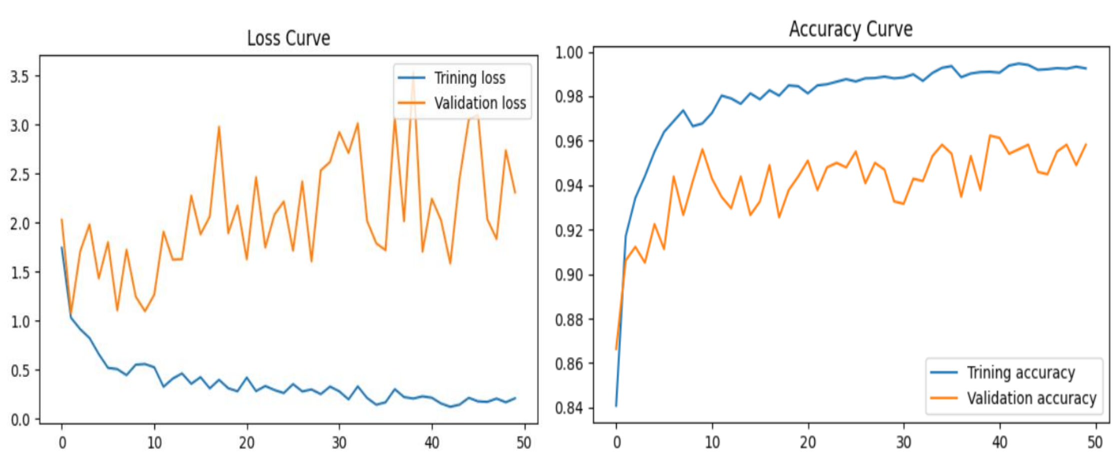


Figure 5.2.3: Training and validation accuracy and loss over the epochs (MobileNetV2).

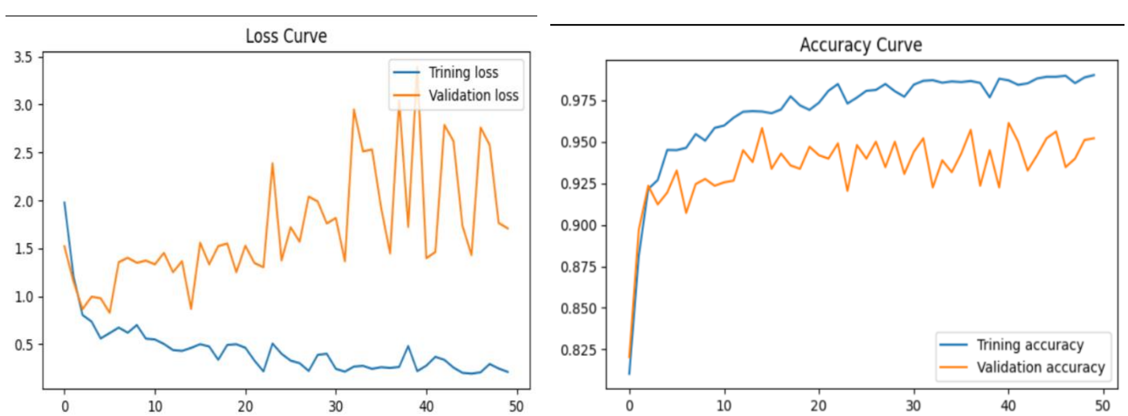


Figure 5.2.4: Training and validation accuracy and loss over the epochs (InceptionV3).

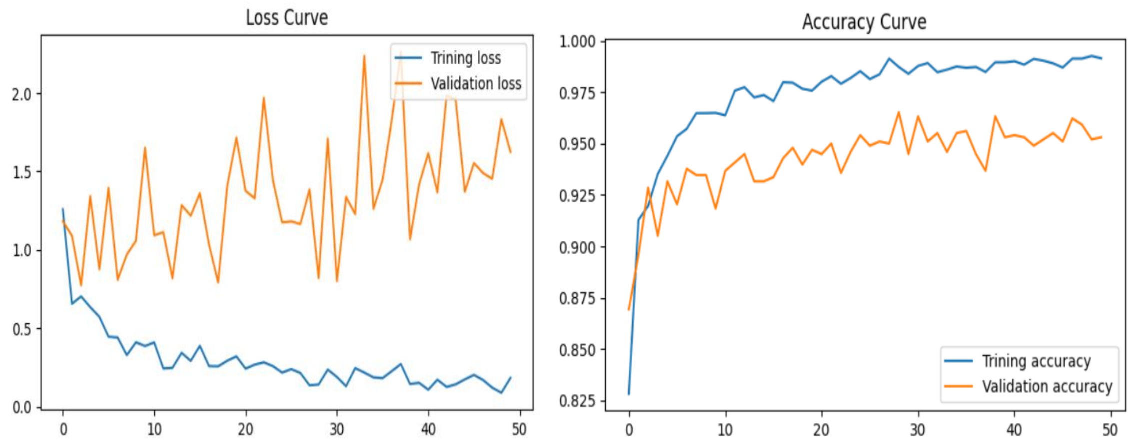


Figure 5.2.5: Training and validation accuracy and loss over the epochs (Xception).

Confusion Matrix after Transfer Learning (TL) Based on the number of images:

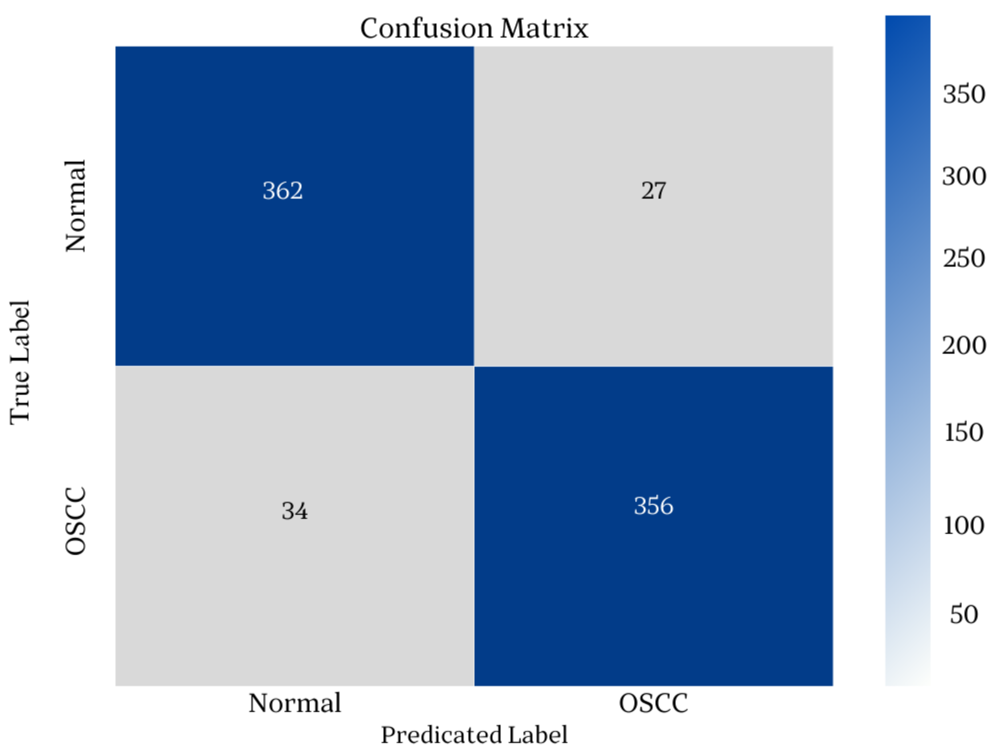


Figure 5.2.6: CM after Original Vgg16

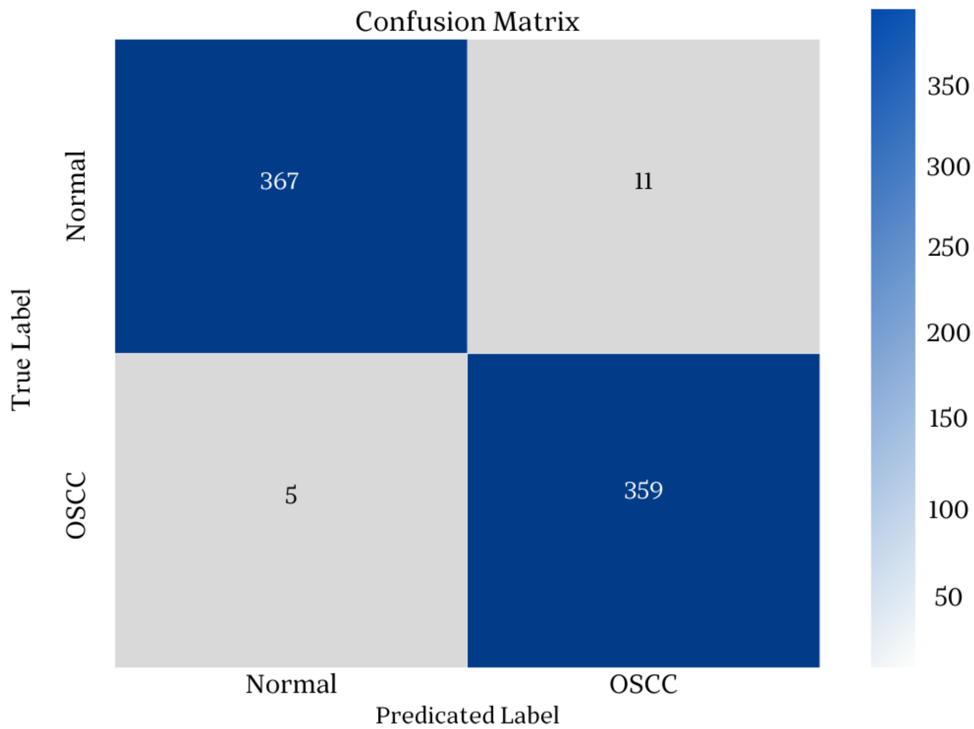


Figure 5.2.7: CM after Original ResNet50

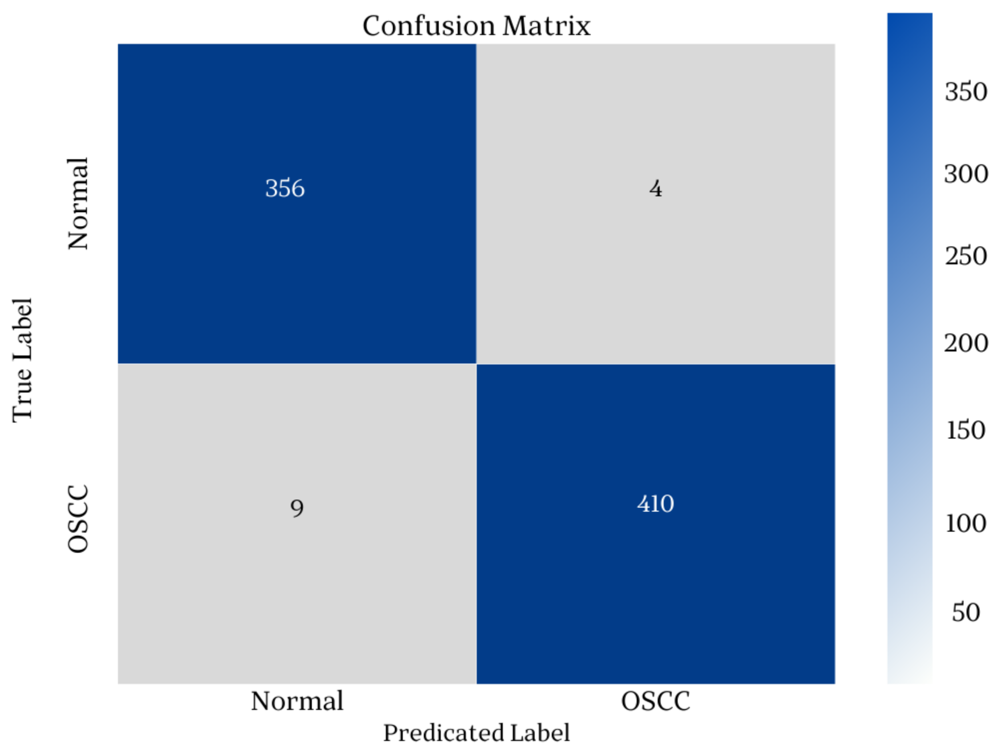


Figure 5.2.8: CM after Original MobileNetv2

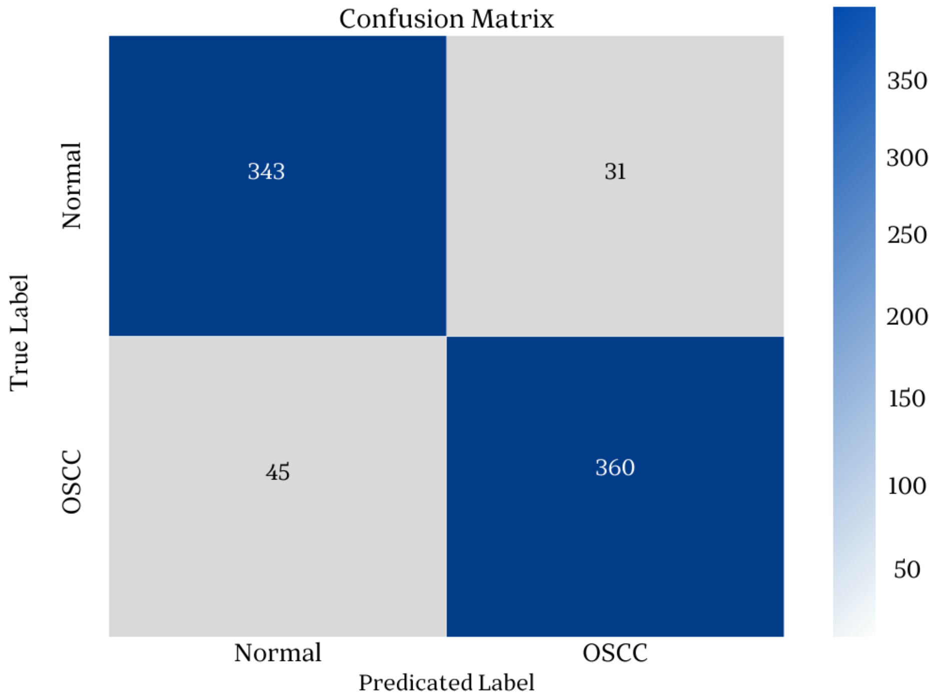


Figure 5.2.9: CM after Original InceptionV3

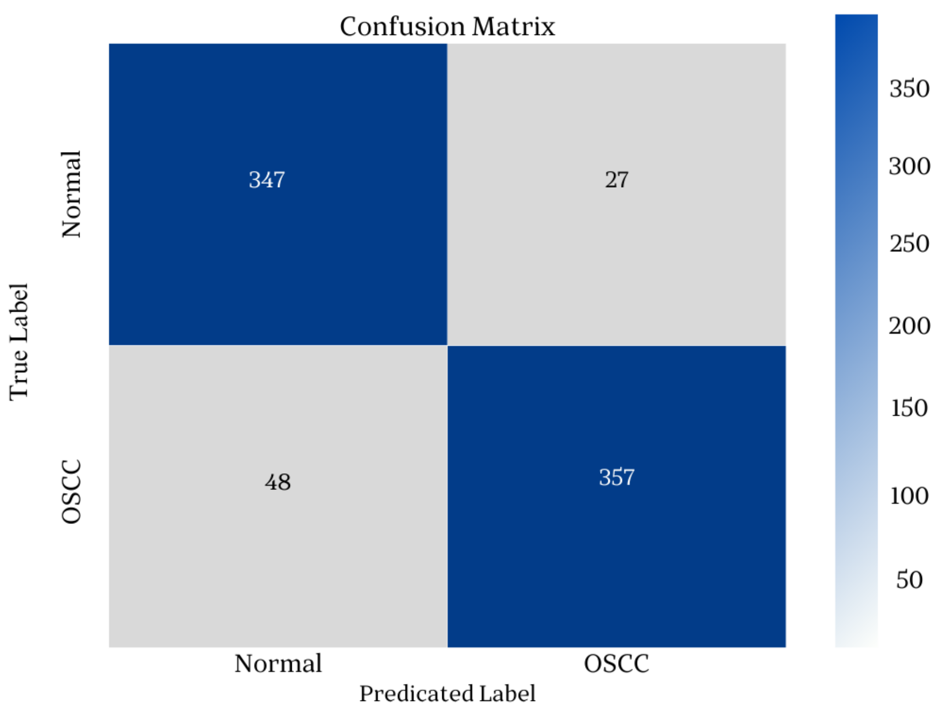


Figure 5.2.10: CM after Original Xception

Result of Experiment 2: Comparison Between Transfer Learning Model with Proposed Model.

TABLE 5.2.3: ACCURACY FOR COMPARISON BETWEEN TRANSFER LEARNING MODEL WITH PROPOSED MODEL

Architecture	Training Accuracy	Test Accuracy	Validation Accuracy
VGG16	95.10%	94.28%	95.102%
ResNet50	66.83%	65.81%	66.836%
MobileNetV2	96.22%	95.20%	96.224%
InceptionV3	96.12%	95.51%	96.122%
Xception	96.53%	95.40%	96.530%
Ensemble Model	**98.73%**	**98.07%**	**97.64%**

The comparative analysis of various pre-trained deep Convolutional Neural Network (CNN) architectures (VGG16, ResNet50, MobileNetV2, InceptionV3, and Xception) compare with the ensemble model is detailed in Table 5.2.4, highlighting their performance metrics for the task of determining oral squamous cell carcinoma (OSCC) from histopathological images.

TABLE 5.2.4: PRECISION, RECALL, F1-SCORE, AND SUPPORT (N) RESULT OF EMSEMBLE MODEL.

Ensemble Model				
	Precision	**Recall**	**F1-Score**	**Support**
Normal	0.93	0.99	0.96	374
OSCC	0.99	0.94	0.96	405
Accuracy			0.96	779
Macro Avg	0.96	0.96	0.96	779
Weighted Avg	0.96	0.96	0.96	779

Shows the accuracy of the ensemble model's training and validation, with the accuracy and loss percentages on the y-axis and the number of epochs on the x-axis.

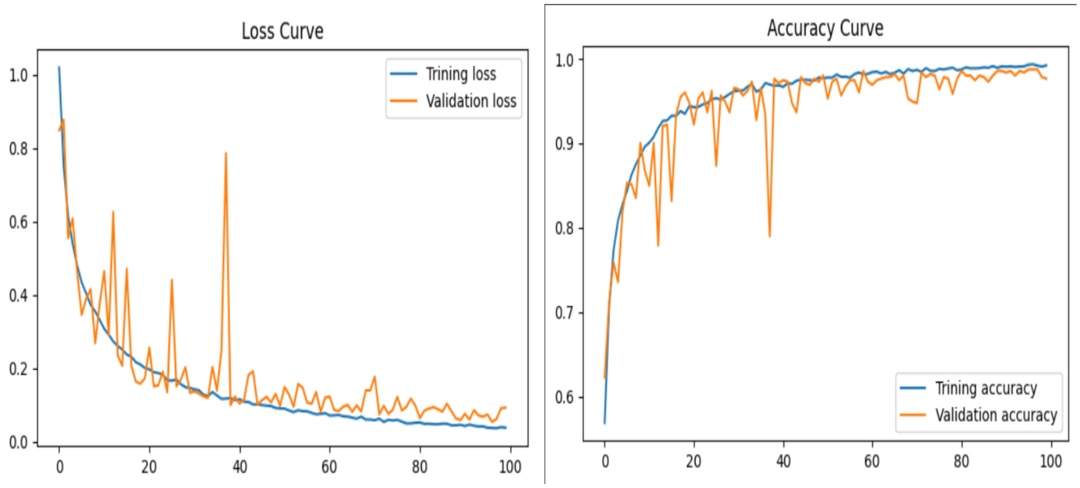


Figure 5.2.11: Training and validation accuracy and loss over the epochs (Ensemble).

Confusion Matrix after Ensemble Model Based on the number ofimages:

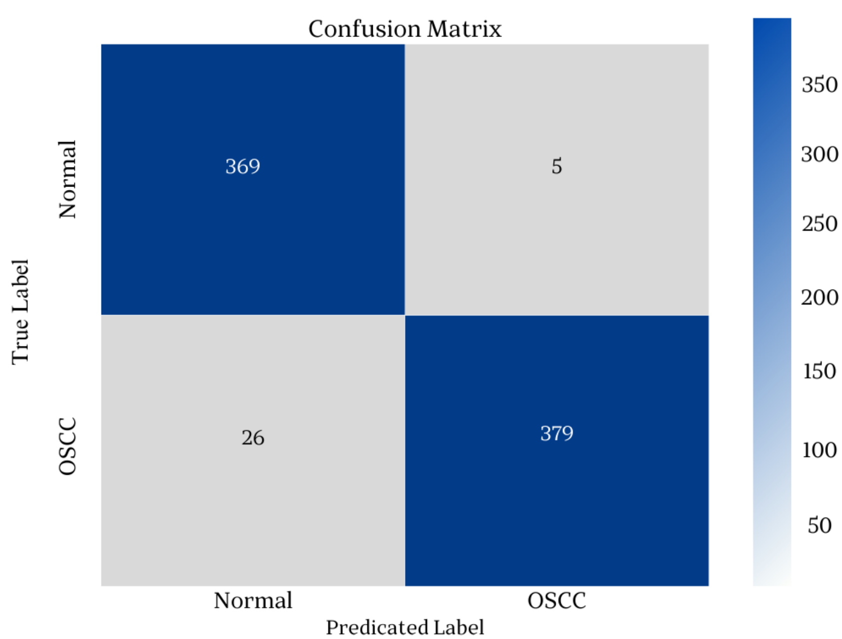


Figure 5.2.12: CM after Ensemble Model

5.3 Comparative Analysis

The accuracy of various models used in a study for detecting oral squamous cell carcinoma (OSCC). The Ensemble Model stands out with nearly 100% accuracy, indicating its superior performance in this task. TL VGG16 also demonstrates high accuracy, slightly below the ensemble model, showcasing its effectiveness. However, TL ResNet50 experiences a significant drop in accuracy, falling to around 60%, which suggests challenges in its application for this specific task. In contrast, TL MobileNetV2 shows a remarkable recovery, achieving around 90% accuracy, similar to TL InceptionV3 and TL Xception, both of which maintain accuracy levels close to 90%. Overall, the ensemble model proves to be the most effective, while most individual CNN architectures, except for ResNet50, perform with high accuracy. This comparison highlights the robustness and reliability of ensemble learning and specific CNN architectures in the early detection of OSCC.

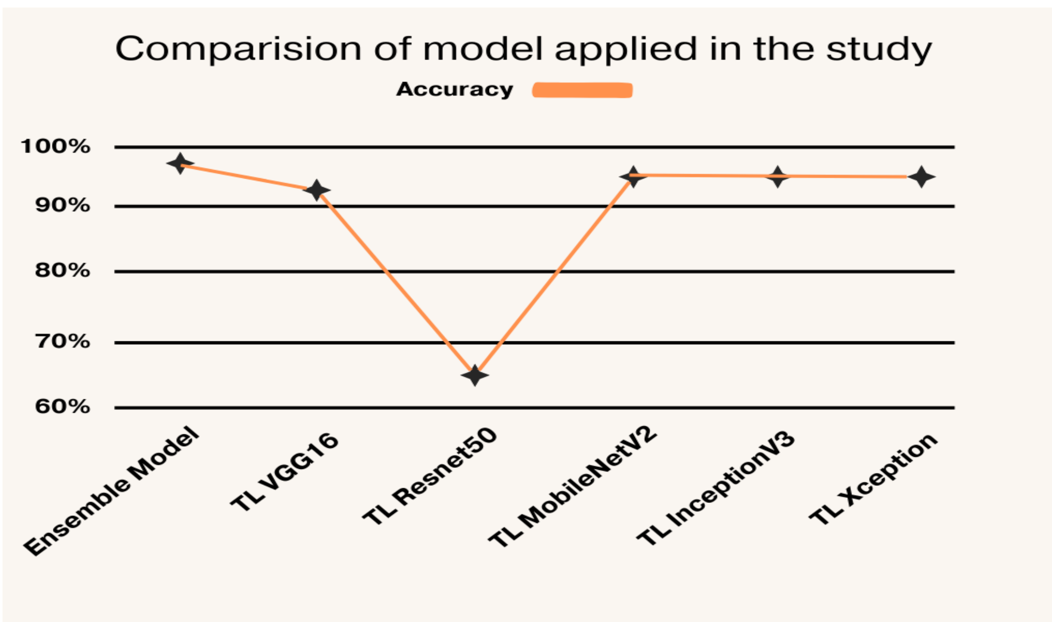


Figure 5.3.1: Accuracy comparison among transfer learning and ensemble models.

5.4 Summary

Throughout the research project, the sustainability plan for "Automated Diagnosis of Oral Squamous Cell Carcinoma Using Deep Learning: A Comparative Analysis of Transfer Learning Approaches" seeks to respect environmental responsibility and make a good impact on society. The plan is centred on reducing the project's environmental impact by using resources wisely and implementing sustainable practices in all project aspects.The optimisation of computing resources to lower energy usage during model training and deployment will be given priority. This involves reducing the carbon footprint.

CHAPTER 6

Impact on Society, Environment and Sustainability

6.1 Impact on Life

The study "Utilising Histopathological Images to Determine Oral Squamous Cell Carcinoma with Deep Convolutional Neural Networks" has implications that go beyond academic bounds and could lead to important improvements in healthcare and societal benefits. Advanced deep learning algorithms have the potential to transform medical diagnostics and improve patient outcomes while also benefiting society at large by accurately and efficiently detecting Oral Squamous Cell Carcinoma (OSCC). Through the use of deep Convolutional Neural Networks (CNNs) and transfer learning, the research hopes to improve the precision and dependability of OSCC diagnosis, enabling medical practitioners to make more confident and well-informed decisions.This research has significant societal ramifications, especially in the field of public health. One common type of oral cancer that presents major issues to global healthcare systems is OSCC. Using stronger and more precise diagnostic instruments can speed treatment plans, reduce misdiagnoses, and improve patient care. This may result in fewer hospital stays, fewer OSCC-related problems, and overall lower healthcare expenses. The practical applicability of the research is highlighted by its emphasis on comparative analysis and evaluation of different transfer learning methodologies. This will facilitate the creation of optimal diagnostic solutions that can be smoothly incorporated into clinical practice.

Moreover, impoverished communities and areas with restricted access to healthcare resources stand to gain from the price and accessibility of improved OSCC detection techniques. The technology used by this research has the ability to cross geographical boundaries and provide advanced diagnostic capabilities to places that might not have access to standard medical facilities. The democratisation of cutting-edge medical technology is in line with global health ambitions, supporting global efforts to improve healthcare equity and reduce health disparities.

To sum up, the significance of this research for society is that it could bring about a new era of precision medicine, especially when it comes to diagnosing oral cancer. Utilising state-of-the-art technologies, the research promises to improve public health outcomes, healthcare accessibility, and the general well-being of various populations worldwide in addition to advancing scientific understanding.

6.2 Impact on Society & Environment

In addition to its primary focus on technology and healthcare, the study article "Automated Diagnosis of Oral Squamous Cell Carcinoma Using Deep Learning: A Comparative Analysis of Transfer Learning Approaches" also raises important environmental considerations. In order to improve diagnostic accuracy in the diagnosis of oral cancer, deep Convolutional Neural Networks (CNNs) and transfer learning must be integrated, which requires intensive computing methods.

Significant energy consumption is required for these computational tasks, which typically rely on power-hungry devices like graphics processing units (GPUs). This is especially the case while training and optimising intricate neural networks. Because of the increased energy needed to complete these computations, the environmental impact is therefore substantial. The carbon footprint of these computer activities highlights how crucial proper energy resource management is. Hardware efficiency gains, the use of cloud computing strategies, and the adoption of sustainable computing practices are all being undertaken in an effort to allay these environmental concerns. Using renewable energy sources in data centres and optimising algorithms for energy efficiency are two key steps in lowering the environmental effect of AI-driven healthcare technology.

Therefore, the research raises significant concerns about mitigating environmental consequences even as it seeks to improve oral cancer diagnostics through innovative AI applications. Finding a balance between environmental sustainability and technological advancement is crucial for ensuring that healthcare innovations have a positive social impact while leaving the least amount of environmental footprint feasible.

6.3 Ethical Aspects

Based on a strong foundation of ethical considerations woven throughout its technique, the research on "Automated Diagnosis of Oral Squamous Cell Carcinoma Using Deep Learning: A Comparative Analysis of Transfer Learning Approaches" is conducted. Because histopathological pictures are used, great care is taken to protect patient privacy and confidentiality, closely following legal and ethical requirements. When appropriate, people whose data is used in the research are asked for their informed consent, guaranteeing that their rights will be upheld during the entire investigation.

Given the potential impact this research may have on public health, it must be deployed carefully, with the goal of ensuring that patient interests are protected and that improvements in diagnostic accuracy are converted into real benefits for patients. Ensuring that technology advancements serve the greater good without violating individual rights or society norms requires a strong ethical component.

In addition, the research places a strong emphasis on accountability and transparency when it comes to recording its processes, allowing for responsible information transmission, examination, and reproducibility. The research's dedication to improving healthcare outcomes through the moral use of cutting-edge deep learning technologies in the field of oral cancer diagnosis is highlighted by this commitment to ethical practice.

6.4 Sustainability Plan

Throughout the research project, the sustainability plan for "Utilising Histopathological Images to Determine Oral Squamous Cell Carcinoma with Deep Convolutional Neural Networks" seeks to respect environmental responsibility and make a good impact on society. The plan is centred on reducing the project's environmental impact by using resources wisely and implementing sustainable practices in all project aspects.The optimisation of computing resources to lower energy usage during model training and deployment will be given priority. This involves reducing the carbon footprint associated with computationally intensive jobs and streamlining operations by investigating energy-efficient methods and utilising cloud computing solutions whenever possible.

The research team not only prioritises computational efficiency but also environmentally sustainable data management and storage methods. This entails using environmentally friendly data management systems and putting measures into place to lower the amount of data that needs to be stored. The team's goal is to coordinate research endeavours with environmentally responsible behaviours by keeping up to date on the most recent developments in sustainable technology and approaches.

To guarantee continuous progress and adherence to environmental norms, the research process will incorporate regular review and adaption of sustainable techniques. The sustainability plan seeks to advance scientific understanding in oral cancer diagnostics while promoting environmental stewardship through the integration of these concepts into every stage of the project.

6.5 Summary

The study "Utilizing Histopathological Images to Determine Oral Squamous Cell Carcinoma with Deep Convolutional Neural Networks" holds significant promise for healthcare and society. By leveraging advanced deep learning techniques like CNNs and transfer learning, it aims to revolutionize OSCC diagnosis, enhancing accuracy and efficiency. This innovation could lead to improved patient outcomes, reduced healthcare costs, and broader accessibility to advanced diagnostics, especially in underserved regions. Ethical considerations ensure patient privacy and consent are upheld, while a robust sustainability plan addresses the environmental impact of intensive computational processes. Overall, the research integrates cutting-edge technology with ethical standards and sustainability goals, poised to advance both healthcare diagnostics and global public health initiatives.

CHAPTER 7
Conclusion and Future work

7.1 Conclusions

For oral squamous cell carcinoma (OSCC) to be effectively diagnosed and treated, early and precise identification and categorization are essential. In order to detect and classify OSCC using histopathological pictures, this study focuses on a thorough performance evaluation of Deep Convolutional Neural Networks (D-CNN). Our findings provide further evidence for the success of a CNN-based strategy, especially when handling smaller and less detailed datasets. The corpus of existing research on OSCC detection is still limited, making our comparison study all the more important and set to make significant contributions to the field of oral cancer therapy. After carefully studying the performance of multiple CNN models, including VGG16, ResNet50, MobileNetV2, XceptionV3, InceptionV2, and a custom ensemble model, we discovered that the ensemble model beats individual models in terms of accuracy. However, despite the ensemble framework's overall efficacy, several instances of erroneous predictions were identified. This emphasises the need for further research into alternate tactics, such as contrast augmentation or other image-processing methodologies.

We propose integrating picture segmentation before classification to increase the CNN models' capacity to extract relevant features. Although training the ensemble model, which comprises of many CNNs, is computationally costly, the potential for improved accuracy makes the investment worthwhile. To solve this issue, future research could look into techniques such as snapshot ensemble to lessen computing strain.

In summary, this study marks a big step forward in the refinement and advancement of OSCC diagnostic techniques, giving insights that potentially have a considerable impact on clinical practice. Our findings also serve as a platform for future research in the developing field of medical image analysis, with the ultimate goal of improving patient outcomes and the accuracy of oral cancer diagnosis.

7.2 Further Suggested Works

The research findings on "Utilizing Histopathological Images to Determine Oral Squamous Cell Carcinoma with Deep Convolutional Neural Networks" offer a number of promising directions for future investigation and development in the field of diagnostics for oral cancer. First, more research might concentrate on improving and broadening the range of image preprocessing methods designed especially for oral squamous cell carcinoma (OSCC) histopathology pictures. Advanced contrast enhancement algorithms and unique denoising techniques could be explored as ways to improve image quality and increase the resilience of deep learning models in detecting minor diseased abnormalities. Secondly, sophisticated segmentation methods could be investigated as a prelude to classification tasks in CNN models. Through the integration of advanced segmentation techniques, scientists can work toward optimizing the extraction of complex tumor borders and spatial features from histopathology images, which could lead to an improvement in the models' overall diagnostic accuracy.

Furthermore, future studies may focus on improving the efficiency of model training considering the computing needs of deep CNN architectures and transfer learning in medical picture analysis. This could entail investigating methods to lower computing overhead while preserving or even improving diagnostic performance across various datasets and clinical settings, such as federated learning or model distillation. Furthermore, enlarging the research scope to encompass multi-modal data fusion techniques may greatly enhance CNN models' diagnostic potential for oral cancer detection. By combining information from several sources, including radiological images, genomic data, and clinical records with histopathological pictures, it may be possible to gain a more thorough understanding of how the illness progresses and how treatments work, opening the door for personalized medicine methods in OSCC.

Finally, research confirming the deep learning models' resilience and generalizability across various demographic groups and geographic locations is still desperately needed. Future research may make sure that generated models are relevant in a variety of healthcare settings by adding real-world clinical datasets and various patient cohorts. This will ultimately translate research findings into concrete clinical advantages. preprocessing techniques, advancing segmentation methodologies, optimizing computational efficiency, exploring multi-modal data fusion, and validating model generalizability. These avenues collectively aim to enhance the accuracy, efficiency, and applicability of deep learning-based diagnostic tools in improving patient outcomes in oral cancer management.

7.3 Limitations

This study has a number of limitations despite being thorough and novel in its use of deep convolutional neural networks (CNNs) to the diagnosis of oral squamous cell cancer (OSCC). The dependence on a rather limited dataset of 5192 histopathology pictures is one of the main limitations. Although this problem can be addressed by data augmentation approaches, the small size of the dataset may still affect the robustness and generalizability of the models, which could result in overfitting. The intrinsic complexity and processing requirements of deep CNN models represent another drawback. Several computing resources, like as high-performance GPUs, are needed for training and optimizing these models, and not all researchers or healthcare facilities may have access to them. This calls into question whether it is feasible to implement such models in environments with limited resources.

There are issues with the study's interpretation of the CNN models as well. These models perform as "black boxes," offering no insight into the decision-making process even while they achieve high accuracy. Insufficient transparency might impede clinical acceptance and trust, since medical practitioners could be hesitant to depend on systems they don't fully comprehend or can't adequately explain to patients. Finally, ethical issues are still a constraint even after they have been addressed. Obtaining informed consent and protecting patient data privacy are essential, but putting these safeguards into practice consistently across a range of healthcare settings is difficult. Furthermore, although the ecological impact of the computing resources employed was acknowledged, it was not thoroughly investigated, which allows for the implementation of more sustainable approaches in subsequent studies.

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Appendix A

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

Title:

UTILIZING HISTOPATHOLOGICAL IMAGES TO DETERMINE ORAL SQUAMOUS CELL CARCINOMA WITH DEEP CONVOLUTIONAL NEURAL NETWORKS

Student ID: [201-15-3420 || 201-15-3757]

CO Description for FYDP

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

CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

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

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

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	To identify the oral squamous cell carcinoma. we require knowledge from medical Science, which is the theoretical branch of natural science that covers **(K1).** Our research must analyze the needs and handle the data gathered from the medical sector, that collect from kaggle and preprocessing data which is the portion of the theory-based engineering basic that deals with **(K3).**	**Page no:** [1-2] **Section:** [1.1] **Page no:** [17-19] **Section:** [3.2]
				We are design our research proccess flow diagram.we are collecting image, data pre-processing, augmentation & train & test models all process Show	**Page no:** [17-20]

				in proccess flow diagram.that's is a design and cover by **(k5).** we utilize a variety of technical technologies to construct our project, including the python programming language, kaggle platform, statistical analysis tools for the framework, and an ide called jupyter notebook that covers by **(K6).** In our research we are calculating mathematical part under estimate cost which cover **(K2).**	**Section:** [3.2,3.3] **Page no:** [20-21] **Section:** [3.4]
				This through the synthesis of insights from recent studies, this study ensures (**k8)** and advances oscc detection through the use of deep learning, demonstrating a thorough comprehension of current approaches. The study exhibits expert knowledge **(k4)** by conducting transfer learning with advanced cnn architectures including vgg16 and resnet50, mobilenet, and inception, boosting oral cancer detection accuracy in histopathology pictures, which is critical for computer-aided diagnosis.	**Page no:** [10-12] **Section:** [2.2] **Page no:** [23-26] **Section:** [4.2]

2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	We have determined that different people may develop different types of oral squamous cell carcinoma (OSCC) not correspond with every human being's oral cancer cell. It is Cover Requirements Range	**Page no:** [17-19] **Section:** [3.2]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	Through a careful comparison of experimental results, this effort demonstrates that, among several viable strategies, transfer learning is the most important option for improving the detection of oral cancer.	**Page no:** [29-39] **Section:** [5.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	We have to research outside of our area of expertise because we are in the medical field and are discovering oral squamous cell cancer.	**Page no:** [10-14] **Section:** [2.2, 2.3]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting requirements**	No	CO8	N/A	N/A

7.	**EP7: Interdependence**	Yes	CO5	By combining different elements from data collecting and the suggested methodology, this project's comprehensive approach tackles high-level issues and ensures a comprehensive solution to challenging problems in medical diagnostics.	**Page no:** [17-19] **Section:** [3.2]

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

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	In order to assure systematic study and contribute to breakthroughs in Oral Cancer detection through deep CNNs and transfer learning, our project makes use of a variety of resources, including GPUs, deep learning frameworks, annotated datasets, and ethical considerations.	**Page no:** [23-27] **Section:** [4.2,4.3]
2.	**EA2: Level of interaction**	No		N/A	N/A

3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	Yes		This study benefits society by advancing healthcare via cutting-edge OSCC detection techniques, supporting environmental sustainability via the use of effective computational resources, and upholding moral standards for patient privacy.	**Page no:** [43-44] **Section:** [6.3, 6.2]
5.	**EA-5: Familiarity**	Yes		By using deep CNNs and transfer learning to investigate a novel strategy in OSCC detection, as illustrated by preliminary findings and a thorough comparison analysis, this project builds on previous research and provides new insights into the subject.	**Page no:** [10,12-14] **Section:** [2.1, 2.3]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	In order to mitigate **CO4**, this project combines efficient project management with financial control. Careful planning, resource distribution, and budget estimation are guaranteed to provide the best possible resource utilisation throughout the duration of the study project.	**Page no:** [20-21] **Section:** [3.4]
2	CO9	Yes	By putting patient privacy first,	**Page no:**

			getting informed consent, and openly recording the research process, the project demonstrates adherence to ethical principles. It also ensures responsible knowledge dissemination and societal well-being through the moral application of cutting-edge healthcare technologies that abide by **CO9**.	[44] **Section:** [6.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's careful methodology development, extensive data collection, and analysis of the experimental results demonstrate its commitment to continuous learning (CO12) and adaptation in the ever-evolving technological landscape. It also demonstrates a willingness to stay current and improve methods in order to meet new challenges.	**Page no:** [17-19, 29-40] **Section:** [3.2, 5.2,5.3]

UTILIZING HISTOPATHOLOGICAL IMAGES TO DETERMINE ORAL SQUAMOUS CELL CARCINOMA WITH DEEP CONVOLUTIONAL NEURAL NETWORKS

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