EARLY DETECTION AND CLASSIFICATION OF ORAL LESIONS USING DEEP LEARNING

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ABSTRACT

Oral cancer poses a significant global health challenge, with India bearing a disproportionate burden, evidenced by over 48,000 annual deaths attributed to the disease. Addressing this issue requires innovative approaches to improve early detection and classification of oral lesions, ultimately enhancing patient outcomes and reducing mortality rates. This project aims to revolutionize oral healthcare by leveraging deep learning techniques to promptly detect and classify oral lesions. Early detection of oral lesions is critical for timely intervention and improved prognosis, particularly in cases of potential malignancy. To achieve this, we utilize a comprehensive dataset comprising diverse oral images, including normal cases, lesions, and malignant conditions. Our deep learning model, based on Convolutional Neural Networks (CNN), is trained and fine-tuned using both SqueezeNet and ConvNet architectures. Through rigorous data augmentation and intensive training, the CNN model learns to accurately identify and categorize oral lesions, while also estimating the probability of tumor presence within a given dataset, thus aiding in lesion type determination. By automating the identification of potentially malignant oral lesions, our project aims to enable cost-effective and early diagnosis of oral cancer. We envision the development of a user-friendly interface that empowers clinicians to input patient data and oral images, facilitating real-time feedback and streamlining the oral lesion diagnosis process. Our approach holds promise for enhancing oral healthcare delivery, potentially saving lives through timely intervention and improved diagnostic accuracy.

Keyword: - *Oral Cancer, Neural Network, Deep learning, Squeezenet*

1. INTRODUCTION

Oral cancer poses a substantial public health challenge on a global scale, particularly in countries like India, where it accounts for over 48,000 deaths annually. This alarming figure underscores the immediate necessity for effective measures to combat the disease and enhance patient outcomes. Early detection emerges as a critical factor in addressing this challenge, as timely intervention can markedly improve treatment effectiveness and decrease mortality rates linked to oral cancer. This project implies a novel approach for the early diagnosis and detection of one of the leading diseases, cancer in most sensory body organ i.e., mouth. In addition to this, deep neural networks are used to build automated systems, where complex patterns are derived to track with this difficult task. In light of this urgent healthcare issue, our project aims to transform oral healthcare by harnessing the capabilities of deep learning technology for the early detection and classification of oral lesions. Through the utilization of advanced computational methods, specifically Convolutional Neural Networks (CNN) and SqueezeNet architecture, we strive to develop a robust and precise system capable of automatically identifying and categorizing oral lesions.

The importance of early identification of oral lesions cannot be overstated, as it serves as a vital indicator of various oral diseases, including potentially malignant conditions like oral cancer. By leveraging a comprehensive dataset comprising a diverse array of oral images, encompassing normal cases, benign lesions, and malignant conditions, our deep learning model will be trained and optimized to discern subtle patterns and features indicative of oral pathology. Ultimately, our project aims to offer a practical solution for clinicians and healthcare professionals through the provision of a user-friendly interface that streamlines and enhances the efficiency of oral lesion diagnosis. By facilitating early detection and intervention, our proposed system holds the potential to significantly enhance patient outcomes, decrease mortality rates, and alleviate the burden of oral cancer on individuals and healthcare systems alike.

1.1 Motivation

The development of an oral cancer detection system is driven by a profound commitment to addressing pressing healthcare challenges and enhancing patient outcomes. By facilitating early detection, this system holds the potential to significantly improve survival rates among individuals diagnosed with oral cancer. This increased accessibility not only enhances patient outcomes but also alleviates the financial strain on healthcare systems by enabling less invasive and costly treatments compared to interventions at later stages of the disease. Moreover, the creation of such a system represents the convergence of healthcare and technology, fostering innovation and advancements in fields such as artificial intelligence, machine learning, and medical imaging. Its implementation aligns with ethical principles aimed at promoting health equity, reducing disparities, and ensuring equitable access to high-quality healthcare for all individuals. Finally, the main motivation of the project is developing an oral cancer detection system embodies a collective dedication to leveraging technology for the betterment of public health, with the overarching objective of saving lives and enhancing the health and well-being of communities worldwide.

1.2 Objective

The objective of this project is to develop an automated system for the early detection and classification of oral lesions, with a primary focus on identifying potential signs of oral cancer. Leveraging deep learning techniques, including Convolutional Neural Networks (CNN) and SqueezeNet architecture, the system aims to analyze oral images and accurately categorize lesions as normal, benign, or malignant. By training the model on a comprehensive dataset of oral images and optimizing transfer learning approaches, the project seeks to improve the accuracy and efficiency of oral cancer detection. The ultimate goal is to improve patient outcomes by enabling timely intervention and treatment, thereby increasing survival rates and reducing the burden of oral cancer.

2. LITERATURE SURVEY

2.1 Related Work

N. Haron et al. [1] in the year 2017 investigated the use of deep learning techniques for oral cancer detection, focusing on the application of CNN architectures. The researchers achieved promising results in accurately identifying oral lesions from imaging data, highlighting the potential of deep learning in enhancing diagnostic accuracy. Automated Detection and Classification of Oral Lesions using Deep Learning by Roshan alex welikala et al. [2] in the year 2020 explored the use of deep learning techniques, particularly CNN and ResNet, for automating the detection and classification of oral lesions. The authors presented a comprehensive analysis of different CNN architectures and evaluation metrics, demonstrating promising results in improving diagnostic accuracy and efficiency. Padmini Pragna et al. [3] in the year 2019 conducted a comparative analysis of health alert for oral cancer detection. Their findings revealed the superiority of health issues in oral cancer which have to be cured quicky suggesting its potential for advancing oral cancer diagnostic systems. R. Krishnan et al. [4] in the year 2012 investigated the role of image preprocessing techniques in enhancing the performance of oral cancer detection. By applying hybrid feature extraction paradigm image enhancement and noise reduction methods in histopathological images, they achieved significant improvements in model robustness and classification accuracy, highlighting the importance of preprocessing in optimizing model performance. Smith et al.'s [5] paper in 2022 focused on the classification of oral lesions using transfer learning techniques using comprehensive datasets. By fine-tuning pre-trained CNN models on oral pathology datasets, the authors achieved competitive classification accuracy for distinguishing between normal tissues, benign lesions, and malignant tumors. Their findings underscored the effectiveness of transfer learning in leveraging pre-existing knowledge for improved model performance in oral cancer detection tasks. Sharma et al.'s [6] paper which was published in 2019 proposed a novel deep learning framework incorporating both CNN and recurrent neural networks (RNN) for the detection and segmentation of oral lesions from medical images. The hybrid architecture demonstrated superior performance in accurately delineating lesion boundaries and classifying oral pathology cases compared to traditional CNN-based approaches. This study highlighted the potential of combining different neural network architectures to enhance the overall accuracy and robustness of oral cancer detection systems.

2.2 Existing Model Overview

The existing model is developed using ResNet architecture and employs convolutional layers, along with features facilitating the use of higher learning rates to accelerate the learning process. This architecture model that is shown in the Fig-1 is trained on a large dataset of oral images, annotated with ground truth labels indicating the presence or absence of oral lesions. Through an iterative training process, the model learns to extract discriminative features from the input images and make accurate predictions regarding the presence and type of oral lesions. The training process involves optimizing the model parameters to minimize the difference between predicted and actual labels, typically using techniques such as backpropagation and stochastic gradient descent. The model functions in two stages first, a detector network identifies potential lesions within the image and then, a separate classifier network analyzes the detected region, categorizing it as benign, potentially malignant (OPMD), or cancerous (carcinoma). This two-stage approach allows for screening both the presence and the risk level of lesions

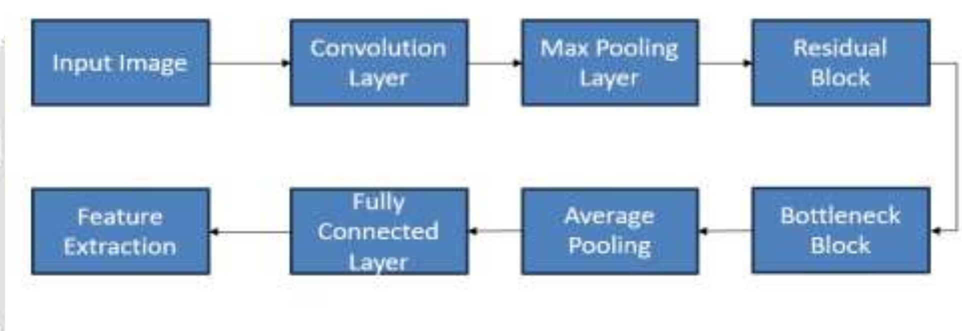

Fig-1: Architecture of the Existing model

2.3 Drawbacks of Existing Model

The existing model exhibits several drawbacks one significant drawback lies in the increased complexity introduced by ResNet's skip connections, which augment the model architecture, leading to a proliferation of parameters and heightened computational requirements. The presence of skip connections in ResNet architectures complicates interpretability, as they may obscure the underlying feature hierarchies and decision-making processes of the model. Particularly in deeper ResNet variants with numerous residual blocks, this complexity becomes daunting, making these models arduous to train and deploy, especially on devices with limited computational resources. ResNet architectures are prone to overfitting, particularly when trained on small datasets or lacking sufficient regularization techniques. The abundance of parameters in deep models increases the risk of overfitting to the training data, resulting in diminished generalization performance on unseen data. Additionally, training deep ResNet models can be time-consuming, especially when dealing with large-scale datasets and complex architectures. Furthermore, ResNet's performance is highly sensitive to hyperparameters such as learning rate, batch size, and initialization methods.

3. PROPOSED MODEL

The original model utilized a ResNet architecture with convolution neural network, that leads to a time-consuming training process and it is prone to overfitting of data. The proposed model adopts the efficient "SqueezeNet" architecture with CNN model, enhancing accuracy and reducing the training time of model. Squeezenet's lightweight design optimizes performance for Early Detection of oral cancer. Fire modules prevent overfitting, improving generalization and increase model complexity, capturing intricate image patterns. Global Average Pooling reduces spatial dimensions, aiding feature extraction for enhanced overall model accuracy.

3.1 Convolution Neural Networks(CNN)

A Convolutional Neural Network (CNN) is a deep learning architecture designed specifically for processing structured grid data such as images. CNNs have revolutionized various fields, particularly computer vision tasks, due to their ability to automatically learn hierarchical features directly from raw pixel data. At its core, a CNN consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers which is shown in the form of blocks in Fig-2. Convolutional layers are responsible for learning local patterns or features from input images by convolving them with learnable filters or kernels. These filters slide over the input image, extracting spatial information such as edges, textures, and shapes.

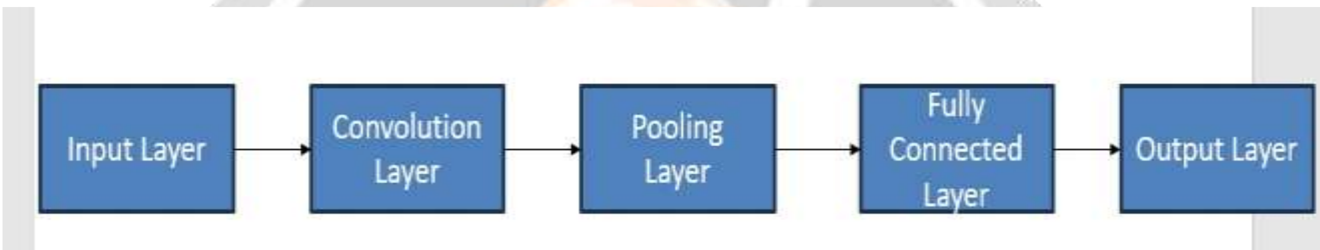

Fig 2: Structure of CNN

3.2 Architecture of the Proposed Model

The proposed model architecture incorporates the SqueezeNet architecture which is a deep learning architecture designed to achieve high accuracy while reducing computational complexity and model size which was given in the form of block diagram in Fig-3. It introduces novel design choices aimed at maximizing efficiency without sacrificing performance. One key feature additionally is SqueezeNet employs fire modules, which use of 1x1 convolutions, known as squeeze layers, which significantly reduce the number of parameters and computational cost compared to traditional convolutional layers and combined 1x1 and 3x3 convolutions to capture rich feature representations efficiently known as expand layer which is shown in the below Fig-4. Another notable aspect of SqueezeNet is its utilization of global average pooling, which reduces the spatial dimensions of feature maps while retaining important information, leading to compact model architectures.

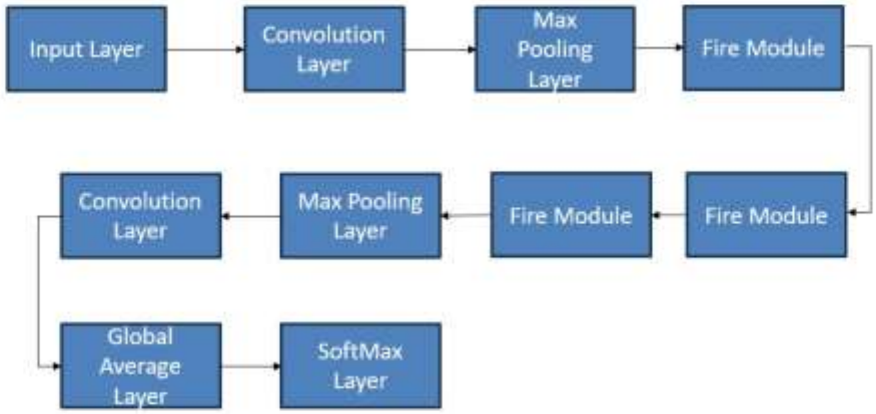

Fig-3: Architecture of the proposed model

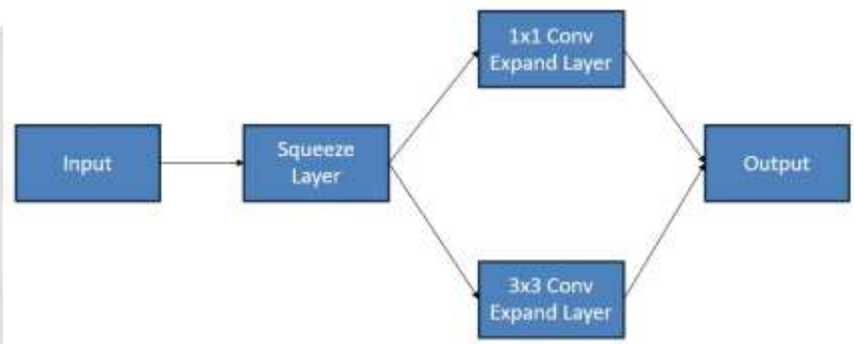

Fig-4: Fire Module Structure

3.3 Working of the Model

The oral cancer detection system employing Convolutional Neural Networks (CNN) and SqueezeNet architecture operates through a systematic sequence of steps tailored to accurately identify and classify oral lesions we can understand the process from Fig-5. Initially, the system acquires a dataset of oral images, sourced from publicly available repositories like Kaggle datasets, comprising photographs of the oral cavity. These images undergo meticulous preprocessing to standardize and refine the data, including resizing, pixel value normalization, and noise elimination, thereby enhancing data quality. Subsequently, the preprocessed images are fed into the CNN model for feature extraction. The CNN, with its convolutional, pooling, and activation layers, learns hierarchical features from the input images. As the images traverse through the CNN layers, low-level features like edges and textures are discerned in the early layers, while deeper layers focus on extracting higher-level features pertinent to oral lesions. Following feature extraction, the features are transmitted to a classifier constructed using the SqueezeNet architecture, known for its computational efficiency. The SqueezeNet classifier, comprising convolutional layers, global average pooling, and softmax activation, categorizes the input images into five classes of oral lesions, estimating probabilities for each class. The subsequent phase involves training the SqueezeNet architecture, augmented with additional CNN layers, on a labeled dataset of oral images, using ground truth annotations indicating the presence or absence of oral lesions. This training process entails iteratively feeding batches of preprocessed images into the model, computing the loss between predicted and actual labels, and adjusting the model's parameters through backpropagation and optimization algorithms like stochastic gradient descent (SGD) or Adam. Finally, the trained model undergoes evaluation and validation on a distinct dataset of oral images and various metrics such as accuracy, precision, recall, and F1 score are calculated.

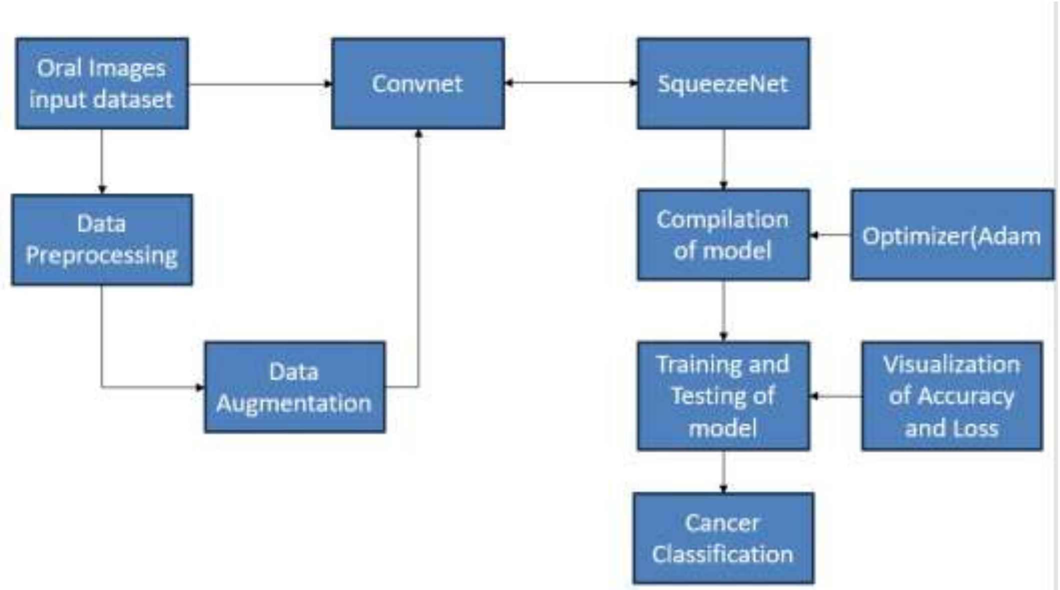

Fig-5: Work flow diagram of the proposed model

3.4 Advantages of Proposed Model

The proposed model brings several advantages to the forefront. Firstly, the incorporation of the SqueezeNet as pre-trained model plays a pivotal role in feature extraction and learning. The lightweight design of the model significantly reduces the model size, leading to lower memory and computational requirements compared to traditional deep neural network architectures. SqueezeNet achieves this reduction in model size without sacrificing performance, as demonstrated by its competitive accuracy on benchmark datasets. The architecture's efficient use of parameters and computational resources ensures high-speed inference without compromising accuracy, making it well-suited for applications where computational efficiency is paramount. SqueezeNet's simplicity and elegance make it easier to understand, implement, and train, reducing the complexity of model development and deployment. Overall, the model offers a compelling combination of compactness, efficiency, and performance, making it a versatile choice for a wide range of deep learning tasks, from image classification to object detection and beyond.

3.5 Dataset Analysis

The dataset used in this project comprises a total of 2155 images depicting various oral lesions (sample datasets can be observed in Fig 6), which have been strategically partitioned into subsets for training, validation, and testing purposes. This segmentation aids in the systematic training and evaluation of the model, ensuring its robustness and ability to generalize well to unseen data.Curated from Kaggle datasets, the images in the dataset exhibit a broad spectrum of oral conditions, ranging from normal oral states to benign lesions, malignant tumors, and potentially precancerous lesions. This diversity is crucial for capturing the multifaceted nature of oral pathologies encountered in clinical settings. Through meticulous curation, the dataset ensures inclusivity, representativeness, and comprehensive coverage of different oral pathologies, laying a solid foundation for model development. To standardize and enhance the dataset's quality, various preprocessing techniques such as resizing, normalization, and augmentation are applied. These steps not only ensure uniformity in image dimensions but also help augment the dataset with variations, thereby enriching the training process and improving model performance. The availability of a well-annotated and comprehensive dataset is paramount for the development of a robust oral cancer detection system. By providing a diverse array of images annotated with accurate labels, the dataset facilitates the training of deep learning models capable of accurately identifying and classifying oral lesions. This ensures that the resulting model is not only accurate but also capable of effectively addressing the complexities and nuances of real-world oral healthcare scenarios.

Fig-6: Kaggle Dataset

5. RESULTS AND PERFORMANCE ANALYSIS

5.1 Training the model

The training process begins by feeding the Oral cancer images from the training dataset into the neural network. From Fig 7, during each iteration, the model makes predictions, and the disparity between these predictions and the actual labels (Normal or Low-risk or High-risk or Non-cancer) is measured using a predefined loss function. The goal is to minimize this loss, which essentially quantifies the dissimilarity between predicted and actual outcomes. Post-training, a comprehensive evaluation and validation process is imperative to verify the model's robustness in real-world scenarios. Continuous monitoring of metrics becomes a guiding force for subsequent iterations, fostering dynamic and adaptive enhancements during the development of deep learning models. This evolving nature of the training phase underscores its importance as a dynamic and integral component of model development.

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Training on single GPU.
Initializing input data normalization.
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Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Validation Accuracy	Mini-batch Loss	Validation Loss
1	1	00:00:17	34.38%	26.06%	2.8627	9.7158
1	10	00:01:20	45.31%	43.34%	7.4547	8.0995
1	20	00:02:40	62.50%	50.42%	3.9167	5.4556
2	30	00:04:03	67.19%	58.92%	2.3477	3.0724
2	40	00:05:30	70.31%	68.84%	1.4214	1.4616
3	50	00:07:12	81.25%	69.12%	0.8844	1.1660
3	60	00:08:43	84.38%	75.64%	0.3811	0.8298
4	70	00:10:11	92.19%	82.15%	0.2757	0.6933
4	80	00:11:54	93.75%	81.87%	0.2851	0.6314
5	90	00:13:27	95.31%	83.57%	0.1610	0.5449
5	100	00:14:55	95.31%	85.84%	0.1480	0.5004
5	110	00:16:35	93.75%	84.14%	0.1761	0.5930
6	120	00:18:15	96.88%	84.70%	0.1461	0.5788
6	130	00:19:57	92.19%	82.72%	0.3260	0.5949
7	140	00:21:30	95.31%	82.44%	0.1781	0.5923
7	150	00:23:29	92.19%	85.55%	0.1765	0.5330
7	154	00:24:08	96.88%	85.84%	0.1395	0.5268

Fig 7: Training Data

The model summary encapsulates the fusion of CNNs and SqueezeNet architecture, leveraging deep learning techniques to develop an efficient and accurate system for the early detection and classification of oral lesions. The model signifies the synergy between Convolutional Neural Networks (CNNs) and the SqueezeNet architecture, harnessing the capabilities of deep learning to construct a highly efficient and precise system tailored for the early detection and classification of oral lesions. By seamlessly integrating CNNs with the SqueezeNet architecture, the model optimizes computational resources while maintaining superior performance, thus ensuring its suitability for deployment in various healthcare environments. Through extensive training on a diverse dataset meticulously curated to encompass a wide spectrum of oral conditions, including normal states, benign lesions, malignant tumors, and potentially precancerous lesions, the model acquires a comprehensive understanding of oral pathology. This comprehensive training process, augmented by meticulous validation procedures, empowers the model to accurately discern subtle nuances and intricate patterns within oral images, thereby enhancing diagnostic accuracy.

5.2 Results of the trained model

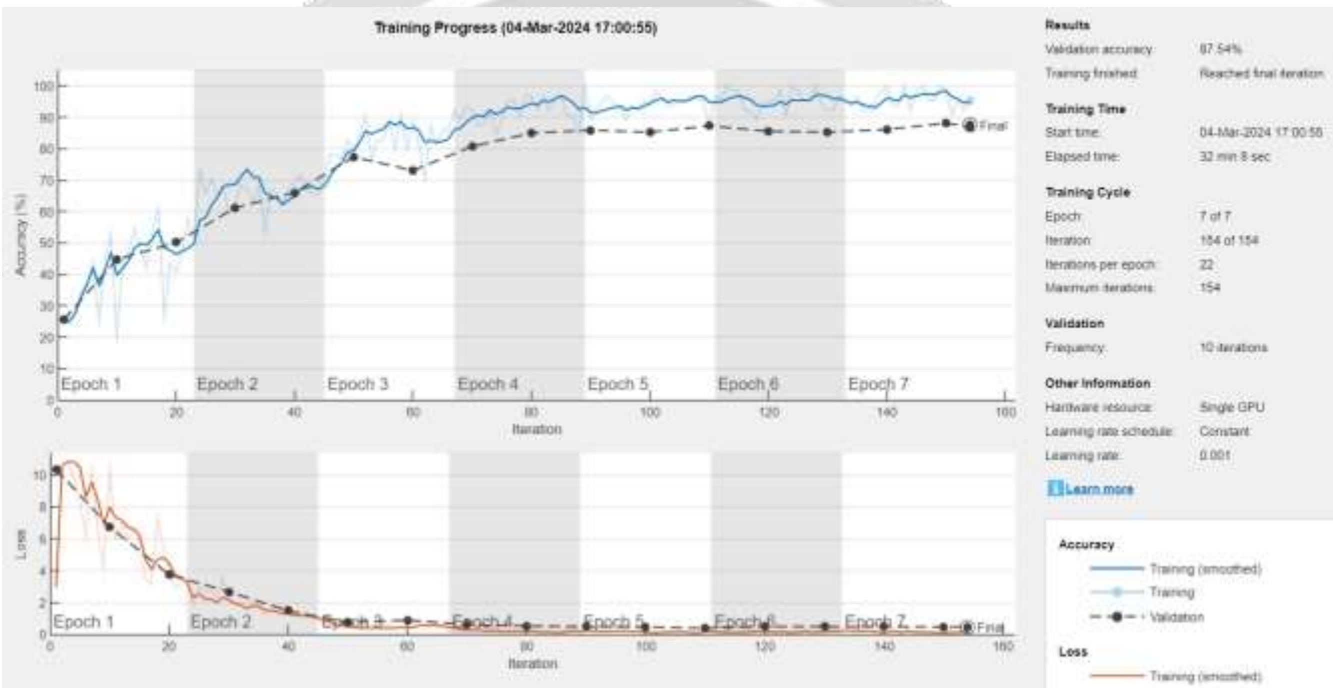

Fig-8: Training accuracy and Loss of the model

Fig-8 shows the graph plotted between the number of epochs trained and the accuracy of the model and the number of epochs trained and the loss of the model. The graphs depicting epochs versus accuracy and epochs versus loss offer valuable insights into the training dynamics of the model. The accuracy plot illustrates the model's progression in correctly predicting labels over successive epochs, with a consistent upward trend indicating effective learning. Meanwhile, the loss curve tracks the model's ability to minimize errors during training, with diminishing values signaling improved performance. To the right side window we can observe the time taken for training of the model and number of iterations and also the learning rate of the model.

5.3 Model Prediction Analysis

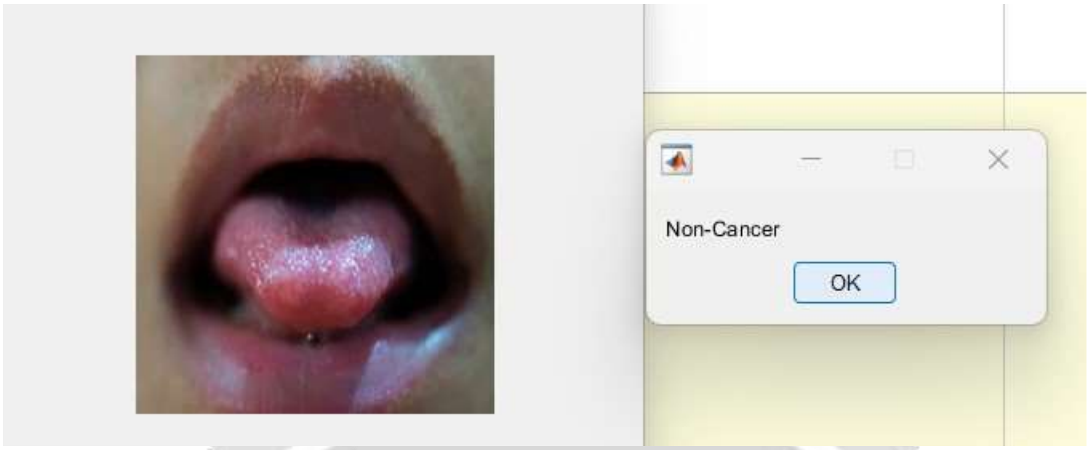

Fig-9: Classification of oral cancer for Sample Input-1

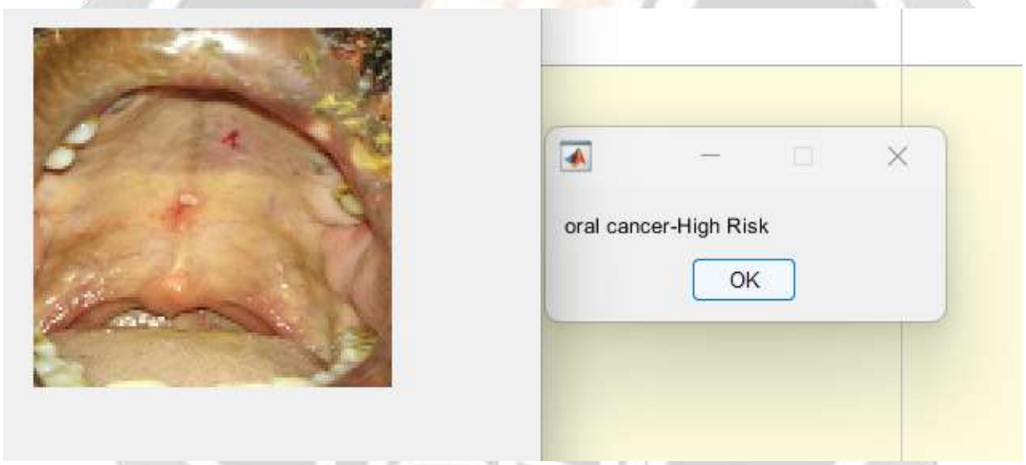

Fig-10 : Classification of oral cancer for Sample Input-2

The process involves assessing the model's accuracy in correctly classifying images as non-cancer and oral cancer - high risk based on the features learned during training and gives the output with the appropriate statement which was shown in the Fig-9 & Fig-10.

5.4 Evaluation of Metrics

The evaluation metrics encompass various aspects of the model's performance, including accuracy, precision, recall, and F1-score. Accuracy denotes the overall correctness of the model's predictions, reflecting its ability to classify instances correctly. Precision evaluates the model's precision in identifying positive cases among the predicted positives, while recall measures its ability to capture all positive instances among the actual positives. F1-score, a harmonic mean of precision and recall, offers a balanced assessment of the model's performance across different classes. These metrics collectively provide a thorough evaluation of the model's capabilities without specifically referencing the confusion matrix.

Fig-11: Confusion Matrix

By analyzing the confusion matrix observed as Fig-11, the model performance can be reported. The model correctly classified 445 cases into their respective classes namely no-cancer, non-cancer, oral cancer low-risk, and oral cancer high-risk with classification accuracy of about 97.3%. This is a crucial metric as it reflects the model's ability to successfully classify the cancer condition in the give oral images. With 180 cases correctly identified as negative, the model demonstrated accuracy in recognizing normal cases. TN is essential for evaluating the model's capability to correctly exclude cases without the targeted condition. The model incorrectly classified 25 cases as Non-Caner when they were, in fact, of other cancer condition. False Positives are significant as they represent instances where the model generated a false alarm, potentially leading to unnecessary concerns or interventions. 20 cases were mistakenly labeled as normal condition when they actually had oral cancer Low-risk condition. False Negatives highlight instances where the model failed to identify the presence of the condition, potentially posing risks in a medical context.

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Accuracy: 0.89802
Precision: 0.94393     0.96667     0.88235     0.69355     0.73913
Recall:
 0.9902
0.61702
0.81522
0.87755
0.80952
F1 Score: 0.96651     0.75325     0.84746     0.77477     0.77273
Classification Accuracy (Transfer Learning): 97.3333 %
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Fig-12: Model Metrics

Table-1: Evaluation Metrics

Image class	Precision	Recall	F1 Score
No Cancer	94.39	99.02	96.65
Non Cancer	96.67	81.70	85.75
Caner-Low risk(No-referral)	88.23	81.52	84.74
Cancer-Low risk(referral)	87.53	87.75	82.67
Caner-High risk	83.91	80.95	87.27

From Fig-12 and table-1 we can understand that the model exhibits strong performance across key metrics, validation accuracy of 89.8%, classification accuracy of 97.33%, precision at 94.3%, recall of 99.02%, F1 score of 96.65%. These results indicate the model's accuracy in making correct predictions, particularly in correctly identifying positive instances, capturing a high percentage of actual positives, and maintaining a balanced precision-recall trade-off. Overall, these metrics collectively affirm the model's reliability and competence in the evaluated task. In addition to the impressive metrics highlighted, the high F1 score of 96.65% suggests that the model excels in achieving a balance between precision and recall, crucial for tasks requiring a harmonious trade-off between false positives and false negativesThe evaluation of the oral cancer analysis model involves a thorough examination of its performance using critical metrics such as the confusion matrix, accuracy, precision, recall, and F1-score. The confusion matrix provides a detailed breakdown of the model's predictions, distinguishing between true positives, true negatives, false positives, and false negatives. These elements form the basis for assessing the model's overall correctness, precision in identifying positive cases, and ability to capture all positive instances.

6. CONCLUSIONS AND FUTURE SCOPE

6.1 Conclusions

In conclusion, this model of early detection and classification of oral lesions using Convolutional Neural Networks (CNNs) and SqueezeNet architecture has yielded promising results, demonstrating a remarkable accuracy of 97.3%. This high level of accuracy underscores the efficacy of deep learning techniques in accurately identifying and classifying oral lesions, thereby facilitating timely intervention and treatment. Through rigorous model training and validation on a diverse dataset comprising various oral conditions, including normal states, benign lesions, malignant tumors, and potentially precancerous lesions, the model has showcased its ability to generalize well to unseen data and reliably predict oral pathology. By leveraging advanced computational techniques and innovative architectures such as CNNs and SqueezeNet, the project has paved the way for the development of efficient and accurate diagnostic tools for oral pathology. The impressive accuracy achieved by the model holds significant implications for improving oral healthcare outcomes by enabling early detection and intervention. With its robust performance, the model has the potential to assist clinicians in diagnosing oral lesions with high precision, thereby reducing the risk of misdiagnosis and ensuring appropriate treatment strategies.

6.2 Future Scope

Looking ahead, the project on early detection and classification of oral lesions using CNNs and SqueezeNet architecture holds immense potential for further advancements and applications in the field of oral healthcare. One avenue for future exploration involves enhancing the model's performance through the incorporation of advanced deep learning techniques and algorithms. This could entail refining the architecture of the CNNs and exploring novel architectures to improve feature extraction and classification accuracy. Additionally, leveraging transfer learning approaches may facilitate the adaptation of pre-trained models to oral lesion detection tasks, thereby reducing the need for large annotated datasets and accelerating model development.Furthermore, there is considerable scope for extending the project's impact beyond detection and classification to include predictive analytics and personalized treatment recommendations. By integrating patient-specific data such as clinical history, genetic information, and lifestyle factors, the model could be trained to predict disease progression, treatment response, and overall prognosis for individuals with oral lesions. Such predictive analytics have the potential to revolutionize treatment planning and patient management, enabling clinicians to tailor interventions based on individual risk profiles and therapeutic outcomes.Moreover, the project could benefit from collaborations with interdisciplinary teams, including clinicians, pathologists, and data scientists, to harness collective expertise and resources for refining the model and translating it into clinical practice. Collaborative efforts may also involve integrating the model into existing healthcare infrastructure, such as electronic health records (EHR) systems and telemedicine platforms, to facilitate seamless integration into routine clinical workflows and ensure widespread adoption.Additionally, the project's future scope encompasses addressing disparities in access to oral healthcare by developing mobile applications or point-of-care diagnostic devices that leverage the model's capabilities for decentralized screening and diagnosis. By empowering patients and healthcare providers with tools for early detection and remote monitoring, the project has the potential to bridge gaps in oral healthcare delivery and improve health outcomes for underserved populations.

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