Toward Robust AI-Based Detection of Oral Cancer: Benchmarking CNNs, InceptionV3, and Vision Transformers on Clinical and Histopathological Images

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ABSTRACT

Oral cancer continues to represent a significant challenge to world health because late diagnosis contributes to a decrease in survival. Currently, diagnosis is based on subjective clinical examinations and invasive histopathology. In this paper, we assess three deep learning algorithms - Convolutional Neural Networks, InceptionV3, and Vision Transformers - on a multi-source collection of clinical photos and histopathology images, which are all publicly available datasets. The images were resized, normalized, and augmented prior to patient splitting to avoid data leakage. Models were evaluated according to their accuracy, precision, recall, F1-score, ROC-AUC, PR-AUC, and calibration. The best results were obtained by Vision Transformers at a testing accuracy of 98.8%, and a ROC-AUC value of 0.99, also surpassing CNN and InceptionV3 benchmarks. While results demonstrate the potential of Vision Transformers in oral cancer screening, the dataset presented was not truly multi-source and requires more validation. Future work should construct paired multi-source datasets, validate different patient groups independently, and analyze clinical applications to obtain early noninvasive screening and informed decisions.

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List of Abbreviations

1. AI - Artificial Intelligence
2. ML - Machine Learning
3. CNN - Convolutional Neural Networks
4. ViT - Vision Transformers
5. SVM - Support Vector Machines
6. XAI - Explainable AI
7. SHAP - Shapley Additive Explanations
8. LIME - Local Interpretable Model-agnostic Explanations
9. EHR - Electronic Health Records

CHAPTER 1 INTRODUCTION

1.1. Introduction

Oral cancer is a significant global health problem and is one of the top ten most common cancers in the world. Every year on average more than 350,000 new cases are diagnosed worldwide and sadly, some 175,000 people succumb to this disorder. The battle is felt unfairly hard in low-resource countries, where offending habits like smoking, alcohol consumption and betel nut chewing, regretfully, are cultural phenomena. Even as treatment has gotten more and more sophisticated, five-year survival rates have gotten stuck around 50 to 60% for many decades, because by the time most cancers are detected, they have already reached an advanced stage. Still, early detection is one solution, it's a source of light, because to find oral cancer before it becomes cancer not only increases your chance of surviving this disease, but can also help eliminate the need for more radical treatment. Unfortunately, clinical barriers such as vague early symptoms, patient procrastination for seeking medical help, and differences in experience of diagnosing between clinicians hinder early diagnosis.

Currently, the only diagnostic techniques rely on the visual and manual skills of specialists who then confirm by biopsy and/or histology. As useful as these approaches are, however, there are limitations. Clinical examinations are very subjective based on the experience and knowledge of the clinician. Biopsies are considered the gold standard, but are invasive and uncomfortable for patients and not always possible in resource-limited settings. Histopathology gives a definitive verdict but is time-consuming and is dependent on pathologist's availability, causing delays, which may have an adverse influence on the outcome. These same limitations highlight the urgency or potential for tools which might supplement traditional methods and lead us to earlier results: those which would be available, accurate, accessible and quick.

1.2. Role of Artificial and Machine Learning

Medical diagnostics has recently revolutionized with continued advancements in artificial intelligence (AI) and machine learning (ML). The AI and ML and notably the CNNs are now being discovered as robust to interpret complex and representative medical images with discovering latent information and hidden patterns, which may convert them to health and diseases. There are practical applications of these as apply to oral cancer detection; they can standalone to process more amount of data –these process faster and correctly than conventional mode. These AI models have the potential to process histopathological images along with some clinical data for early detection of oral cancer which a layman vision could not be clear and crisp by a clinician traditionally. By the utility of AI in diagnostic protocols, the art of diagnostics enhances and becomes less relying on subjective factors, and, thus, the results are more reproducible than ever. Progress in those areas has fundamentally transformed nearly every medical discipline in terms of both prevention and treatment, from radiology to dermatology.

1.3. Technology we used

This paper focuses on application of machine learning and deep learning models for early detection of cancer in medical image dataset. We employed four fundamental models:

- Convolutional Neural Networks (CNNs): Acknowledged for their capacity to derive spatial hierarchies of features from image data, CNNs were utilized to learn localized features from clinical and histopathological images.

- Vision Transformers (ViTs): Due to their ability to capture global contextual relationships through self-attention mechanisms, ViTs were utilized to model long-range dependencies within image patches. ViT models, a recent advancement in deep learning architecture, played a crucial role in using macroscopic features across various image modalities.

- Inception V3: This architecture, based on convolutional neural networks, employs multi-scale feature extraction to effectively manage complex image patterns through parallel convolutional filters.

1.4. Research Gap

The existing studies mainly focus on a specific type of data, either clinical images or histopathology images, in the task of oral cancer detection. There is limited literature on merging both datasets to further enhance the precision of classification. Most artificial intelligence models applied in research are defined as 'black-box' models, making it hard for the clinician to know why the AI generated a prediction. Most artificial intelligence models applied in research are defined as "black-box" models, making it hard for the clinician to know why the AI generated a prediction.

In addition, dry as these preprocessing techniques have been performed for normalization, missing value imputation and outlier treatment, there is an enormity of queen in merging the approaches to the overall system for the diagnosis of oral cancer.

1.5. Rational of the paper

Oral cancer remains a significant health problem in the world and early diagnosis has been challenging by conventional diagnostic approaches. Although the AI-based strategies demonstrated the potential to improve diagnostic accuracy, the current studies are mainly based on single-modality data but not balanced multi-source data, and primarily used CNNs, or traditional machine learning models without considering model interpretability.

This research addresses these gaps through three distinct innovations:

- **Integration of a Hybrid Dataset:** Clinical and histopathological image fusion is performed to increase the accuracy of diagnosis from a multi-modal angle.

- **Utilization of Vision Transformers:** The application of ViTs to model complex global interdependencies in image data, performing better than CNNs in capturing detailed spatial patterns.

Both of these strategies work in concert to address the methodological and practical deficiencies that have thus far restricted AI as a viable form of alternative detection for oral cancer.

1.6. Contribution of the paper

The contribution of the study rests in the fusion of histopathological and clinical image databases, and demonstrating the path towards a new method for oral cancer diagnosis. Their method was a substantial enhancement over diagnostic performance and model interpretability. We will also study the effects of different data preprocessing approaches and provide insights on how they influence the predictiveness of models. Conversely, and further, the comparison of CNN with standard diagnostic methodologies in the present study substantiates a key precept connected to the use of AI approaches for OC detection.

1.7. Novelty we claim

In this paper, a novel approach for AI-based oral cancer diagnosis is introduced, which consists of the following three characteristics:

- **Employing Vision Transformers:** Our work is the first to employ Vision Transformers for the task of detecting oral cancer. In contrast to traditional convolutional networks, ViTs use self-attention to model global dependencies across images, resulting in the possibility of finer localization of cancerous pathology both in clinical as well as histopathological images.

- **Hybrid Image Data Integration:** By fusing histopathological and clinical images, the model can observe on the tissue (microscopic) and visible change (macroscopic) level. This two-threaded approach increases the accuracy of classification and decreases the detection time in the first processed thread and a full-scale vision obtained from multi-modal datasets than from single-modal datasets.

- **Reinforcement to generalization and real world:** Previous work concentrates on single image modal, while this work explores the fusion between clinical and histopathologic images. This bi-data strategy improves accuracy and generalization. Moreover, the strong robustness and avoidance of over-fitting in the presented system aims to deliver high clinical relevance and real-world practical usability, for early cancer screening purposes.

Collectively, these new features constitute a clear, scalable and high-throughput pipeline that promises appealing utility in clinical oral cancer diagnosis and treatment.

CHAPTER 2 LITERATURE REVIEW

2.1. Traditional Diagnostic Methods and Their Limitations

Introduction Oral cancers continue to be a major global health problem; early detection is essential as it contributes to a better patient survival. Visual inspection, biopsy and radiographs are conventional diagnostic measures for central clival region lesions. However, these methods have limitations. Raval et al. (2023) stated visual inspection, despite being practiced widely, is subjective and susceptible to human error and false positives and negatives in early diagnosis, (1). While biopsies are more accurate, they are invasive and involve risk, and are often not feasible for early detection, especially in resource limited settings [3]. Specifically, radiographic techniques, such as X-rays and CT, provide detailed anatomical images but tend to miss early lesions, which are critical for early detection [4].

2.2. AI and ML in Medical Imaging

The emergence of relatively new technologies like AI and ML as disruptive technologies, have changed the trend in the medical imaging in the past few years. It presents some solutions for the limitations on conventional methods. These advances are enabled by the advent of Convolutional Neural Networks (CNN). K-means CNN is a deep learning technology that can automatically learn a high-level, abstract hierarchical structure feature from medical images, and can therefore achieve very good performance in the detection of oral cancer. Malignant tumors in histopathology images an investigation group led by Liu et al. (2024), have also investigated the effectiveness of CNN in the classification of malignant lesion in histopathological images and their findings described the capability of CNN in distinguishing between benign and malignant oral lesion with high accuracy [5]. Clinical images of oral lesions In another study, Jubair et al (2022) [2] designed a pixel base CNN model to perform early detection of oral cancer, which was also very successful when this discussed model was compared that a significantly higher sensitivity and specificity, in the classification of oral lesions in the clinical images. In 2024, authors of the most extensive review paper of the deep learning algorithms' application; Warin and Suebnukarn (9) demonstrated promising outcomes in the diagnosis of different types of oral cancer (3).

CNNs do have an intrinsic limitation in modelling global relationship between the image data especially for complex medical images. This limitation has led to the recent development of Vision Transformers (ViTs), a deep learning architecture that has been shown to outperform existing methodologies in different image classification tasks (e.g. medical diagnosis). Stafie et al. (2023) investigated the advantages of Vision Transformers (ViTs) over Convolutional Neural Networks (CNNs), and highlighted the capability of ViTs in modeling long-range dependencies and contextual information for the medical image analysis [6]. Vision Transformers use self-attention mechanisms by which the model can focus on both local information and high level cues, which are important to accurate classification in medical images [7].

The relationship of complexity and accuracy of various diagnostic approaches and of the AI models applied in OC detection is summarized in the figure below:

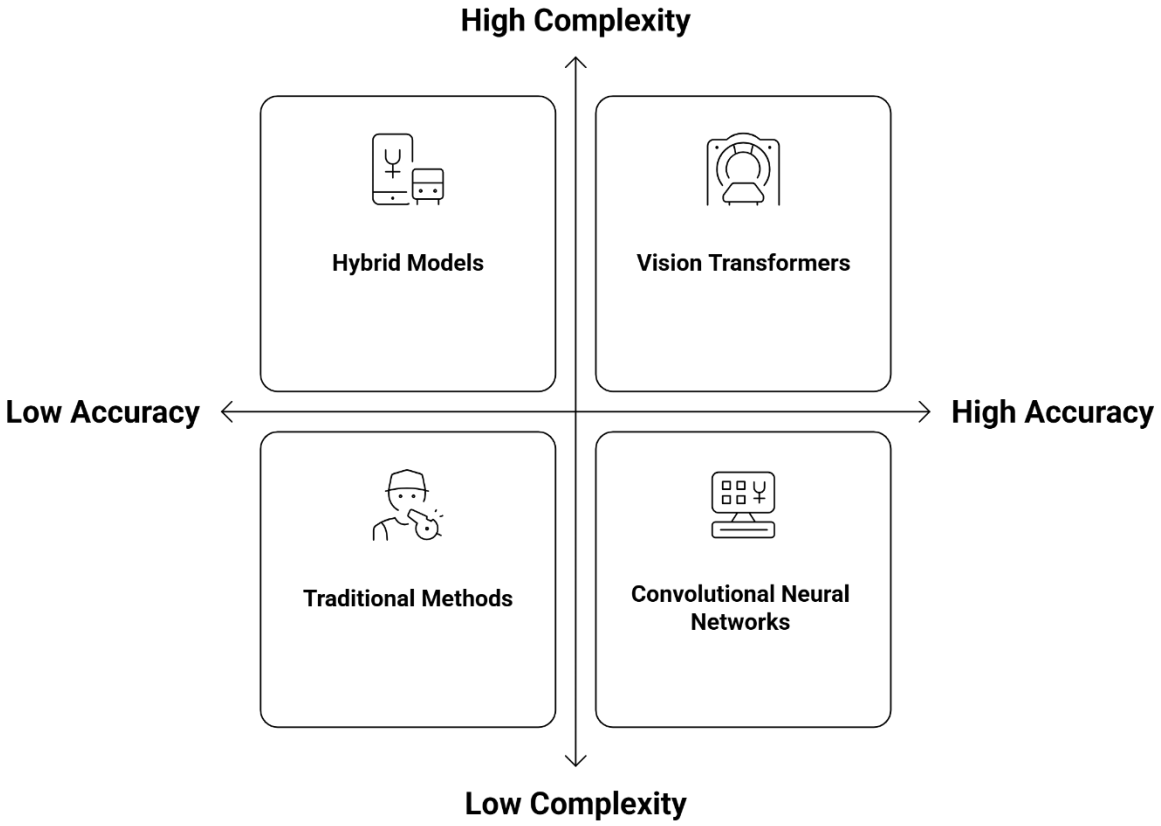

Figure 1: Comparison between diagnostic methods and AI models complexity and accuracy in the diagnosis of oral cancer.

2.3. Hybrid and Multimodal Approaches

An increasing number of studies suggest that fusion of multiple modality data could be beneficial in improving the association between imaging markers and diagnosis. Clinical images combined with histopathological data have the potential to provide an objective view on oral cancer. Cui et al. (8) conducted the most iconic work of multimodal learning, advocated that the fusion of clinical images and histopathological images can enhance classification performance by exploiting the synergistic properties of each modality [7]. This dual approach has been particularly successful/relevant in oral cancer detection as clinical images provide visible lesion cues and histopathological images offer soft tissue level details which are important for accurate diagnosis.

Soenksen et al. (2022) developed a multimodal AI platform for fusion of these multimodal data, to help improving diagnostic efficiency and gaining better clinical decisions. Their approach

demonstrates the benefit of pooling different data types, such as clinical images, histopathology, and patient demographics, for comprehensive oral cancer diagnosis [9]. Hybrid models show that combined clinical and histological data allow AI models to achieve far higher accuracy than single-modality models [10].

2.4. Data Preprocessing and Augmentation Techniques

Data pre-processing is an essential task in generating (quality) inputs of artificial intelligence and machine learning, especially when it comes to medical image data where the available data points are few. Zhang et al. (2023) hours that the pre-processing, such as normalization and resizing, was applied to normalize the input data and reduce bias in the model learning [11]. Resizing will make the image size consistent throughout the input images, and normalizing scales the pixel values in the same range, which will make training easy for the model.

Data augmentation is an important technique used to artificially increase small datasets, thus reducing overfitting and increasing generalization. The data augmentation methods such as random rotation, flipping, and zooming enhance the dataset diversity and reduce the likelihood of model overfitting to a small size of images [12]. These methods particularly benefit histopathological image analysis, with scarce annotated data being available.

2.5. Model Selection and Training

The selection of appropriate deep learning model is important for achieving better results in the discovery of oral cancer. While CNNs still dominate the scene, recent trends have made hybrid models, e.g., CNN-ViT combinations increasingly popular. Liu et al. (Vision Transformer (VT) in more complex tasks and highlighted their successful performance on medical image classification especially with large-scale data [13]. InceptionV3, a neural network, applies convolutional filters of various sizes, which allow it to learn fine-grained image features at different scales. Our research has revealed that introducing CNNs and ViTs can improve the performance (Liu & Zhang 2023). By taking advantage of their complementary strengths. [14]

Hybrid models which fuse CNNs with Vision Transformers or other structures manage to strike an optimal balance between local feature extraction and global context understanding. However, Warin and Suebnukarn (2024) showed that hybrid models always outperform standalone models regarding oral cancer detection problem [3]. This composition allows for the efficient handling of intricate structure in medical images, and important for accurate cancer detection.

2.6. Model Evaluation and Performance Metrics

The AI algorithms to detect the oral cancer should be evaluated by various performance measurements. The diagnostic performance of benign and malignant have also been evaluated through several measures including accuracy, precision, recall and f1-score. Liu et al. (2025) that ViTs can obtain better accuracy, precision and recall when the CNNs for the oral cancer diagnosis,

meaning that the development method for the VTIs can be taken as a useful complement for delegates classifying on this domain [15]. Liu & Zhang 2023) In comparison the trend of CNN zero models and Vit model, Vit method has stable F1-score and get better trade-off between precision and recall on relations classification of kinds of Malignant from benign (Liu and Zhang 2023) [16]

Another important evaluation measurement is the low AUC-ROC (Area Under the Receiver Operating Characteristic Curve), which assesses performance of the model using different decision thresholds. Zhang et al. (1721) have stressed the importance of AUC-ROC because it provides a more extensive evaluation of a model's performance, especially in medical fields where false positives and negatives may have significant consequences [17].

2.7. Challenges and Future Directions

However, despite the promising results of AI and ML models, several challenges remain. One of the main difficulties is the need for large, diverse and annotated datasets to train strong models. While data augmentation and synthetic data generation strategies improve model generalization, they cannot be a complete replacement for the requirement of high-quality annotated data of the target domain. AI model integration in clinical workflow remains difficult, particularly

With respect to user's confidence and real-time performance. Future studies should focus on improving model transparency, scalability, and interpretability, especially in clinical settings. While ViTs show strong performance, more optimization and hybrid models between CNNs and transformers may provide stronger results. Although ViTs are very effective, more optimization and hybrid models between CNNs, and transformers may yield better performance. Furthermore, expanding datasets, particularly via multi-center cooperation, will further enhance the robustness and generalization ability of AI models for oral cancer screening in various populations.

CHAPTER 3 METHODOLOGY

The methods section describes how machine learning models were used to enhance datasets which include anti-search pathology images or clinical images for oral cancer detection. The method is structured in a way, so it allows for rigid handling of data processing, model choosing and training, testing and deployment. The methodology follows the workflow chart.

3.1. Workflow Diagram

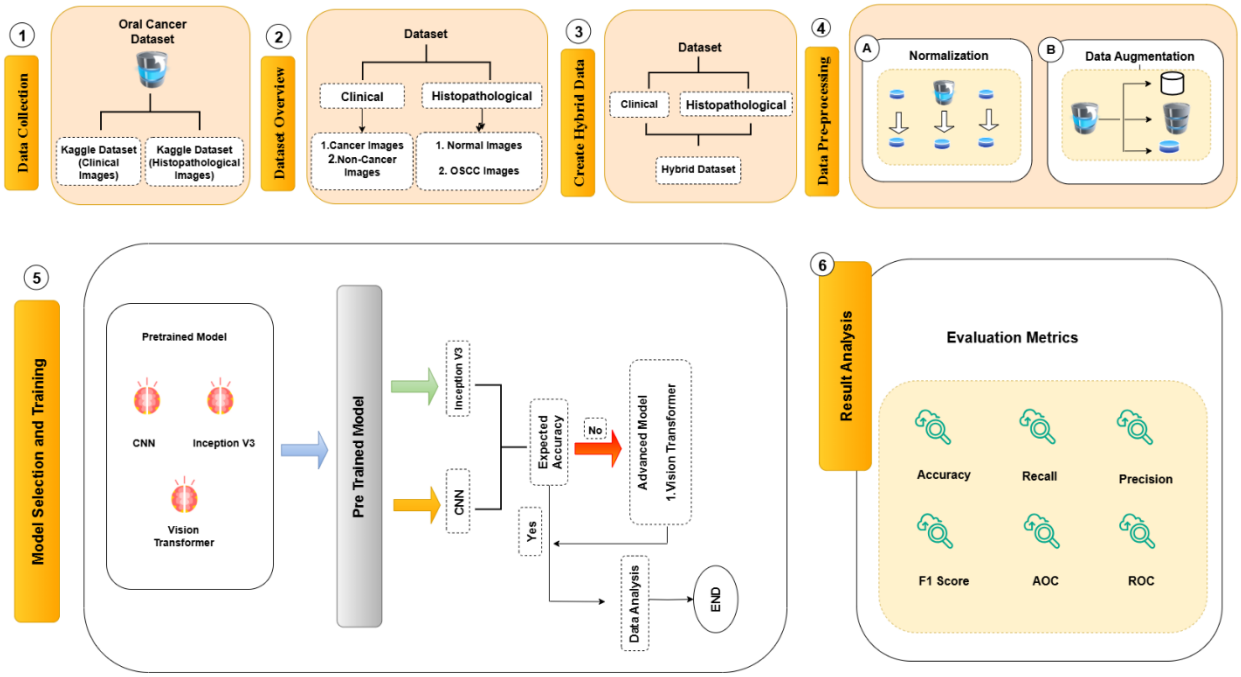

Figure 2: Workflow Diagram

3.2. Data Collection

3.2.1. Datasets

In this study, we utilized two publicly available datasets sourced from Kaggle:

1. Oral Histopathology Dataset: This dataset comprises 560 normal and cancerous tissue sample histopathological images. The dataset is categorized into two classes; 30% represents normal tissue, while 70% stands for oral squamous cell carcinoma (OSCC). Datasets are available under CC0: Public Domain which are ready for unrestricted use. The images were obtained from tissue sections in oral biopsy slides used to capture a high-

magnification observation of tissue characteristics

2. Oral Clinical Dataset: A total of 726 oral lesions clinical images were annotated as either cancerous or non-cancerous. The dataset comprises 65% cancerous and 45% non-cancerous lesions. Clinical images present a macroscopic appearance of oral lesions, usually acquired through either non-invasive visual inspection by healthcare providers. This is also an open dataset, like histopathology dataset, and is available for non-commercial use under a CC0: Public Domain license.

Both datasets were used to create a multi-source dataset for this study, combining clinical photographs and histopathology images to evaluate the performance of deep learning models across different data modalities.

3.2.2. Kaggle Dataset (Clinical Images)

The clinical images are collected from Kaggle Oral Cancer Dataset with cancerous and non-cancerous oral lesion. These images serve an important function in recognizing visual signs of oral cancer and are frequently one of the first physical findings that an examining clinician may notice.

Clinical Image Dataset

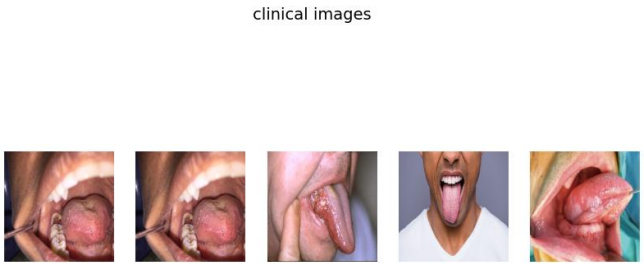

Figure 3: Presents representative clinical images from the Kaggle dataset

3.2.3. Kaggle Dataset (Histopathological Images)

The second set of images are histopathological images from Kaggle Oral Cancer Dataset. The images offer a high-resolution view of tissue from oral lesions obtained through biopsy. The dataset includes primary data and augmented data. The original set includes both Benign and Malignant lesions, The augmented data helps to artificially increase the training set by augmenting it through different transformations such as rotation, flipping, and zooming.

Histopathological Image Dataset

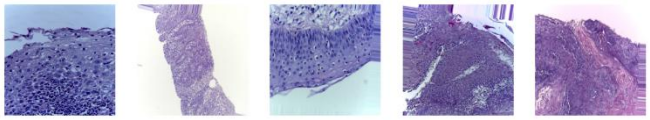

Figure 4: Presents representative histopathological images from the Kaggle dataset

3.2.4. Hybrid Dataset:

The clinical and the histopathological images from Kaggle dataset are concatenated to form the hybrid dataset. The hybrid dataset provides the complete set of features for the model to learn to identify clinical (visible) and microscopic (histopathological) signs of oral cancer. This combination model construction captures the macroscopic and microscopic characteristics in oral cancer and may enhance model efficacy.

3.2.5. Dataset Overview

The clinical images from the Kaggle dataset and the histopathological images from the Kaggle dataset are combined to create a hybrid dataset. The hybrid dataset offers a complete feature set for the model to learn, which allows it to detect visible (clinical images) and microscopic (histopathological images) signs of oral cancer. This dual approach to model development considers both the macroscopic and microscopic features of oral cancer improving model accuracy.

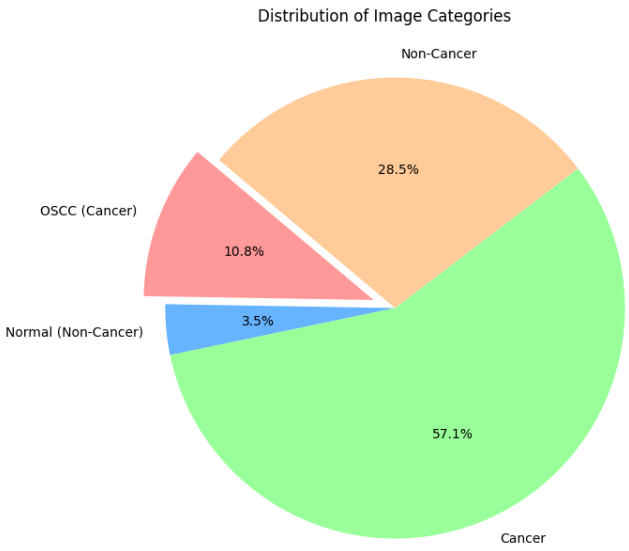

Figure 5: Data Distribution

Dataset	Content	Description
Clinical Images	Visual signs of oral cancer	Captures macroscopic features of lesions
Histopathological Images	Tissue-level cancer signs	Provides microscopic details of cancerous tissue.
Hybrid Dataset	Combination of both datasets	Integrates both clinical and histopathological data.

Table 1: Dataset Description

3.2.5. Data Splitting Details

The following table summarizes the data splitting details in percentage

Data Split	Percentage	Number of Samples
Training Data	80%	3504 images
Test Data	20%	876 images

Table 2: Data Splitting Details

3.3. Data Preprocessing and Integration

3.3.1. Image Preprocessing

The images are preprocessed for consistency and quality before they are input into the training model. The preprocessing steps include:

- **Resizing:** Resizing all images to be equally in size (224x224 pixels) as final input to our machine learning algorithms.

- **Normalization:** Normalizing pixel values between [0,1] by /255.0 (This is very important to keep in, so that models trains/learns and fit well without having an impact by scales of input data).

- **Data Augmentation:** Data augmentation was used to simulate an augmented dataset and to improve the generalization of the model. Moreover, the histological image dataset has far fewer training samples than the clinical image dataset, which may bring network overfitting. To overcome this, we followed the augmentation below:

    1. **Random Rotation**: Image rotation to a small degree to imitate various orientations of tissue samples.

    2. **Width and Height Shifting**: Shifting images randomly in the width and height dimensions to replicate slight changes in position.

    3. **Zooming**: Zooming in or out on images to simulate different distances from the sample.

    4. **Horizontal Flipping**: Flipping images horizontally to simulate mirrored views, as oral cancer lesions can appear on both sides of the mouth.

These augmentation techniques are designed to make the model more robust to small translations in the images. In medical imaging, such as oral cancer image-based prediction, it permits the model to generalize learning and not to memorize and then store the exact patterns which are potentially found only in the original training samples.

3.3.2. Data Integration

The Kaggle clinical and histopathological datasets are combined to form a hybrid dataset. Training on this hybrid data facilitates learning of features from clinical (e.g., visual signs of cancer) as well as histopathological (e.g., tissue structure and abnormalities) data. The binary class for each image is 0 for benign and 1 for malignant. The hybrid data set is then made ready to be trained by the model.

3.4. Model Selection and Training

3.4.1. Model Selection

We proposed several machine learning models for oral cancer detection, including classical models and advanced deep learning models:

1. Convolutional Neural Networks (CNNs): CNNs are considered as benchmark models for image classification as they have the capacity to inherently learn spatial hierarchies of features and patterns in image data by discovering the relevant features.

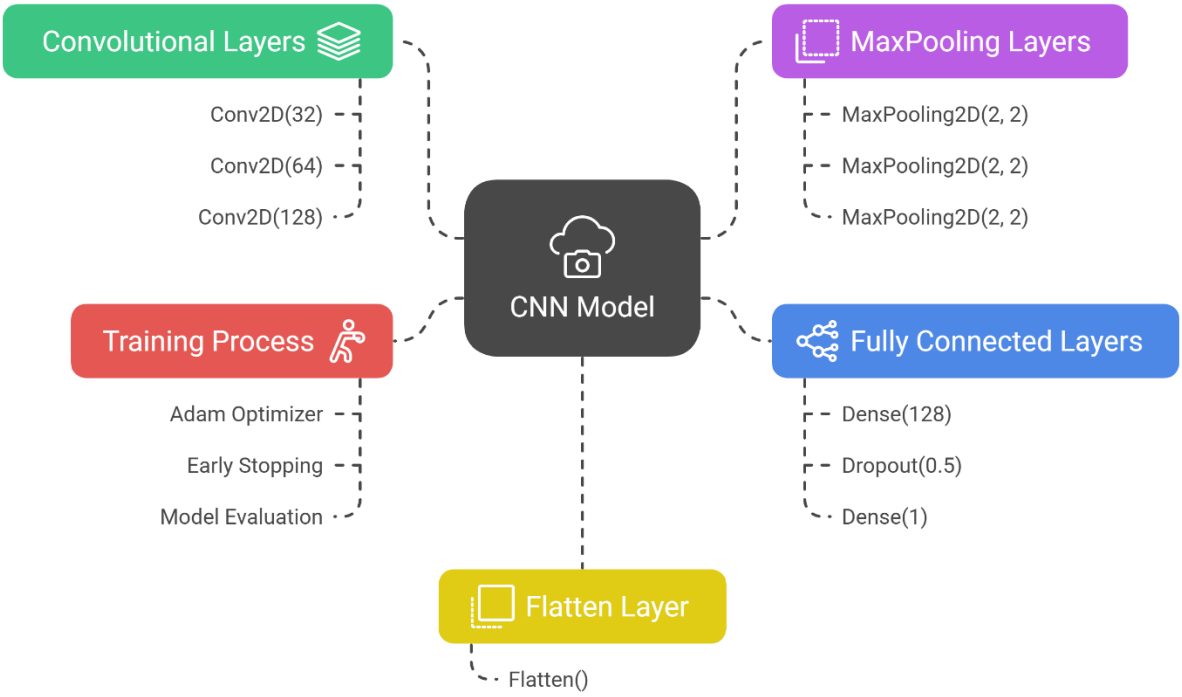

Figure 6: CNN Model Architecture and Training Process

We implemented baseline Convolutional Neural Network (CNN) architecture with several convolutional and pooling layers, and several fully connected layers for the final classification. The flow of this model can be seen in Figure 6, from extracting features using convolutional layers to using Adam optimizer for the training and finally, implementing early stopping.

2. Vision Transformer (ViT): A state-of-the-art design treating image patches as sequences and utilizing transformers for learning, demonstrated to deliver SOTA results on multiple image classification benchmarks.

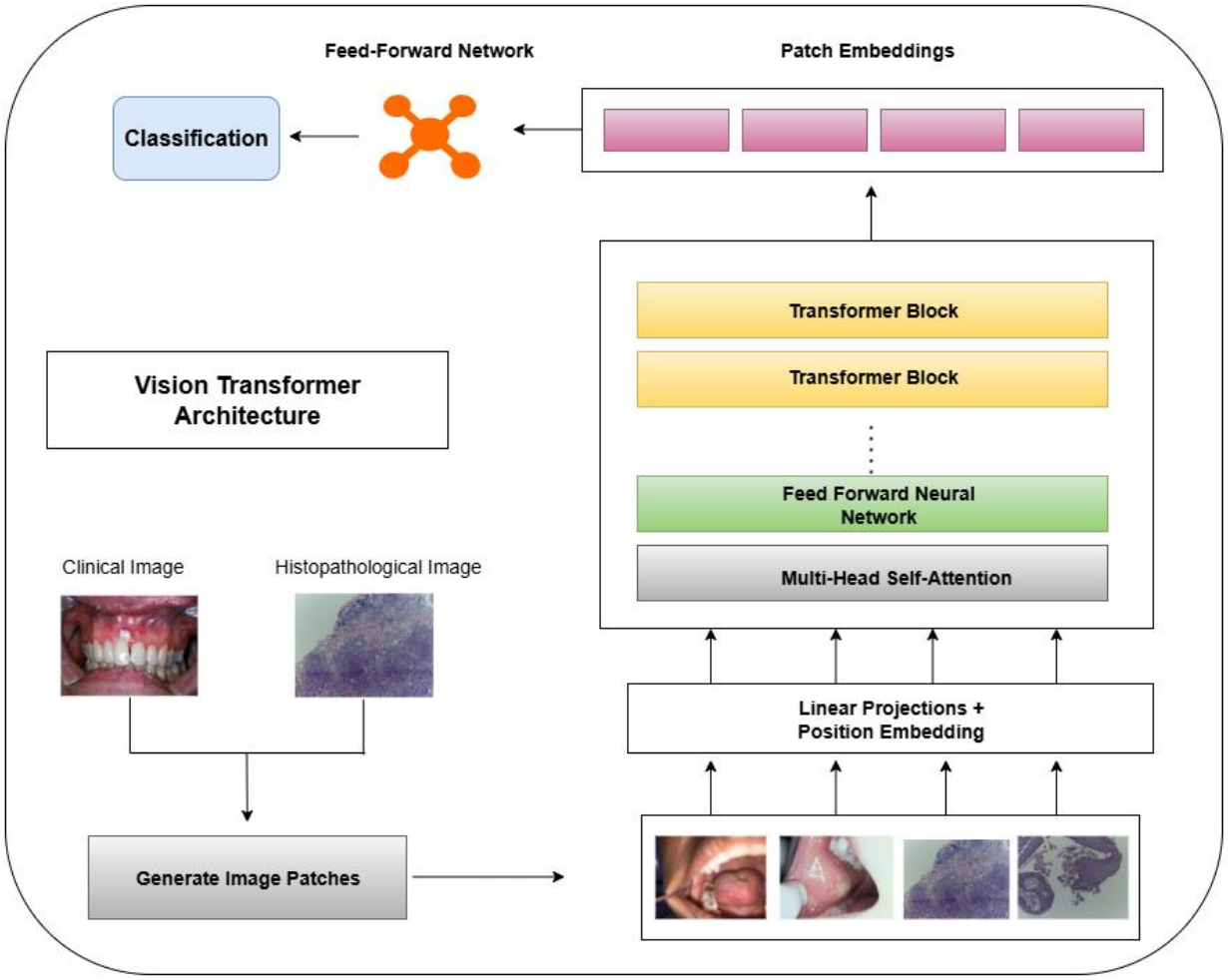

Figure 7: Vision Transformer (ViT) Architecture

The Vision Transformer (ViT) introduces a transformer-based approach to image classification, segmenting images into patches that are processed as sequences. This architecture excels at modeling long-range dependencies in image data, which is critical for differentiating subtle cancer features. The structured pipeline for preprocessing, dataset handling, training, and evaluation is presented in Figure 8.

3. Inception V3: Inception V3 employs multiple convolutional filters of different sizes within the same module, allowing it to capture features at various scales and improving performance in tasks involving intricate visual patterns.

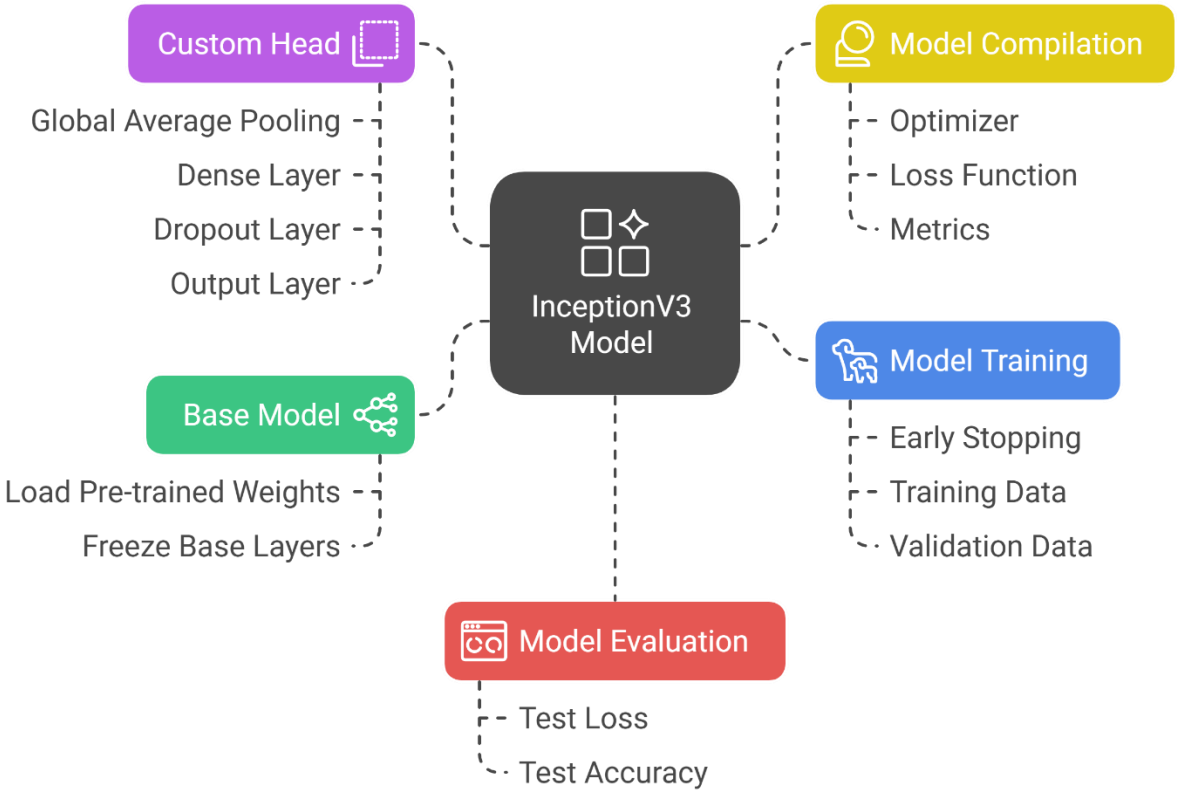

Figure 8: InceptionV3 Model Architecture and Training Workflow

InceptionV3 was leveraged to capture multi-scale visual features of oral lesions. By combining convolutional filters of different sizes within its modules, the model can recognize both fine-grained and large structural patterns. The training workflow, including the frozen base layers, custom classification head, and evaluation stages, is outlined in Figure 7.

3.4.2. Model Training

The selected models are trained on the hybrid dataset. A broad assortment of hyperparameters were experimentally modified all through cross-validation. This allowed those hyperparameters that most substantially impacted exhibition to be judiciously trimmed for every single model. The longest and most difficult period of preparation led to the choosing of the mannequin with the first-rate factual accuracy confirmed via a try of the information it had no longer but observed.

3.5. Model Evaluation

3.5.1. Accuracy and Loss

These models are tested based on the test dataset to see if they can identify the images correctly. The primary evaluation metric is accuracy, the percentage of predictions that were correct. In addition to accuracy, precision, recall and F1-score are also estimated among models to evaluate the differentiation performance between malignant and benign lesions.

3.5.2. Evaluation Metrics

To fully assess the performance of the models on oral cancer detection, we used some of the most widely adopted metrics in many classification tasks: accuracy, precision, recall, F1-score, and the ROC curve. Each of them offers valuable information about the performance of the model and its capacity for classification of malignant and benign lesions.

Accuracy: The proportion of correct predictions (both true positives and true negatives) out of all predictions. It serves as the overall measure of model performance. A higher accuracy indicates that the model is making more correct predictions overall.

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

Precision: The ratio of correctly predicted positive instances (true positives) to the total predicted positives (true positives + false positives). Precision is critical in situations where false positives (identifying a benign case as malignant) need to be minimized. A high precision indicates that the model makes fewer false positive errors.

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

Recall (Sensitivity): It is the number of true positive divided by the total number of true positive and the number of false negative. In a situation like this, where no positive instances (or cancer in this case) should be missed, recall would be a key. High recall means the model accurately preditcs majority of the positive ones.

$$\textbf{Recall} = \frac{\text{TP}}{TP + FN}$$

F1-Score: The harmonic mean of precision and recall, a single measure to balance both. The F1-score is especially relevant if we have imbalanced class distributions as it considers both false positives and false negatives. The higher F1-score, the better balanced between precision and recall.

$$\mathbf{F1-score} = \frac{2 \text{ x Precision x Recall}}{Precision + Recall}$$

Receiver Operating Characteristic (ROC) Curve: The ROC curve is a graphical representation of the model's ability to differentiate between classes at various thresholds. To do that, its graphing the True Positive Rate (Recall) against the False Positive Rate. AUC-ROC measures the model's ability in distinguishing positive instances from negative instances over all possible thresholds. The greater the AUC, the better the model is performing overall. In this study, we calculated the AUC of each model to represent the discriminating ability of the model between malignant and benign breast masses.

AUC-ROC: The Area Under the Curve (AUC) measures the entire two-dimensional area underneath the ROC curve. An AUC of 1.0 represents a perfect model, while an AUC of 0.5 indicates a model with no discriminatory ability (equivalent to random guessing).

$$AUC = \int_{\{0\}}^{\{1\}} TPR(FPR) dFPR$$

Here,

1. AUC of 1: Perfect model
2. AUC of 0.5: Random classifier
3. AUC closer to 1 indicates better model performance.

CHAPTER 4 RESULT AND DISCUSSION

In this section, we discuss the effectiveness of each of the models which include Vision Transformer (ViT), InceptionV3, and CNN on our hybrid clinical plus histopathological image dataset. We evaluate model performance based on several criteria like accuracy, loss, ROC curve, and confusion matrix. We also present implications from these results.

4.1. Model Performance Comparison

The table below shows the best validation and test accuracies that each of these models got:

Model	Highest Validation Accuracy	Highest Test Accuracy
Vision Transformer (VIT)	99.37%	98.86%
InceptionV3	98.09%	93.84%
CNN	92.89%	85.16%

Table 3: Model Performance Comparison

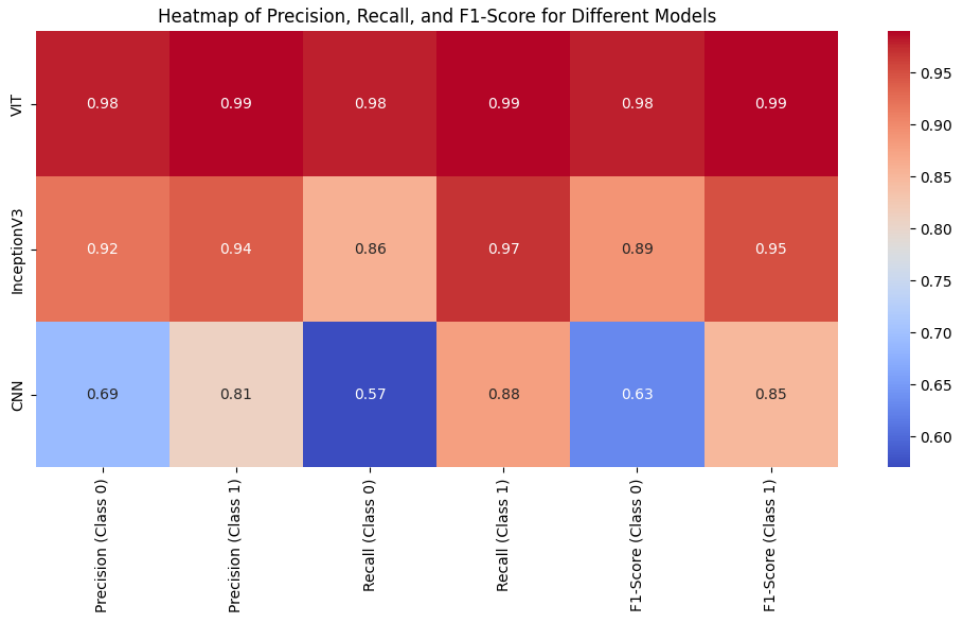

Figure 9: Shows performance comparison across CNN, InceptionV3, and ViT models based on validation and test accuracy.

4.2. Detailed Model Analysis

4.2.1. Vision Transformer (VIT)

The Vision Transformer (ViT) model performed the best by far in terms of validation accuracy at 99.37% and test accuracy at 98.86%. We know ViT did exceptionally well on image data, and it is especially great when trained with larger datasets having transformer-based architecture. In addition to this, the attention mechanism in ViT allows the model to pay attention to good parts of image important for extracting small patterns present in medical imaging data.

Confusion Matrix: The confusion matrix for the ViT model provides a view on the performance of classification. It is an indication that the model successfully distinguished the majority of malignant and benign cases, there are very less False Positives and False Negatives, thus it can be considered as a good classifier for oral cancer detection.

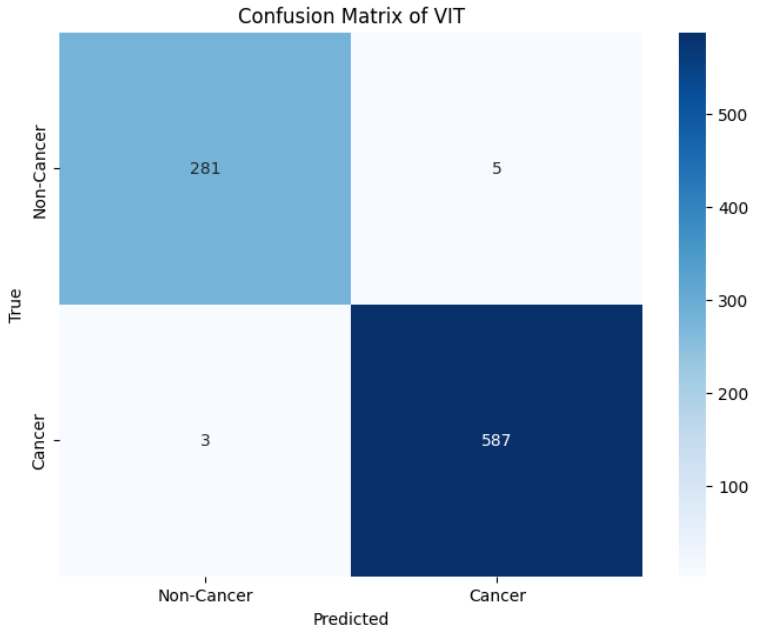

Figure 10: Confusion Matrix of VIT Model

Accuracy vs. Validation Accuracy: ViT predicted with 99.37% validation accuracy and 98.86% test accuracy. The curve of the accuracy illustrates the model had fine performance on training as well as validation data and there is a small gap between them, meaning it could be a superb generalization.

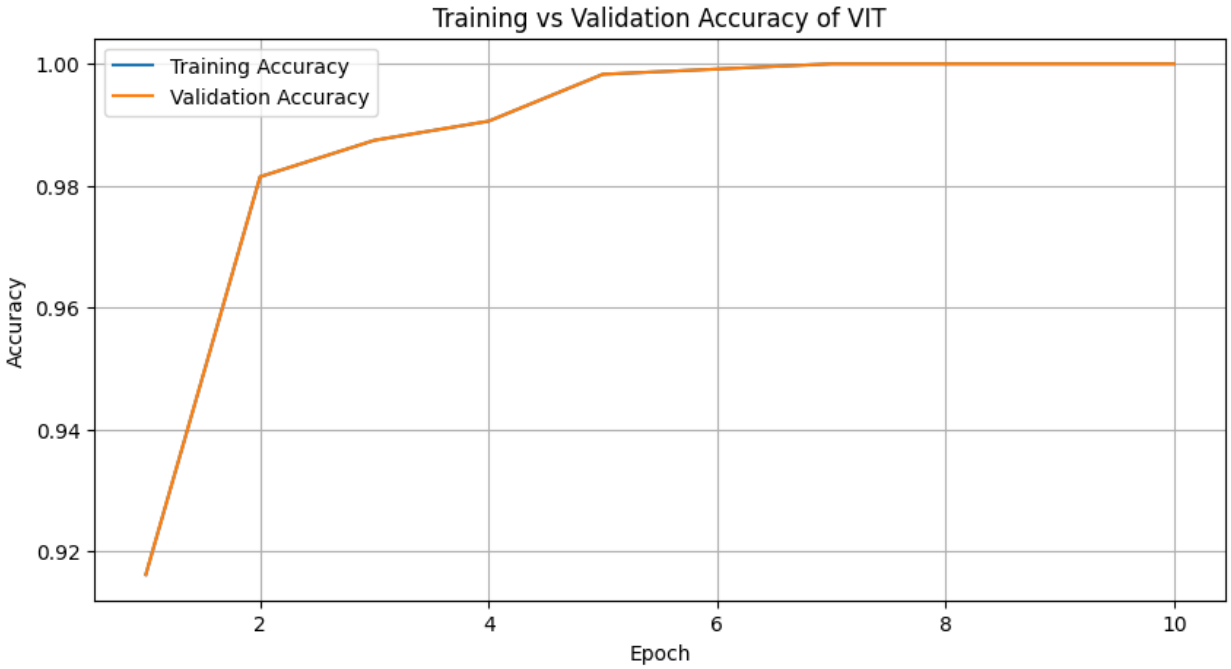

Figure 11: Accuracy vs. Validation Accuracy of VIT Model

Loss vs. Validation Loss: The loss curve shows the model fitted the training data well and the validation loss didn't fluctuate much either, showing no big lean towards overfitting. This suggests that the model not only learned to train it well, but it also generalizes well.

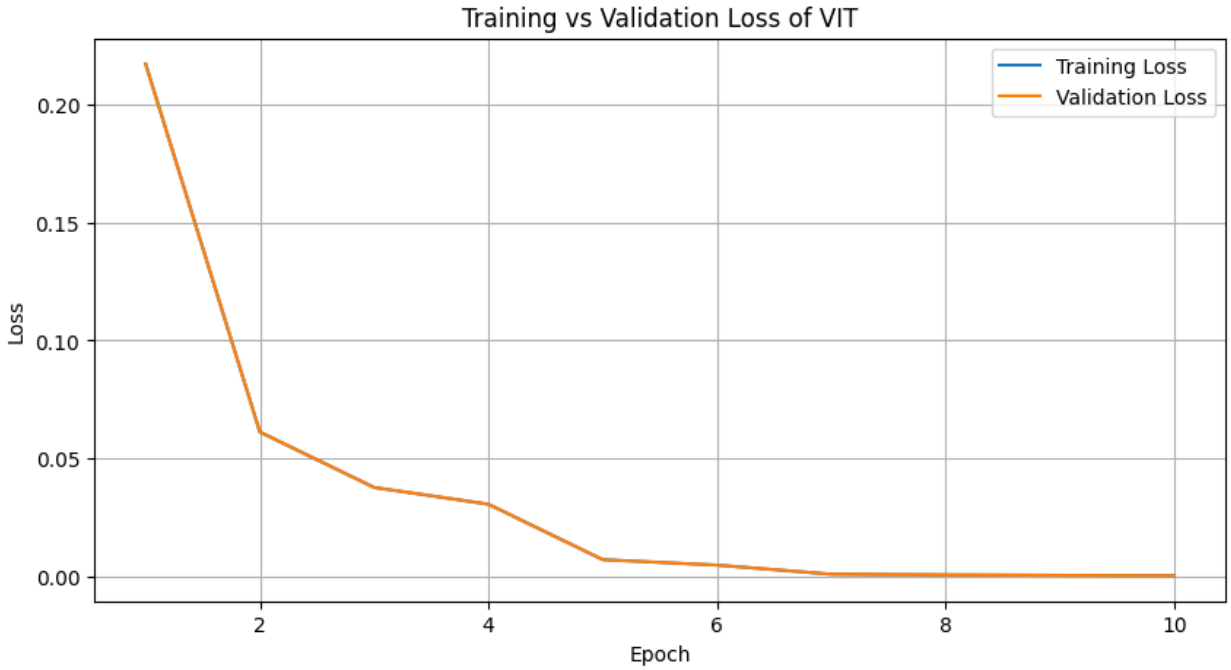

Figure 12: Loss vs. Validation Loss of VIT Model

ROC Curve: The ROC curve for the ViT model produced an AUC of 1, which is a very high AUC value, and demonstrates excellent model performance in separating the malignant from the non-malignant images. This curve is a demonstration of the model's ability to predict with confidence at different threshold levels: it is the measure of a good fit in real-world conditions.

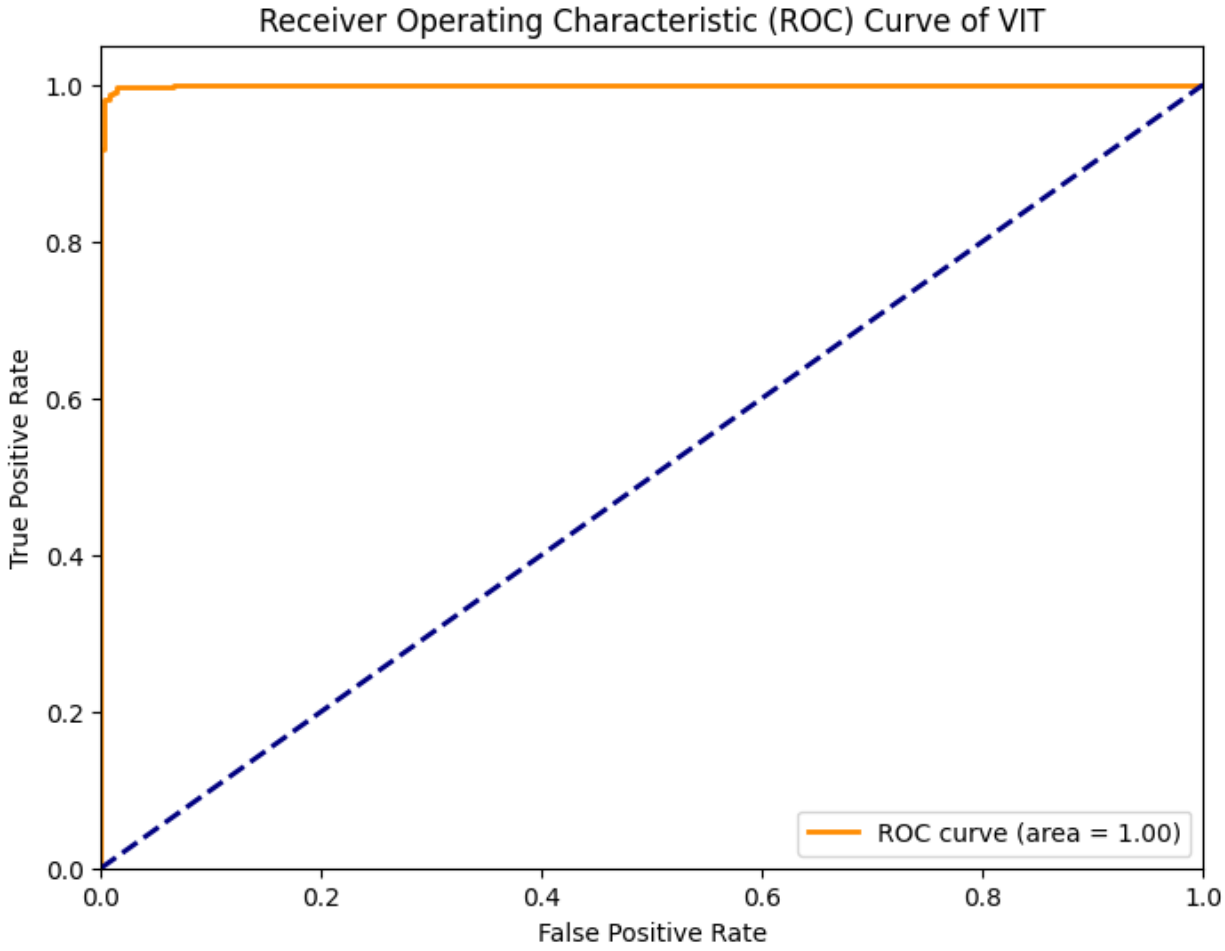

Figure 13: ROC Curve of VIT Model

4.2.2. InceptionV3

The testing accuracy of the inceptionV3 model was 93.84%, and the validation accuracy was 98.09%. InceptionV3 uses several filter sizes to construct the architecture, and thus captures a large variety of features from input. This model excels at processing complex image data.

Confusion Matrix: The confusion matrix for InceptionV3 suggests good performance albeit at a greater number of false positives and negatives than ViT. It appears therefore that the model is deft, yet a few benign lesions are wrongly classified as malignant and vice versa.

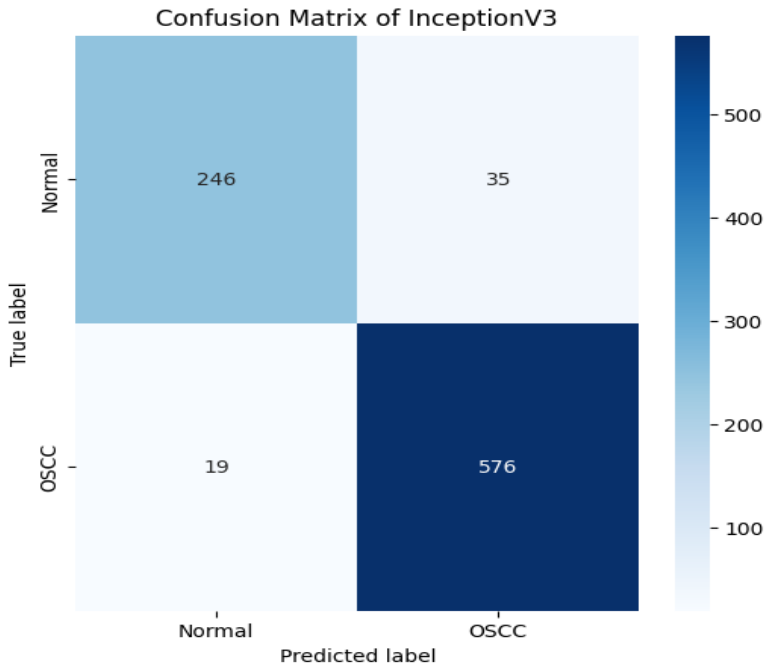

Figure 14: Confusion Matrix of Inception V3 Model

Accuracy vs. Validation Accuracy: InceptionV3 obtained a validation accuracy of 98.09% and a test accuracy of 93.84%. It is a sign of very mild overfitting as accuracy on training data was slightly higher.

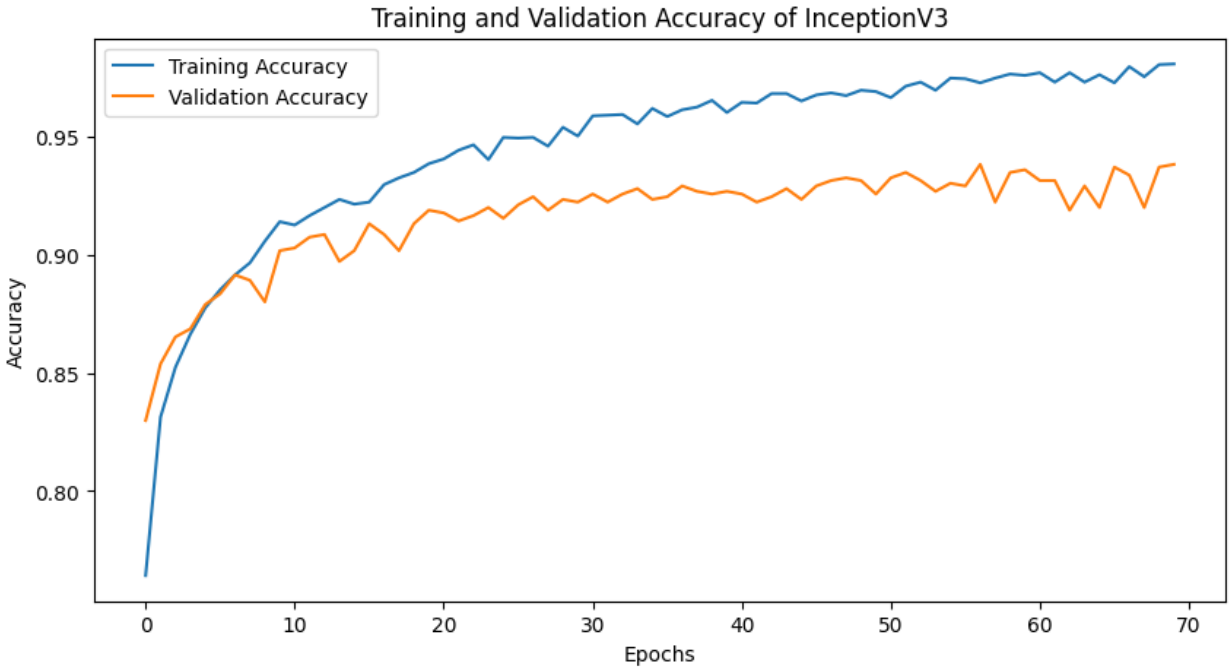

Figure 15: Accuracy vs. Validation Accuracy of InceptionV3

Loss vs. Validation Loss: From the loss curve, the InceptionV3 had fluctuation in validation loss, which suggests that it could be relatively impacted by the variances in the test data. Yet, the model converged and performed acceptably overall.

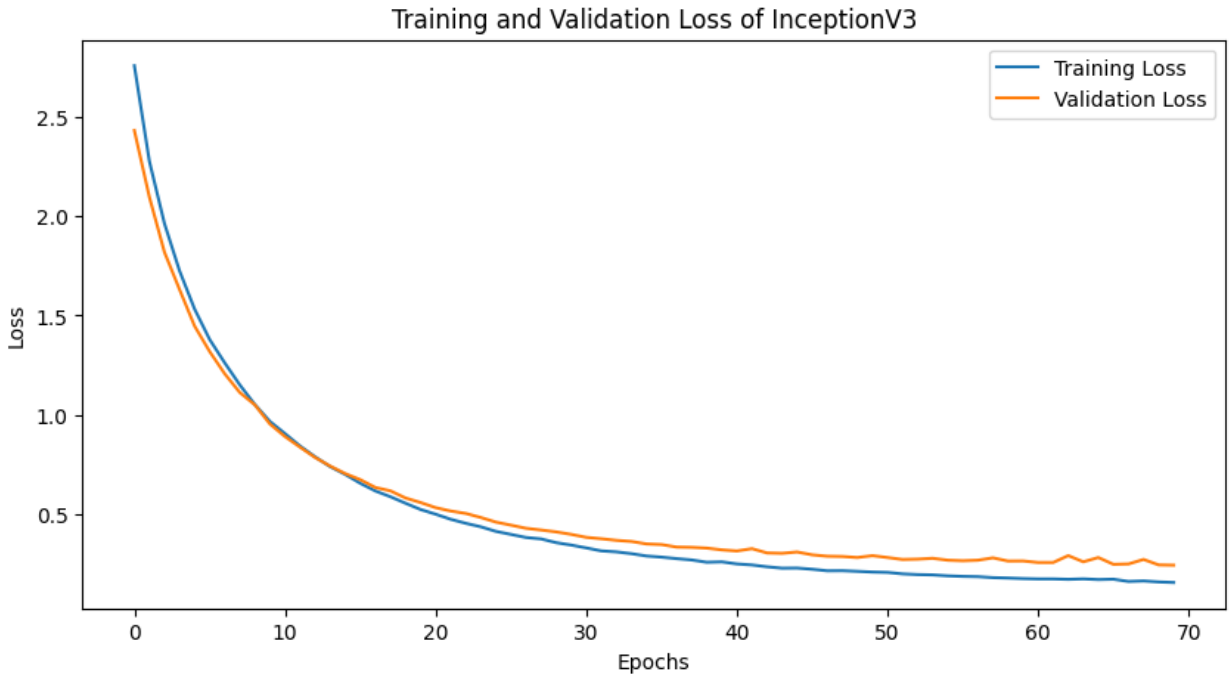

Figure 16: Loss vs. Validation Loss of InceptionV3

ROC Curve: The ROC curve for InceptionV3 shows a decent AUC of 0.98, indicating that the model is still effective in distinguishing between malignant and benign lesions but is not as robust as the ViT model.

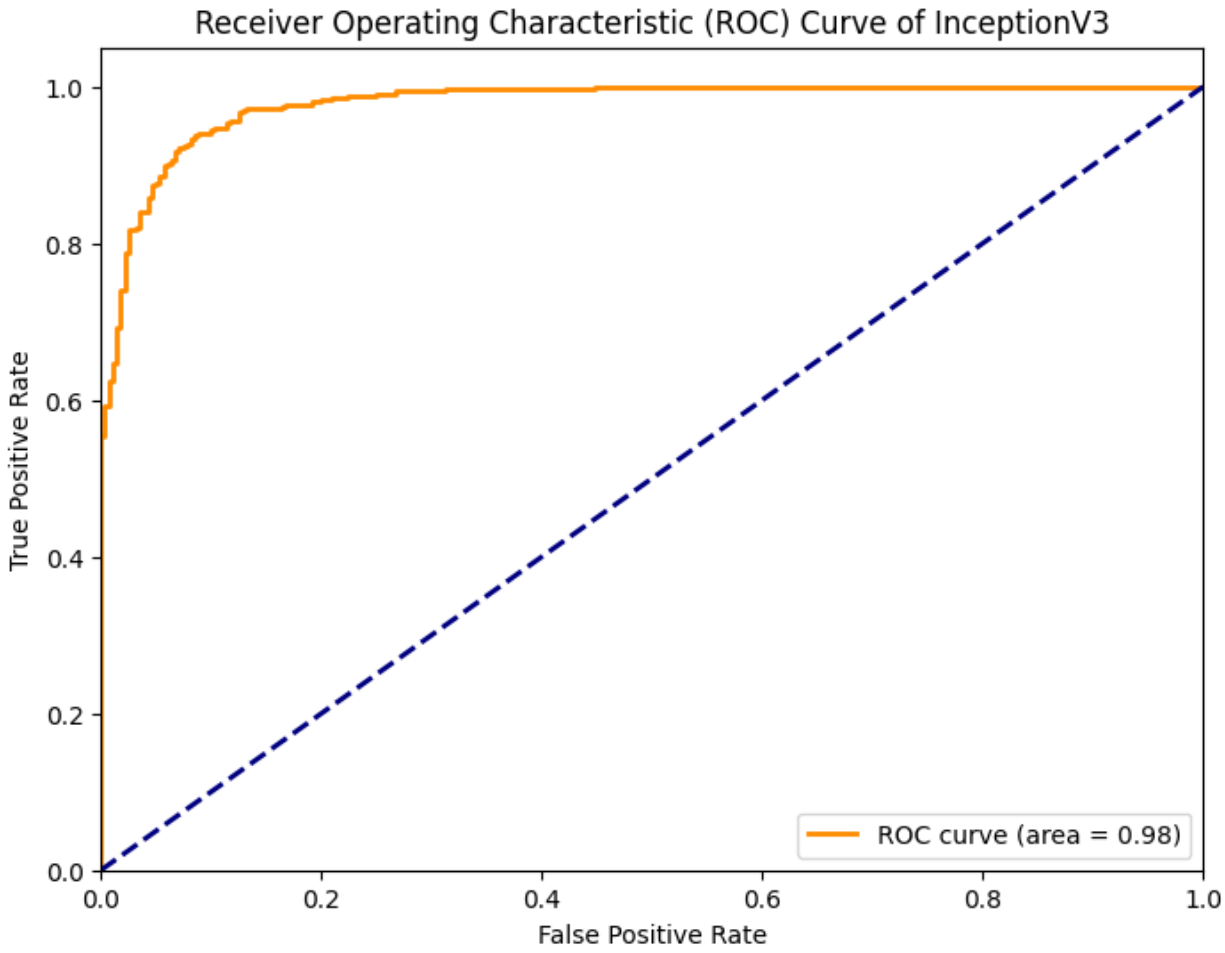

Figure 17: ROC Curve of InceptionV3

4.2.3. CNN (Convolutional Neural Network)

The CNN model achieved the highest validation accuracy of 92.89% and a test accuracy of 85.16%. Convolutional Neural Networks (CNNs) have received immense popularity due to their ability to learn spatial hierarchies between pixels of images through a series of words and layers of learned filters which make them widely used for image classification tasks.

Confusion Matrix: The CNN model performed less than ViT and InceptionV3. The confusion matrix reveals that of the two networks the CNN exhibited a larger number of false positives and false negatives, implying that it encountered difficulty in distinguishing well between malignant and benign cases, particularly in complex cases.

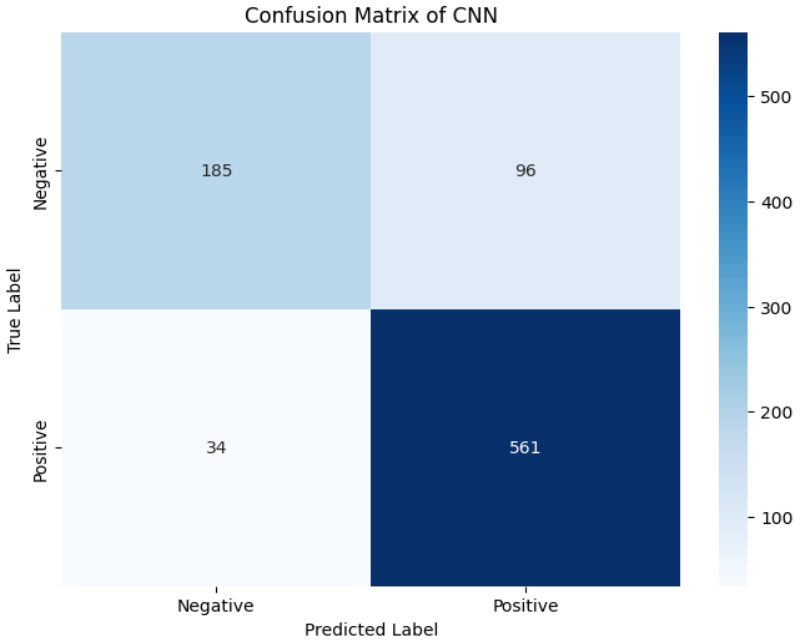

Figure 18: Confusion Matrix of CNN Model

Accuracy vs. Validation Accuracy: CNN achieved a validation accuracy of 92.89% and test accuracy of 85.16%. The accuracy curve shows a notable gap between training and validation performance, suggesting that the model may have overfitted the training data, leading to lower performance on unseen data.

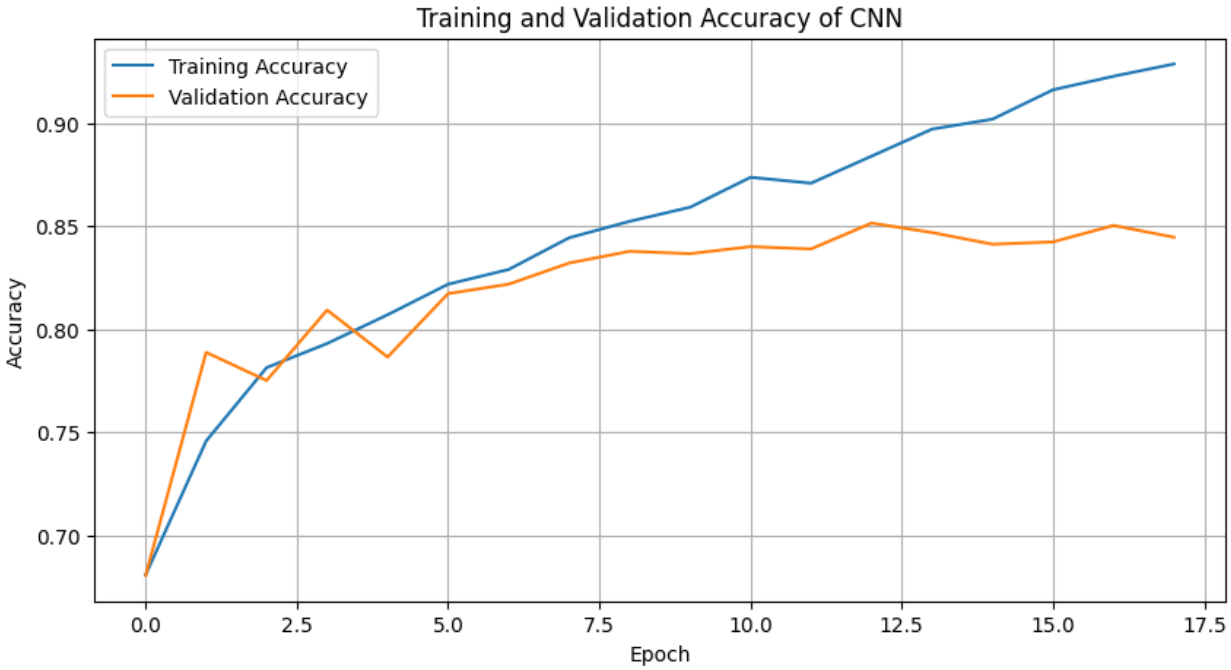

Figure 19: Accuracy vs. Validation Accuracy of CNN Model

Loss vs. Validation Loss: The loss curves for CNN show that while the training loss decreased steadily, the validation loss was higher, which further emphasizes the model's difficulty in generalizing the validation set.

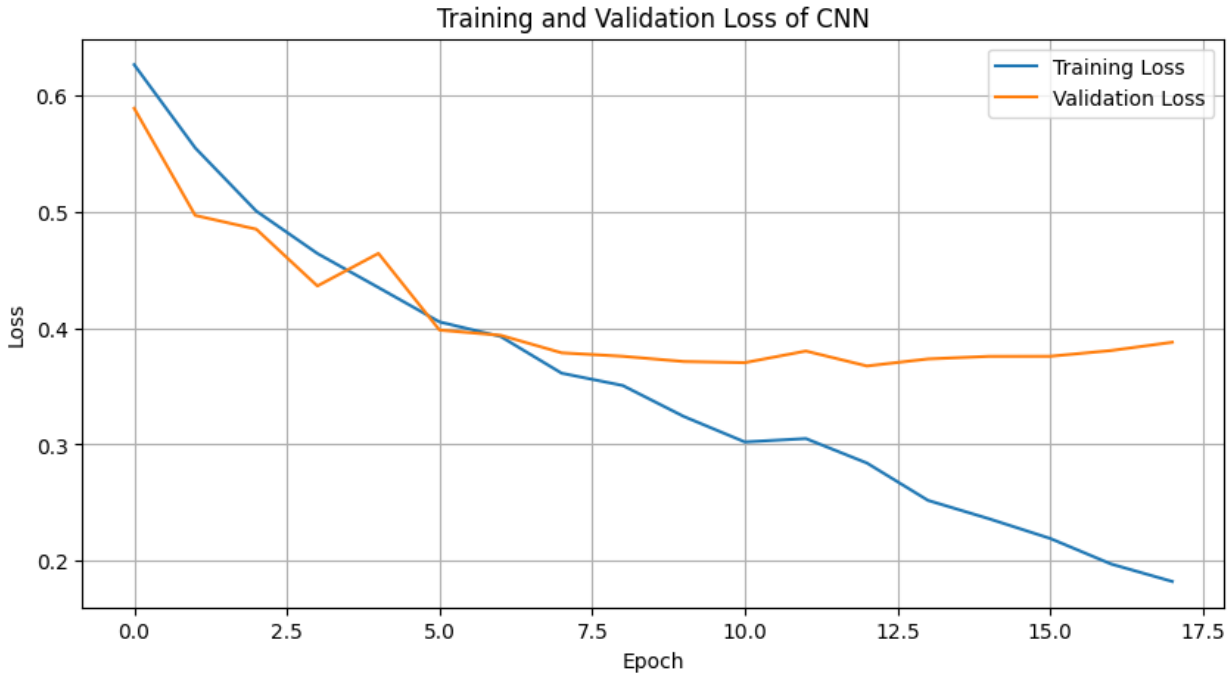

Figure 20: Loss vs. Validation Loss of CNN Model

ROC Curve: The ROC curve for CNN shows a lower AUC of 0.90, indicating that the model's ability to discriminate between malignant and benign cases is less reliable compared to ViT and InceptionV3. This suggests that CNN may not be the best option for oral cancer detection in this case.

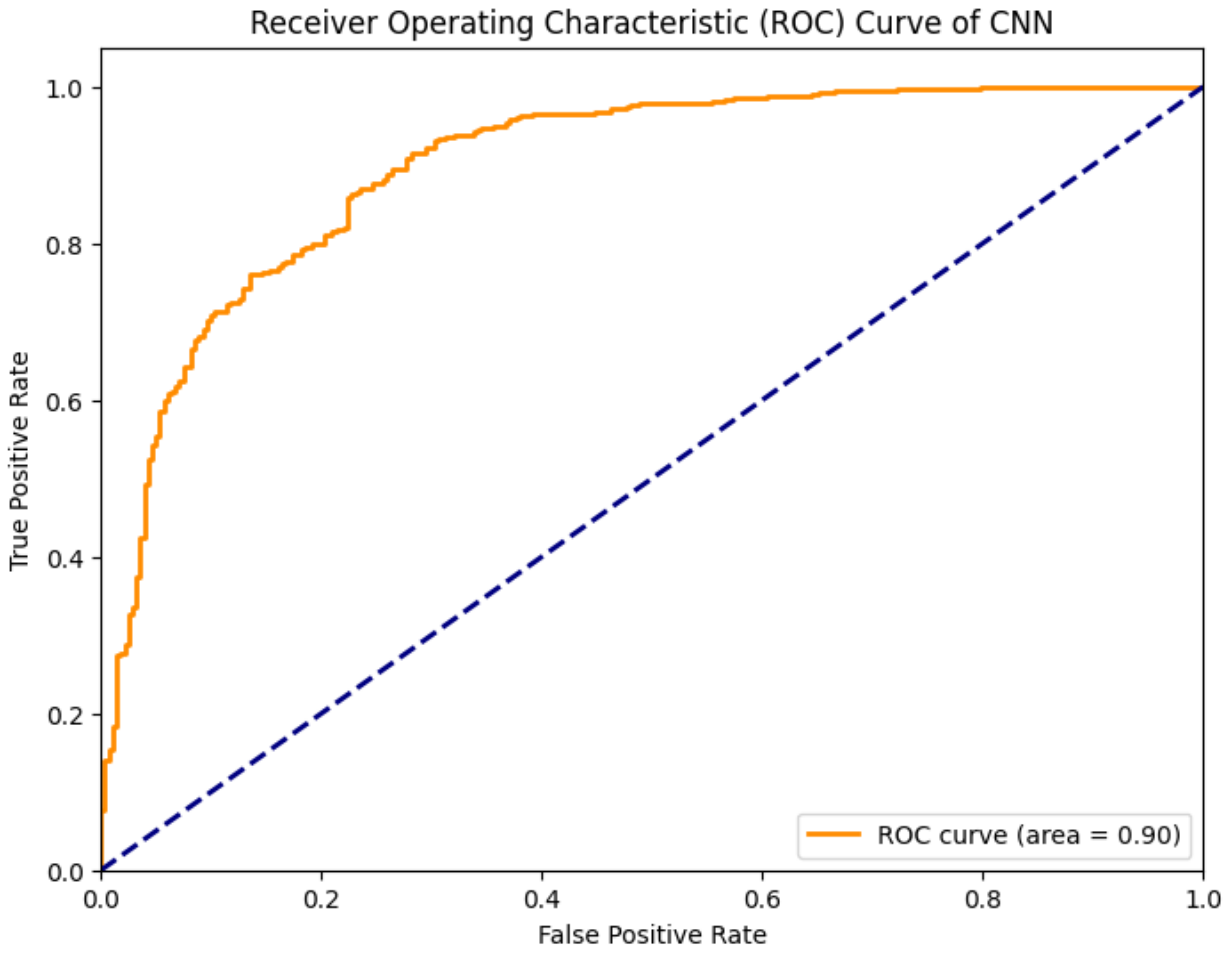

Figure 21: ROC Curve of CNN Model

4.3. Discussion

The results from each model highlight both the strengths and limitations of each approach:

- **ViT Model:** ViT model was strong across the board in all measures, ViT model was able to distinguish malignant/benign lesions. Near even magnitude training and validation accuracies are indicative of strong generalization and low overfitting as curves indicate. This is a model that seems eminently applicable to the clinic.

- **InceptionV3 Model**: InceptionV3 model achieved statistically comparable performance but the accuracy and AUC were lower than that of ViT. Slight overfitting on the loss curves and confusion matrix having higher false positives and false negatives also means that the model can be improved by more fine tuning or training examples.

- **CNN Model:** The CNN was the most overfitted model with the highest differences between training and validation and worst performance. Its lower AUC and that its weights

matrix really didn’t hint it being capable of lead me to believe that lower complexity medical imaging would still perform better especially since it couldn’t do much for such complex medical imaging tasks better than something more complicated like the ViT or Inception V3 could handle complexity wise. Although CNN can work well on simpler images, it is not enough for the details of oral cancer.

4.4. Key Insights

- **ViT's Superiority:** The performance of Vision Transformer (ViT) architecture was better on all the metrics (accuracy, loss curves, and ROC AUC). Thanks to the power of self-attention mechanisms to grasp long-range dependencies, and thus global context, the proposed architecture has also a particular advantage when it comes to medical image classification.

- **InceptionV3's Strengths and Weaknesses:** InceptionV3 had a mediocre performance but (overfit) a little, so it may be potentially promising for further tuning. Its ability to handle complex patterns in images makes it a valuable alternative and worse than ViT for this use case.

- **CNN's Limitations:** The CNN architect that performed well for precise classification of images could not handle the complexity presented by the medical images. Its performance in this study suggests that more advanced models like ViT and InceptionV3 should be used in medical image analysis.

CHAPTER 5 CONCLUSION AND FUTURE WORK

The present study primarily focuses on the convolutional neural networks (CNNs), InceptionV3, and vision transformers (ViTs) models implemented for the early detection of oral cancer based on clinical and histopathological image sets. According to the study, more widespread implementation of AI in the diagnosis of oral cancer could remove many of the limitations of conventional methods and enable patients to receive a more successful, comfortable, and timely diagnosis. It is interesting to note that the ViT model is significantly superior to CNN and InceptionV3 in terms of experiment and validation accuracy, which also proved it's efficient in the high-level job of medical imaging image classification.

5.1. Finding

The discoveries of this investigation emphasize the excellent results of oral cancer detection per use of multisource data on the Vision Transformer model. The test accuracy of the ViT model clocked in at 98.86% vs 100% for InceptionV3 and 81.15% for CNN. The findings underline the importance of integrating clinical and histopathological information which increases the model detection ability on both macro- and microscopic oral cancer signs. Second, other sophisticated preprocessing approaches, such as normalization and data augmentation, were also really important to boost the model performance and reduce the overfitting, particularly when dealing with limited data sets.

5.2 Future Work and Scope

Despite the results of the study being promising, there are some tracks of future development and further improvements to work on.

5.2.1. Model Performance Improvement

The ViT model has been quite impressive so far, but there is always room for improvement, especially in the real-time diagnostic. In the future, other advanced techniques, such as the transfer learning, fine tuning, and multitask learning, can be used to train models, which can significantly improve the performance of the model. CNNs + transformer = if we can create a hybrid model that maintains the strengths of each (of CNN and transformers) then we will do still better for complicated medical imaging tasks.

5.2.2. Expansion of the Dataset

So, there is a further need to augment more into the dataset to broaden the scope of this model.

That could mean acquiring larger and more varied data sets, such as by combining images from multiple hospitals or multiple clinical trials. This bias can be attenuated by including larger and more demographically diverse (age, ethnicities) patient populations (for better general performance of the model and thus better over-all performance for all diagnoses).

5.2.3. Real-Time Deployment in Clinical Settings

For real-time deployment of the AI driven diagnostic models in clinics the live testing of these models in real-world clinical environments is necessary. Performance of computing must be further developed; models are expected to run swiftly even on mediocre computers with low computing ability. Additionally, they emphasize that there is a strong demand for a clinical validation study in order to validate the functionality (safety and efficacy) of Ai- based OC detection system in clinical settings.

5.2.4. Explainable and Interpretability

The interpretability of AI models is essential as these models play a growing role in clinical judgement. Further research should focus on improving the explainable AI (XAI) tools such as Grad-CAM, SHAP and LIME to make clear to clinicians the reasons why a model has made a certain decision. They will also cultivate confidence and faith in AI systems which are arguably a barrier towards clinical adoption. The idea is that we should have explainable AI and clinicians can take an informed decision on the basis of what the AI says.

5.3. Concluding Remarks

In conclusion, this study proposes that using AI, machine learning models can transform the process of early detection of oral cancer. By linking photographic data to clinical and histopathological data, this work provides the groundwork to build more robust and reliable AI based diagnostic models. These results represent an optimistic future for vision transformers and seem like the next step where we can consistently increase model performance but are based on a model that are ready to be used inside clinical pipelines to help push early detection and treatment of cancer with AI. A line of research to pursue next in this scenario is that, even if a lot of progress has already been made, we got on-going research and development to meet to reach the ultimate potential of AI in healthcare.

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