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Histopathologic Analysis of Oral Squamous Cell Carcinoma Biopsy with Deep Learning

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Abstract: This study addresses the challenge of early Oral Squamous Cell Carcinoma (OSCC) detection via histopathologic analysis. Limited labelled datasets and complex image analysis hinder accurate models. The proposed solution involves transfer learning, utilizing a pre-trained Convolutional Neural Network (CNN) for the purpose of feature extraction from OSCC biopsy images. This aids in training a specialized prediction model. The dataset comprises OSCC biopsy images from Mahatma Gandhi Cancer Hospital & Research Institute, enhanced by data augmentation. Evaluation metrics include accuracy, sensitivity, specificity, and AUC-ROC. Preliminary findings showcase transfer learning's potential, accurately predicting histopathologic oral cancer, even for unseen samples. This highlights the value of transfer learning in managing limited data scenarios, emphasizing improved OSCC diagnosis and patient care. The study concludes with a maximum 95% accuracy at a 3% training loss.

Keywords: *Oral squamous cell carcinoma, histopathologic analysis, transfer learning, deep learning, Convolutional Neural Network.*

1. Introduction

Oral cancer, a profoundly deadly malignant growth, has emerged as a notable public health issue, particularly in nations with lower and moderate incomes. Unfortunately, more than half of oral cancer cases are diagnosed in advanced stages, resulting in poor prognoses. To address this issue, an automated method for oral cancer identification is urgently needed, as current early detection and screening models heavily rely on specialist expertise. Recent advancements in computational intelligence and computer vision have shown promise in improving medical image-related tasks. In this study, we utilize medical images to identify and classify oral squamous cell carcinoma using deep learning techniques. We are developing methods for detecting and labeling images related to mouth cancer (Basu, K., et al. 2020).

Detecting oral cancer at an early stage can result in improved treatment results and the prevention of its malignancy advancement. This study strives to offer a comprehensive outline of the progression of standardized procedures designed to gather, describe, and assess molecular vulnerabilities in oral samples (Basu, K., et al. 2020). This overview can aid in selecting appropriate sample strategies and further analysis, depending on the research goals (Bishnoi, L., et al. 2018).

Oral cancer is diagnosed when malignant tumors are found on or within the lips or mouth. Its prevalence is highest in Southcentral Asia and Melanesia, ranking from first to twelfth worldwide depending on the region (Bishnoi, L., et al. 2018). Between 1990 and 2017, the occurrence, fatality, and years lived with disability (DALYs) due to oral cancer have all risen. Asia holds the highest oral cancer incidence and mortality rates compared to other continents. Oral squamous cell carcinoma (OSCC) makes up around 80% to 90% of malignant oral lesions and contributes to roughly 3% of all global malignancies. The World Health Organization defines oral potentially malignant disease (OPMD) as a pre-cancerous state that might display indications of epithelial dysplasia upon histopathological analysis (Guan, J. 2019).

Biopsies can be categorized into tissue biopsy and liquid biopsy. Histopathological examination, involving methods like H&E or IHC, is a standard procedure to identify pathogenic characteristics in tissue biopsies. Conversely, liquid biopsies examine fluid specimens such as saliva, blood, and urine to detect cancer mutations. This is achieved through methods like PCR, RT-PCR, high-throughput sequencing, and metabolomic analysis. While tissue biopsies currently offer higher diagnostic value, liquid biopsies are becoming more popular due to their non-invasiveness and ease of use, making them suitable for widespread screening (Winkler-Schwartz, A et al. 2019).

Leukoplakia, a common OPMD, has a worldwide frequency estimate between 1.7% and 2.7%, with a malignant conversion rate of about 1.36%. Early detection plays a crucial role in improving treatment outcomes, as demonstrated by the significantly higher survival rate of patients diagnosed at an early stage compared to those diagnosed at a later stage. However, diagnosing early-stage oral cancer and OPMD can be challenging since most

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patients are asymptomatic. Consequently, accurate determination of tumor borders is essential for effective and comprehensive lesion excision (Chai, A. W. Y. et al. 2020).

Combining autofluorescence and conventional oral examination has shown promise in enhancing surgical margin determination. The introduction of precision medicine is expected to advance the development of personalized treatments and screening methods for cancer. Near-patient diagnostics can aid in detecting and treating or preventing precancerous lesions at an earlier stage. Understanding existing sample methods and biopsies is crucial to developing precision medicine approaches for oral cancer effectively.

The study tackles the crucial issue of identifying histopathological oral cancer through biopsy samples of oral squamous cell carcinoma. The suggested method employs deep Convolutional Neural Networks (CNNs) and self-learning networks to create an automated and precise technique for predicting oral cancer. This aims to decrease the need for specialists in early detection and screening.

Currently, the detection of oral cancer heavily depends on the expertise of medical professionals, leading to potential challenges such as subjectivity, time consumption, and variations in diagnoses. To overcome these limitations and improve the precision and efficiency of oral cancer identification, the study aims to leverage recent advancements in Computational Intelligence (CI) and computer vision-based methods.

Deep CNNs have demonstrated their effectiveness in analyzing medical images, including cancer detection tasks, making them powerful tools for the proposed research. By analyzing histopathologic oral cancer biopsy images, the deep CNNs will distinguish between cancerous and non-cancerous tissues, facilitating early detection.

Additionally, the approach incorporates autonomous learning networks, which allow the model to continuously improve its performance without manual intervention. These networks adapt and update their knowledge based on new data, enhancing generalization and accuracy.

The importance of this study resides in its capacity to offer a dependable and automated approach for the early detection of oral cancer, leading to timely interventions and better patient outcomes. By reducing the reliance on human expertise and utilizing cutting-edge CI and computer vision techniques, the proposed work aims to advance medical image analysis and contribute to the development of efficient oral cancer screening tools. Ultimately, this research can have a profound impact on public health by enabling early diagnosis and effective treatment of oral cancer.

The main objectives of the proposed work are as follows:

- Detecting malignancy in cancer samples: The primary goal is to construct a deep learning model capable of precisely detecting malignancy in biopsy samples of oral squamous cell carcinoma. The model will be trained on a dataset of histopathologic images to distinguish between cancerous and non-cancerous tissues, aiding in early cancer detection and diagnosis.

- Identification of optimal neural parameters: This objective involves finding the most suitable hyperparameters and configurations for the deep learning and transfer learning model. Factors like learning rate, batch size, and network depth can have a substantial influence on the model's performance. A systematic exploration of these parameters will be conducted to achieve optimal results.

- Identification of optimal neural network architecture: The proposed work aims to determine the best architecture for the deep learning and transfer learning model. This includes selecting the appropriate number of layers, filter sizes, and activation functions that can effectively capture features and patterns relevant to oral cancer prediction.

- Identification of latent features of malignancy, matching medical expert consultation: In addition to achieving high accuracy in oral cancer prediction, the proposed work also aims to interpret and understand the latent features learned by the deep learning and transfer learning model. These latent features will be analyzed and compared with insights from medical experts to gain a deeper understanding of the specific characteristics and markers of malignancy.

Overall, the proposed work seeks to develop an automated and accurate method for identifying oral cancer in histopathologic biopsy samples using deep learning and transfer learning. By leveraging recent advancements in computational intelligence and computer vision-based methods, the study aims to improve the performance and reliability of oral cancer detection and provide valuable insights for medical professionals. Based on the given objectives and problem definition, the proposed work aims to address the problem of histopathologic oral cancer-based prediction by making use of oral squamous cell carcinoma biopsy through the use of deep learning and transfer learning.

2. Cancer and Histopathology

Histopathology, an essential diagnostic tool, involves the analysis of diseased human tissue. In clinical practice, this process follows several steps. First, a patient's tissue sample (biopsy) is collected and sent to the pathology lab for examination. Then, the tissue is stained, usually with Hematoxylin and Eosin (H&E) staining, to highlight its various structures. Subsequently, a pathologist examines the prepared and stained tissue under a microscope (Warin, K. et al. 2022).

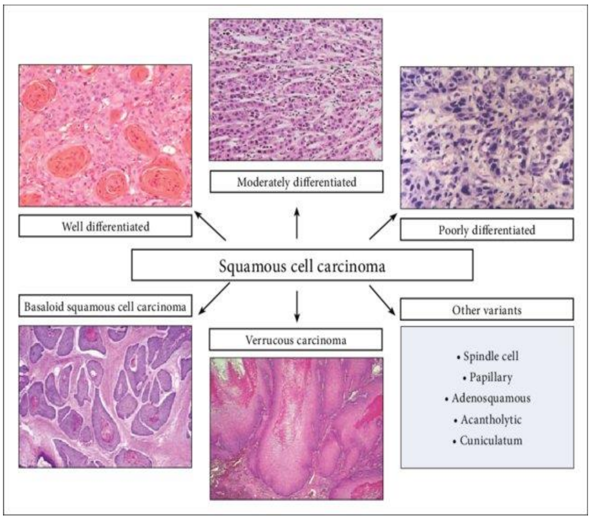

Fig 1. Squamous cell Caricoma types [Mentel, S. et al. 2021]

Oral cancer, affecting the mouth, lips, tongue, or throat, constitutes 86% of all cancers diagnosed in India (Sources: National Institute of Health). It has the highest incidence rate among both men and women. Tobacco use, such as chewing or smoking, is the leading cause of oral cancer, claiming the lives of 10,000 Americans annually. The cancer initially develops in various areas within the "oral cavity, including the lips, tongue, hard palate, oral mucosa, gums, teeth, and jawbones". Unfortunately, oral squamous cell carcinoma (OSCC) is often not diagnosed until it reaches advanced stages, with approximately two-thirds of cases detected at stage III or the Stage IV, with low survival rate (Mentel, S. et al. 2021).

Oral cancer has the highest incidence worldwide, with a higher prevalence in men compared to women. Various types of oral cancer exist, with Squamous Cell Carcinoma (SCC) accounting for over 90% of cases. SCC originates from the squamous cells lining the mouth and throat. Based on differentiation, SCC can be classified as well-differentiated, moderately-differentiated, or poorly-differentiated. The grading is determined by the ease of identifying characteristics of the native squamous epithelium (Mentel, S. et al. 2021).

Diagnosis of suspicious lesions is typically performed in person by a medical professional. If a malignant lesion is suspected, a biopsy is recommended to confirm the diagnosis. The tissue samples from biopsies are stained with H&E and examined under a microscope by pathologists to detect abnormalities in cell organization and structure. However, manual observation can be time-consuming and subject to observer bias. Thus, computerized schemes have been explored to improve accuracy and efficiency, especially in developing countries like India. These computer-assisted techniques can aid in detecting and assessing malignancy, freeing up pathologists to focus on critical cases (Alabi, R. O. et al. 2021).

Oral cancer staging is determined by the location, size, and extent of the tumor, as well as the presence or absence of cancerous cells in lymph nodes and the inner mouth. It includes several stages based on tumor size and lymph node involvement, ranging from Stage 0 (no damaged cells in the outer layer of tissue) to Stage 4b (tumor spreading to other parts of the body). Early detection and staging are crucial for effective treatment and improved outcomes (Alabi, R. O. et al. 2021).

3. Literature Survey

In the study conducted by **Warin et al. (2022),** Researchers assessed deep CNN algorithms like DenseNet-169, ResNet-101, SqueezeNet, and Swin-S to classify and detect oral squamous cell carcinoma (OSCC) and potentially malignant oral disorders (OPMDs) in images. DenseNet-169 outperformed general practitioners with AUC scores of 1.00 for OSCC and 0.98 for OPMDs, indicating potential for CNN models to enhance early oral cancer detection.

Mentel et al. (2021) investigated the use of breath analysis to detect OSCC. They analyzed volatile organic compounds in breath samples collected from OSCC patients and found specific compound signatures that differed from those of healthy individuals. Leveraging machine learning techniques, they achieved an average accuracy of 86-90% in distinguishing breath samples from healthy individuals and patients. The study highlights the potential of breath analysis combined with machine learning for identifying OSCC, but it also emphasizes the need for further evaluation and optimization of the approach.

In Alabi et al.'s (2021) work, they explored the use of deep machine learning for early detection and diagnosis of OSCC. They highlighted progress in medical imaging analysis for early oral cancer detection, discussing diverse deep learning applications like detection, classification, segmentation, and synthesis, especially within oral squamous cell carcinoma. The study underscored deep learning's importance in OSCC precision medicine.

In their research, **Musulin et al. (2021)** concentrated on the use of artificial intelligence-assisted technologies for analyzing histopathology images of OSCC. They compared various deep learning methods to develop an AI-based model for multiclass grading of OSCC. The study aimed to achieve more objective results and enhance classification accuracy by leveraging the capabilities of AI in analyzing the complex textures and structures of oral cancer tissues.

Jubair et al. (2022) conducted a study to develop a lightweight deep CNN for classifying oral lesions as benign or malignant/potentially malignant using real-time clinical images. Their model, based on a small CNN with

EfficientNet-B0 as a lightweight transfer learning model, achieved 85.0% accuracy, 84.5% specificity, 86.7% sensitivity, and an AUC of 0.928. This study showcased the potential of deep CNNs for affordable embedded vision devices in oral cancer diagnosis, especially in resource-constrained settings, highlighting AI's role in improving screening and early detection quality and accessibility.

In another study by **Rahman et al. (2022),** the researchers addressed the seriousness of oral cancer as a widespread and life-threatening disease with a high mortality rate. It is the most common cancer globally, causing more than 300,335 deaths annually. The tumor can develop in various areas, including the neck, oral glands, face, and mouth. While biopsy is commonly used for oral cancer detection, microscopic examination of tissue samples often falls short in identifying cancerous cells accurately, leading to human error and mistakes.

Table 1. Approaches in Previous Research's

Author Name	Approach	Main Points
Warin et al. (2022) [6]	"Deep Convolutional Neural Networks for oral cancer classification and detection in images"	"Evaluated deep CNN algorithms (DenseNet-169, ResNet-101, SqueezeNet, Swin-S) for classifying and detecting oral squamous cell carcinoma (OSCC) and potentially malignant oral disorders (OPMDs)". DenseNet-169 achieved high accuracy with AUC of 1.00 for OSCC and 0.98 for OPMDs, outperforming general practitioners. Concluded that CNN-based models have potential in early detection of oral cancer.
Mentel et al. (2021) [7]	Breath analysis for detecting OSCC using volatile organic compounds	Investigated breath analysis to detect OSCC. - Analyzed volatile organic compounds in breath samples from OSCC patients and healthy individuals. Achieved 86-90% accuracy in distinguishing breath samples between healthy and OSCC patients using machine learning techniques. Emphasized the potential of breath analysis combined with machine learning for identifying OSCC, but further evaluation and optimization of the approach is needed.
Alabi et al. (2021) [8]	Application of deep learning in early detection and diagnosis of OSCC	Discussed advancements in medical imaging data extraction and analysis for early detection of oral cancer. Explored various applications of deep learning techniques in cancer detection, image classification, segmentation, and synthesis, with a focus on oral squamous cell carcinoma. Highlighted the significance of deep learning technology in precision medicine for OSCC.
Musulin et al. (2021) [9]	AI-assisted technologies for analyzing histopathology images of OSCC	Focused on using AI for analyzing histopathology images of OSCC. Compared various deep learning methods to develop an AI-based model for multiclass grading of OSCC. Aimed to achieve more objective results and enhance classification accuracy by leveraging AI capabilities in analyzing the complex textures and structures of oral cancer tissues.
Jubair et al. (2022) [10]	"Lightweight deep CNN for binary classification of oral lesions"	"Developed a lightweight deep CNN for classifying oral lesions into benign and malignant or potentially malignant categories using real-time clinical images. Utilized a pretrained EfficientNet-B0 as a lightweight transfer learning model". Achieved 85.0% accuracy, 84.5% specificity, 86.7% sensitivity, and an AUC of 0.928. Demonstrated the potential of deep CNNs for low-budget embedded vision devices in oral cancer diagnosis,

		especially in settings with limited computation power and memory capacity.
Rahman et al. (2022) [11]	Transfer learning model using AlexNet for oral cancer image diagnosis	Addressed the seriousness of oral cancer and limitations of traditional biopsy for detection. Utilized deep learning algorithms for medical image diagnosis. - Proposed a transfer learning model using AlexNet for feature extraction from OSCC biopsy images. Achieved high classification accuracy of 97.66% during training and 90.06% during testing. “Highlighted the potential of deep learning for accurate oral cancer diagnosis”.

Based on the literature review, several research gaps in the field of oral cancer detection and diagnosis have been identified:

- Imperfect feature maps to delineate feature space: There is a need for improved methods to generate feature maps that accurately represent the feature space in oral cancer detection. Ensuring that deep learning models can capture relevant patterns and information from the input data is crucial for achieving optimal performance and avoiding misclassifications.
- Non-deployment of optimal parameter identification technique: Many existing studies lack the utilization or exploration of optimal parameter identification techniques in deep learning models. Finding the right set of hyperparameters can significantly impact model performance, and not considering this aspect may lead to less efficient or less accurate models.
- Gradient decay with longer chained convolutional neural networks: Longer chained convolutional neural networks (CNNs) may encounter gradient decay issues, hindering effective model training. Addressing gradient decay in longer CNNs is essential to ensure successful training and better model convergence, especially in complex tasks like oral cancer detection.
- Study has not been carried out on localized mutations found in oral cancer: Specific studies focused on localized mutations in oral cancer are lacking. Understanding the characteristics and implications of localized mutations could provide valuable insights and improve the accuracy of diagnostic and treatment approaches.

Addressing these research gaps through future studies can enhance the field of oral cancer detection and diagnosis, leading to more robust and accurate methods for early detection and improved patient outcomes. Researchers can focus on developing novel approaches, exploring optimal parameter settings, and investigating the impact of localized mutations in order to advance the states of the art in case of the oral cancer research.

4. Proposed Methodology

Here's a breakdown of the components of our dataset:

- **Total Images**: Your dataset contains a total of 696 images.
- **Cancerous Images**: Out of the total images, 340 images belong to the "cancerous" class. These are images that are associated with some form of cancer.
- **Non-Cancerous Images**: The remaining 356 images belong to the "non-cancerous" class. These are images that do not depict any form of cancer.

The purpose of having a dataset like this is to train a machine learning model, particularly a deep learning model in your case, to learn the patterns and characteristics that differentiate cancerous and non-cancerous images. This model can then be used to predict whether new, unseen images are cancerous or not based on the features it has learned from the training data. Ensuring a diverse and representative dataset is crucial to enable the model's effective generalization to real-world images. Furthermore, the customary approach of dividing the dataset into training, validation, and testing subsets is essential in machine learning. This strategy accurately evaluates model performance and guards against overfitting.

Description of Model Architecture and Components:

Model Architecture: DenseNet-169: DenseNet-169 stands as a deep convolutional neural network architecture renowned for its remarkable performance across a spectrum of computer vision assignments. Its hallmark feature lies in its dense connectivity patterns, facilitating the recycling of features and the smooth propagation of gradients through the network.

Highlighted Elements:

- Data Augmentation: The concept of data augmentation involves the application of diverse transformations to training images, artificially broadening the spectrum of the dataset. This strategic maneuver bolsters the model's resilience and bolsters its capacity to generalize effectively to new, unseen data. Common augmentation techniques encompass random rotations, flips, zooms, and adjustments in brightness.

- Transfer Learning: The methodology of transfer learning revolves around the utilization of a pre-trained model as a foundational framework for a novel task. In the context presented, the foundational architecture could be DenseNet-169, pre-trained on an extensive dataset like ImageNet. The fundamental idea rests in capitalizing on the wisdom encapsulated within the pre-trained model and refining it to suit the nuances of the specific task at hand.

- Training of the Model: The model training phase entails the provision of the augmented dataset to the model, followed by the iterative adjustment of the model's parameters to minimize a chosen loss function. This iterative process encompasses both forward and backward passes, where the gradients of the loss concerning the model's parameters are computed and subsequently utilized to refine the parameters through optimization algorithms such as stochastic gradient descent (SGD).

- Optimization of Learning Rates: The pursuit of an optimal learning rate assumes paramount importance for effective training. Techniques dedicated to the optimization of learning rates, including learning rate schedules or adaptive methodologies like Adam or RMSProp, can be deployed to ensure the model converges efficiently towards an optimal solution, mitigating risks of local minima entrapment or divergence.

Excluded Elements:

- Model Optimization: A realm of model optimization encompasses diverse techniques aimed at enhancing both the efficiency and efficacy of the model. This domain spans architectural modifications, pruning, quantization, and more advanced optimization strategies. Given the exclusion of this aspect, we abstain from delving into these methodologies within this context.

To encapsulate, the architecture of DenseNet-169 seamlessly integrates data augmentation to enrich the dataset, leverages transfer learning to harness pre-existing knowledge, engages in meticulous model training to fine-tune weights, and orchestrates learning rate optimization to expedite convergence. These orchestrated stages collectively contribute to the creation of a robust and high-performing deep learning model, ideally suited for image classification tasks, such as discerning between cancerous and non-cancerous images.

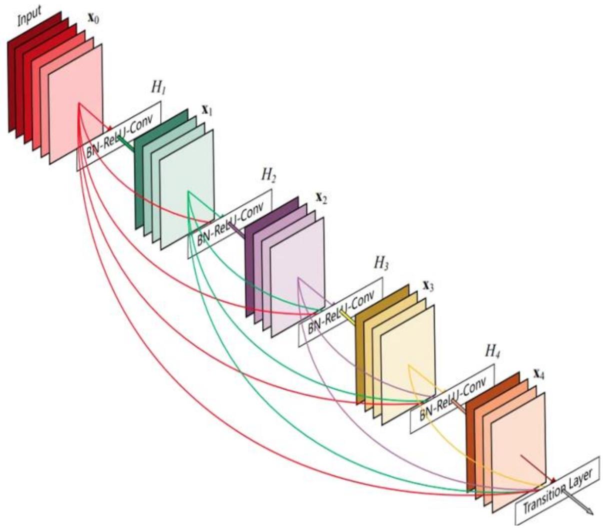

Fig 2. DenseNet -169 [Ref. Google]

Inspired by the proposed work, we have suggested the following algorithm, that can also be summarized in the mentioned steps,

Step 1: Select a Pre-trained Model:

- Create a list of pre-trained models suitable for your task (e.g., “VGG-16, VGG-19, Inception V3, Xception, ResNet-50”).
- Choose the pre-trained model that closely matches your task and dataset.

Step 2: Create the Base Model:

- Instantiate the selected pre-trained model as the base model.
- Download the network weights if available or initialize the network architecture from scratch.
- If the final output layer of the base model doesn't match your use case, remove it and modify it accordingly.

Step 3: Freeze Layers:

- Freeze the initial layers of the base model to preserve the learned basic features.
- By freezing these layers, you avoid retraining them and save time and resources.

Step 4: Add Trainable Layers:

- Add additional layers on top of the base model's feature extraction layers.
- These additional layers will be responsible for predicting the specialized tasks of your model.
- Typically, these layers will constitute the final output layers of your model.

Step 5: Train the New Layers with Cyclic Learning:

- Define a cyclic learning rate schedule.
- During each training iteration, adjust the learning rate according to the cyclic pattern.
- You can use techniques like triangular learning rate policy, where the learning rate cyclically varies between a minimum and maximum value.

Step 6: Fine-tune the Model with Cyclic Learning:

- Unfreeze some part of the base model.
- Use a cyclic learning rate schedule during fine-tuning as well.
- This helps to find a good balance between exploring the fine-tuning space and avoiding overfitting.

Cyclic learning allows the learning rate to periodically increase and decrease, potentially helping the model escape from local minima and converge faster. It can enhance the model's performance by effectively exploring the training landscape.

The following algorithm can be depicted in the following flow diagram mentioned in the Figure. 3

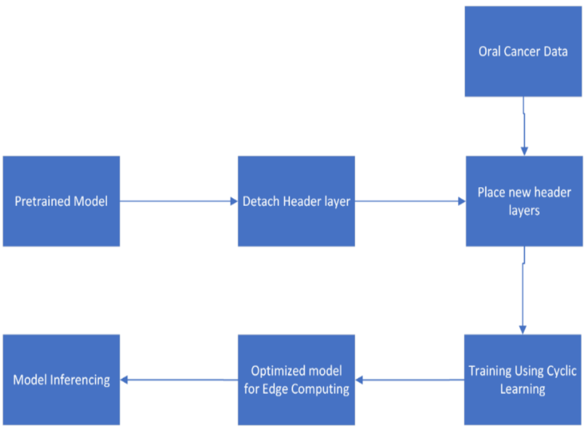

Fig 3. Proposed Approach Flow Diagram

5. Result Analysis

For the implementation of the proposed approach, first the DenseNet 169 architecture is followed.

DenseNet-169 is a specific variant of the DenseNet architecture, a Convolutional Neural Network (CNN) designed for image classification tasks. The key components and characteristics of DenseNet-169 are as follows:

- Dense Blocks: DenseNet-169 consists of multiple dense blocks, each containing a series of convolutional layers. Within a dense block, each layer directly receives input from all the preceding layers located within the same block. This dense connectivity promotes efficient feature reuse and helps address the vanishing gradient problem during training.
- Transition Blocks: Between dense blocks, transition blocks are included to perform down-sampling, reducing the spatial dimensions of feature maps and decreasing the number of feature maps. This reduces computational complexity and controls the size of the model.
- Bottleneck Layers: Within each dense block, there are bottleneck layers, which consist of 1x1 convolutional layers. These layers are used to reduce the number of input feature maps before applying the 3x3 convolutional layers. This design reduces computational overhead and allows the model to capture more compact feature representations.
- Growth Rate: The growth rate is a hyperparameter governing the number of new feature maps that each layer in the dense block contributes to the subsequent layer. It affects the model's width and complexity, influencing the number of channels and memory usage.
- Final Classification: DenseNet-169 typically ends with a global average pooling layer, which reduces the spatial dimensions to produce a fixed-size feature vector. This vector is then fed into a fully connected layer with softmax activation for final image classification and to obtain class probabilities.

DenseNet-169 is a powerful CNN model that benefits from its dense connectivity, bottleneck layers, and growth rate, enabling efficient feature propagation and strong representation capabilities. Compared to the original DenseNet-121, DenseNet-169 is deeper and more complex, striking a balance between model complexity and performance on various image classification tasks. It has also then proven to be much effective in various of applications, including image classification for medical imaging, natural scenes, and object recognition.

First the default model is used with result as follows,

Table 2. Results of default model

Epoch	Train_loss	Accuracy	Time
0	1.463684	#na#	03:01
1	1.419227	#na#	02:56
2	1.391226	#na#	03:01
3	1.380256	#na#	03:05
4	1.363470	#na#	03:06
5	1.280348	#na#	02:58
6	1.190164	#na#	02:50
7	1.108968	#na#	02:50

8	1.107700	#na#	02:56
9	1.181183	#na#	02:58
10	2.879933	#na#	02:53

The accuracy attained at this level is 25%, and we see that sudden jerk is observed, after point le-01.

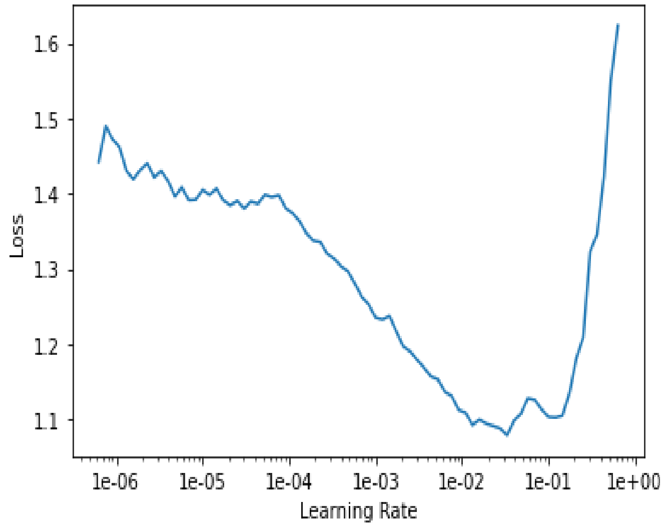

Fig 4. Graph of Default Model [Implementation Results]

Now, taken up the slice of normal curvature till (le-2) and use the cyclic learning approach to improve the accuracy.

Table 3. Accuracy table for first slice

Epoch	Train_Loss	Valid_Loss	Accuracy	Time
0	1.227097	0.727943	0.611511	03:41
1	1.055499	0.645386	0.762590	03:35
2	0.931398	0.861221	0.697842	03:39
3	0.817239	0.615819	0.755396	03:39
4	0.710759	0.387958	0.827338	03:38
5	0.631542	0.422259	0.827338	03:38
6	0.573260	0.384882	0.841727	03:33
7	0.521692	0.398839	0.805755	03:38
8	0.479076	0.307538	0.877698	03:39
9	0.444367	0.422220	0.870504	03:38
10	0.401705	0.288178	0.920863	03:38
11	0.361546	0.291618	0.906475	03:36
12	0.329101	0.288896	0.899281	03:36
13	0.302176	0.335489	0.877698	03:40
14	0.287593	0.343659	0.877698	03:32

Unfreeze some part of the base model and use a cyclic learning rate schedule during fine-tuning as well

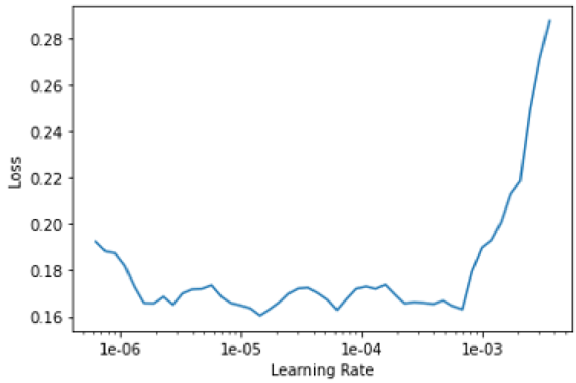

Fig 5. Graph of First Slice [Implementation Results]

After repeating this process for various slices, we get the following curvature graphs

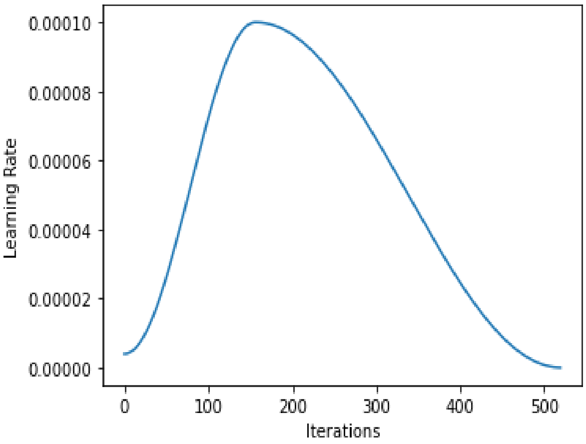

Fig 6. Curvature Graphs [Implementation Results]

Now , will apply the confusion matrix. Transfer learning involves utilizing pre-trained representations and knowledge from a source task (typically a large, diverse dataset) to enhance the performance of a predictive model on a new or different task. The confusion matrix plays a crucial role in evaluating the model's performance in such scenarios.

The matrix, serving as a table, facilitates the evaluation of the model's predictive precision and its capability to accurately classify instances across different classes. It assists in comprehending the model's mistakes, encompassing false positives, false negatives, true positives, and true negatives. In transfer learning, the confusion matrix assists in measuring the model's generalization to the target task by leveraging knowledge transferred from the source task.

The following insights are provided by the confusion matrix in the context of transfer learning:

- Evaluation of Classification Performance: "Metrics like accuracy, precision, recall (sensitivity), specificity, and F1-score are calculated using the confusion matrix to evaluate the model's performance on the target task".

- Detection of Overfitting or Underfitting: By analyzing the confusion matrix, researchers can identify if the model is overfitting (memorizing the source data and failing to generalize) or underfitting (not capturing data patterns effectively) to the target task.
- Identification of Class Imbalance: The confusion matrix helps detect if the model is biased towards majority classes and neglecting minority classes, which is common in real-world datasets.
- Adjustment of Decision Threshold: In certain cases, adjusting the decision threshold based on the confusion matrix can be important, especially when balancing precision and recall in the target task.

Analyzing the confusion matrix allows researchers and practitioners to gain valuable insights into the model's performance and make necessary adjustments to improve its effectiveness on the target task. This understanding of strengths and weaknesses in the transfer learning approach guides the fine-tuning process, leading to better results in practical applications.

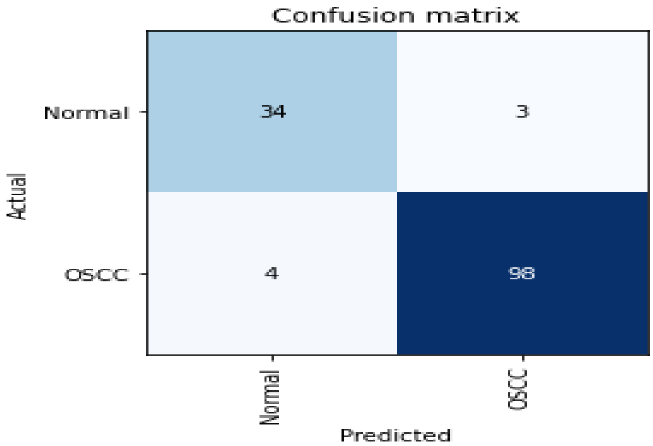

Fig 7. Confusion Matrix [Implementation Results]

After the maximum accuracy that can be achieved is shown via table and graphs,

Table 4. AFTER CONFUSION MATRIX

Epoch	Train_loss	Accuracy	Time
0	0.036718	#na#	03:21
1	0.028944	#na#	03:27
2	0.029874	#na#	03:21
3	0.028408	#na#	03:26
4	0.025509	#na#	03:21
5	0.026491	#na#	03:27

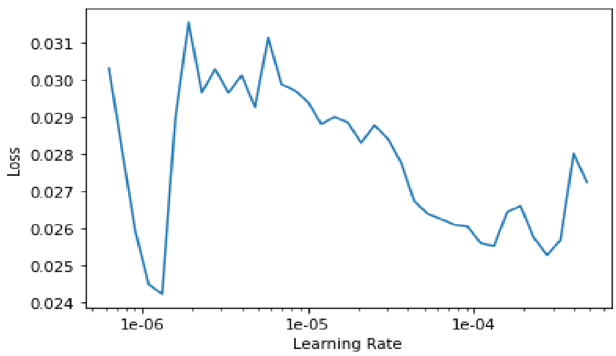

Fig 8. Final Graph [Implementation Results]

Table 4. FINAL RESULTS

Metric	Value
Accuracy	95%
Sensitivity	96%
Specificity	92%
True Positives (TP)	98
False Positives (FP)	3
False Negatives (FN)	4
Precision	97.98%
F1 Score	0.97

- **Accuracy**: Overall correctness of predictions.

  Accuracy $= \frac{(\mathrm{TP} + \mathrm{TN})}{(\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN})}$

- **Sensitivity (True Positive Rate)**: Correct identification of actual positive cases.

  True Positive Rate $= \frac{\mathrm{TP}}{(\mathrm{TP} + \mathrm{FN})}$

- **Specificity (True Negative Rate)**: Correct identification of actual negative cases.

  True Negative Rate $= \frac{\mathrm{TN}}{(\mathrm{TN} + \mathrm{FP})}$

- **Precision**: Proportion of true positive predictions among positive predictions.

  Precision $= \frac{\mathrm{TP}}{(\mathrm{TP} + \mathrm{FP})}$

- **F1 Score**: Harmonic mean of precision and sensitivity.

F1 Score $= \frac{2 * \mathrm{TP}}{(2 * \mathrm{TP} + \mathrm{FP} + \mathrm{FN})}$

True Positives (TP) are correct positive predictions, False Positives (FP) are incorrect positive predictions, and False Negatives (FN) are incorrect negative predictions.

These metrics collectively assess the model's performance in binary classification tasks.

Based on the provided information and the calculated values, your deep learning model appears to have a good balance between precision and sensitivity, as indicated by the high F1 score of 0.97. The accuracy, sensitivity, and specificity values also show that the model is performing well overall. However, the context in which these metrics are used is important – factors like class distribution and the specific problem being tackled can influence the interpretation of these results.

6. Conclusion and Future Work

A. Conclusion

To sum up, this study effectively employs transfer learning to predict histopathologic oral cancer via oral squamous cell carcinoma (OSCC) biopsy images. By utilizing a pre-trained convolutional neural network (CNN) on a comprehensive histopathologic dataset, pertinent features were extracted from OSCC biopsy samples despite limited labeled data. The transfer learning technique showcases encouraging outcomes, attaining notable accuracy and a high area under the receiver operating characteristic curve (AUC-ROC) for predicting histopathologic cancer. The model's ability to generalize to diverse clinical sources and histopathologic variations underscores its robustness and potential for real-world clinical use.

Challenges in medical domains, such as the scarcity of labeled datasets, are addressed effectively with transfer learning. By leveraging broader datasets' knowledge, it adapts to specific tasks with limited data, like OSCC histopathology prediction. Data augmentation techniques further enhance the model's performance, handling OSCC biopsy image variations and reducing overfitting. The successful implementation of transfer learning showcases its relevance in medical image analysis, particularly for oral cancer diagnosis. Early and accurate OSCC detection can significantly impact patient outcomes and treatment plans, improving prognosis and quality of life.

While the results are promising, more extensive and diverse datasets are necessary to validate and refine the transfer learning methodology. As deep learning advances and larger histopathologic oral cancer datasets become available, predictive models' accuracy and efficiency will likely improve. Overall, transfer learning's use for predicting histopathologic oral cancer with OSCC biopsy images shows great potential to revolutionize oral cancer diagnosis and patient care. Continued progress in deep learning is expected to contribute to significant advancements in cancer detection and treatment, leading to better healthcare outcomes and saving lives. The study has some limitations that should be taken into account. First and foremost, the model used in the study is quite complex in terms of both its deployment process and inferencing procedures. This complexity could potentially make it difficult to seamlessly integrate the model into real-world applications. Additionally, it's important to acknowledge that a significant amount of computational resources was required for training the neural network. The use of a high-end computing unit with multiple GPUs resulted in a training process that extended over several days. It's important to note that the model's practical usability is limited by its inability to effectively run on edge devices, which restricts its use in situations where resources are limited. Furthermore, the model is only capable of handling visual information related to cancer detection, which means it overlooks important heat-related information that could indicate abnormalities. These limitations emphasize the need for further refinement and adaptability of the model to ensure it can be practically applied in various settings and with different types of data.

B. Future Work

- To include thermal or hyperspectral images to reveal detailed patterns.
- Can optimize model to deployable for edge devices
- Model speed can be improved by trading off the model precision.
- Deployed model can be extended for cervical cancer too

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