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Enhancing Oral Squamous Cell Carcinoma Detection: A Transfer Learning Perspective on Histopathological Analysis Using ResNet-18, AlexNet, DenseNet-169, and DenseNet-201 with Cyclic Learning Rate

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Abstract: In this study, an innovative method is introduced for the early identification of Oral Squamous Cell Carcinoma (OSCC) by employing deep learning techniques to analyze histopathological samples. Four prominent neural network architectures, ResNet-18, AlexNet, DenseNet-169, and DenseNet-201, are utilized to scrutinize biopsy specimens for cancerous anomalies. The approach incorporates Cyclic Learning Rate (CLR) for dynamic adaptation of learning rates during the model's training. ResNet-18 benefits from skip connections to enhance gradient flow, while AlexNet and DenseNet architectures significantly contribute to precise image categorization. DenseNet's distinctive feature reuse mechanism effectively mitigates the vanishing gradient issue. The research underscores the potential of deep learning in enhancing early OSCC detection, offering a promising avenue for more efficient cancer screening and treatment.

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

1. Introduction

Oral Squamous Cell Carcinoma, commonly abbreviated as OSCC, is a form of cancer that initiates in the squamous cells—a type of flat, thin cells that line the oral cavity. This includes the lips, tongue, gums, inside of the cheeks, floor of the mouth, and the hard palate, which is the roof of the mouth. Notably, squamous cell carcinoma ranks as the most prevalent type of cancer within the oral cavity, accounting for a significant portion of all oral cancer cases [1].

Importance of Oral Squamous Cell Carcinoma as Oral Cancer:

- **High Prevalence and Impact:** OSCC holds paramount significance in the domain of oral cancer due to its widespread occurrence. It plays a substantial role in the overall burden of oral cancer on a global scale [1].
- **Health Ramifications:** Oral cancer, including OSCC, carries profound health consequences for individuals. It can lead to physical pain and significantly impair essential functions such as speaking, eating, and swallowing, often presenting life-threatening risks.
- **Early Detection and Prognosis:** The timely identification of OSCC is of critical importance. Early diagnosis paves the way for more effective treatment options and markedly improves the chances of a positive patient outcome. Conversely, late-stage diagnosis results in advanced disease, higher mortality rates, and complex, less successful treatments [1].
- **Functional Impairments:** OSCC frequently impairs crucial functions of the oral cavity, including speech, swallowing, and chewing. These functional impairments can significantly diminish an individual's quality of life.
- **Psychological and Aesthetic Impact:** The disfigurement that may arise from OSCC surgery or treatment can have profound psychological and aesthetic repercussions, affecting an individual's self-esteem and emotional well-being [1].

Problem Gravity in India:

- **Elevated Prevalence in India:** India experiences one of the highest rates of OSCC on a global scale. This is primarily attributed to prevalent habits such as tobacco and betel nut consumption, coupled with suboptimal oral hygiene practices [2].
- **Late-Stage Diagnosis:** In India, OSCC is frequently diagnosed at an advanced stage, which is a significant concern. Late diagnosis leads to less favorable treatment outcomes, increased suffering, and a heightened risk of mortality.
- **Pervasive Risk Factors:** Well-established risk factors in India encompass the use of tobacco in both smoking and smokeless forms, as well as excessive alcohol consumption. Additionally, the common practice of chewing areca nut, often wrapped in betel quid, amplifies the risk of OSCC [2].

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- **Limited Healthcare Access:** Rural and underserved regions in India often lack adequate access to early screening and quality healthcare services, compounding the OSCC problem.
- **Socioeconomic Impact:** Treating OSCC can pose significant financial burdens for affected individuals and their families. In a country where a substantial portion of the population lacks sufficient health insurance coverage, the socioeconomic impact of OSCC is notable.

Overview of Causes:

- **Tobacco Usage:** Both smoking, as seen with cigarettes and bidis, and the use of smokeless tobacco products contribute significantly to OSCC. These products contain carcinogens capable of inducing oral cancer [3].
- **Alcohol Consumption:** Prolonged and heavy alcohol consumption, particularly when combined with tobacco use, stands as a prominent risk factor for OSCC. Alcohol can potentiate the carcinogenic effects of other risk factors.
- **Areca Nut and Betel Quid:** Chewing areca nut, frequently paired with betel quid, is a widespread practice in India and is linked to an increased risk of OSCC. These substances carry carcinogenic potential [3].
- **Poor Oral Hygiene:** Neglecting oral hygiene and enduring chronic irritation, often arising from ill-fitting dentures or dental abnormalities, can contribute to the development of OSCC. Inflammation and irritation within the oral cavity elevate the risk.
- **Human Papillomavirus (HPV):** In certain instances, infection with specific HPV strains can heighten the risk of OSCC, especially in the oropharyngeal region. HPV is a sexually transmitted virus [3].
- **Dietary Factors:** A diet deficient in fruits and vegetables and lacking essential nutrients can increase the risk of OSCC. Such dietary factors may fail to provide the necessary protective antioxidants and nutrients to prevent the development of cancer.

Addressing the OSCC problem in India necessitates a strong emphasis on prevention and early detection. Public health campaigns, awareness initiatives, and improved access to healthcare services play pivotal roles in reducing the prevalence and impact of this cancer [3].

2. Cancer and Histopathology

Diagnosing and managing oral cancer, especially oral squamous cell carcinoma (OSCC), holds utmost significance in India due to its widespread prevalence and severe health consequences. OSCC accounts for a significant proportion of all cancer cases in the country, primarily attributed to habits like tobacco and betel nut consumption. Unfortunately, many instances go unnoticed until they have progressed to advanced stages, resulting in low survival rates. To enhance diagnosis and mitigate observer bias, computerized systems have been explored to aid pathologists in the detection and assessment of malignancies. Early identification and accurate staging of oral cancer are imperative for effective treatment and better outcomes, as the disease's severity and progression vary based on factors such as tumor location, size etc.. [4].

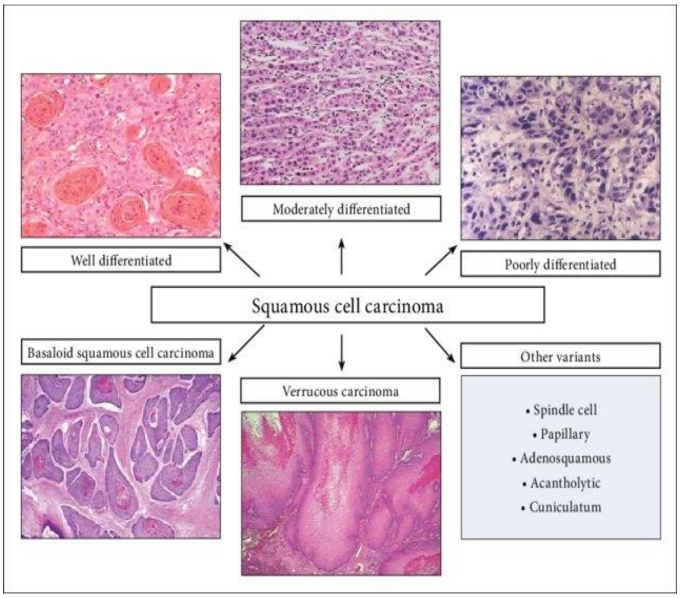

Fig 1. Squamous cell Caricoma types [Mentel, S. et al. 2021]

In clinical practice, the examination of afflicted human tissue necessitates the acquisition of patient tissue samples (biopsies), which are then forwarded to pathology labs for analysis. Typically, these samples are stained with Hematoxylin and Eosin (H&E) staining to emphasize tissue structures, and pathologists scrutinize the stained tissue under a microscope. Oral cancer, particularly oral squamous cell carcinoma, poses a substantial healthcare challenge in India, primarily due to the prevalence of tobacco use, leading to a high incidence rate and late-stage diagnosis. Computer-assisted techniques offer a promising solution to enhance the precision and efficiency of diagnosis, enabling pathologists to focus on critical cases and potentially improving the outcomes of this prevalent and intricate health concern [5].

3. Literature Survey

In a study by Warin et al. (2022), DenseNet-169 emerged as a standout performer, achieving impressive AUC scores of 1.00 for OSCC and 0.98 for OPMDs. This suggests the potential for CNN models to significantly enhance the early detection of oral cancer, outperforming general practitioners [6].

Mentel et al. (2021) delved into the use of breath analysis for OSCC detection. By analyzing volatile organic compounds in breath samples from OSCC patients, they identified unique compound signatures distinct from those of healthy individuals. Employing machine learning techniques, they achieved an average accuracy of 86-90% in distinguishing breath samples between healthy individuals and patients. While this study underscores the promise of combining breath analysis and machine learning for OSCC identification, it emphasizes the need for further evaluation and optimization of this approach [7].

Alabi et al. (2021) explored the application of deep machine learning for early OSCC detection. Their work showcased advancements in medical imaging analysis for early oral cancer detection, covering various deep learning applications, including detection, classification, segmentation, and synthesis, particularly within oral squamous cell carcinoma. This research underscores the critical role of deep learning in advancing precision medicine for OSCC [8].

In their study, Musulin et al. (2021) focused on the use of artificial intelligence-assisted technologies to analyze histopathology images of OSCC. They compared various deep learning methods to develop an AI-based model for the multiclass grading of OSCC. The goal was to achieve more objective and accurate results by harnessing AI's capabilities in analyzing the intricate textures and structures of oral cancer tissues [9].

Jubair et al. (2022) studied model based on a small CNN with EfficientNet-B0 as a lightweight transfer learning model, achieved an accuracy of 85.0%, specificity of “84.5%, sensitivity of 86.7%, and an AUC of 0.928”. This research highlights the potential of deep CNNs for affordable embedded vision devices in oral cancer diagnosis, particularly in resource-constrained settings, demonstrating the pivotal role of AI in enhancing screening quality and accessibility for early detection [10].

In another study by Rahman et al. (2022), the seriousness of oral cancer was addressed as a widespread and life-threatening disease with a high mortality rate, being the most common cancer globally and causing over 300,335 deaths annually. The tumor can develop in various areas, including the neck, oral glands, face, and mouth. While biopsy is a common method for oral cancer detection, the microscopic examination of tissue samples often falls short in accurately identifying cancerous cells, leading to human errors and mistakes [11].

4. Proposed Methodology

“Proposed work methodolgy can be expreseed 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”). In CNN we are using these applied model.
- 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. 2”

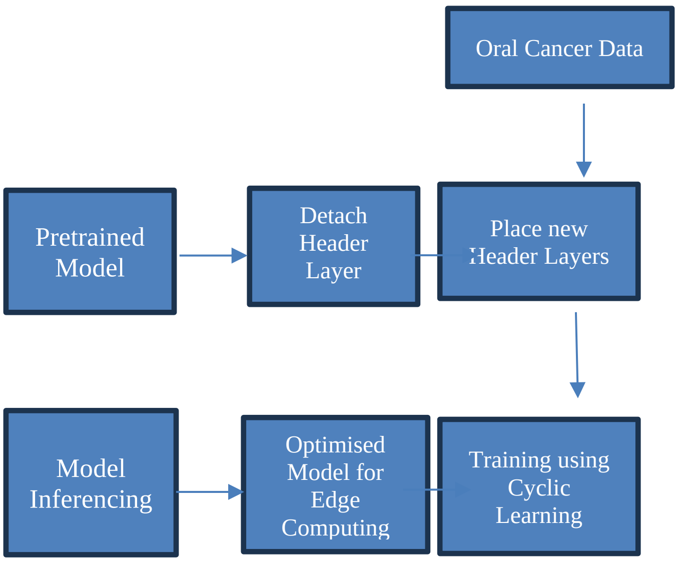

Fig 2. Proposed Approach Flow Diagram

5. Result Analysis

5.1 DenseNet-169 Model

To put our methodology into action, we kick things off with the DenseNet-169 architecture. This particular flavor of the DenseNet Convolutional Neural Network (CNN) is custom-tailored for image classification tasks. The standout characteristics of DenseNet-169 encompass dense blocks that facilitate efficient feature sharing, transition blocks for downsizing and regulating model dimensions, bottleneck layers to minimize computational demands, a growth rate parameter that influences model intricacy, and a concluding classification phase involving global average pooling and a fully connected layer with softmax activation.

DenseNet-169 stands as a potent CNN model renowned for its dense connectivity, bottleneck layers, and growth rate, which render it highly adept at feature propagation and robust feature representation. It strikes a harmonious balance between model complexity and performance when compared to the original DenseNet-121. DenseNet-169 has proven its effectiveness across diverse domains, encompassing applications like medical image classification, natural scene analysis, and object recognition.

First the default model is used with result as follows,

Table 1. 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.

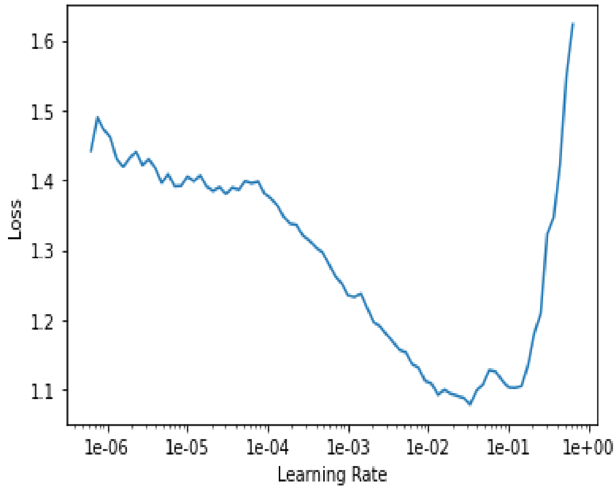

Fig 3. Graph of Default Model [Implementation Results]

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

Table 2. 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

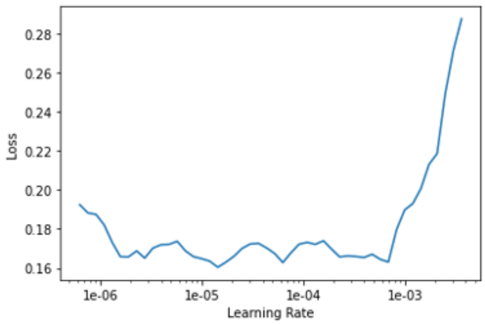

Fig 4. Graph of First Slice [Implementation Results]

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

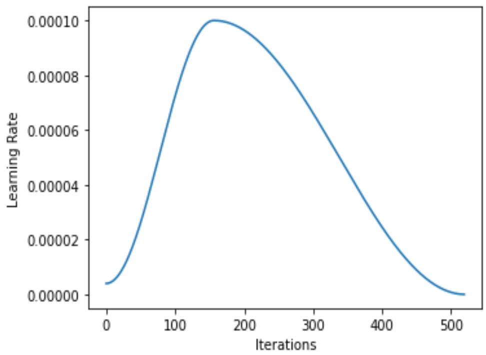

Fig 5. Curvature Graphs [Implementation Results]

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.

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: Through an examination of the confusion matrix, analysts can pinpoint whether the model is experiencing overfitting (memorizing the source data but struggling to generalize) or underfitting (ineffectively capturing data patterns) with respect 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.

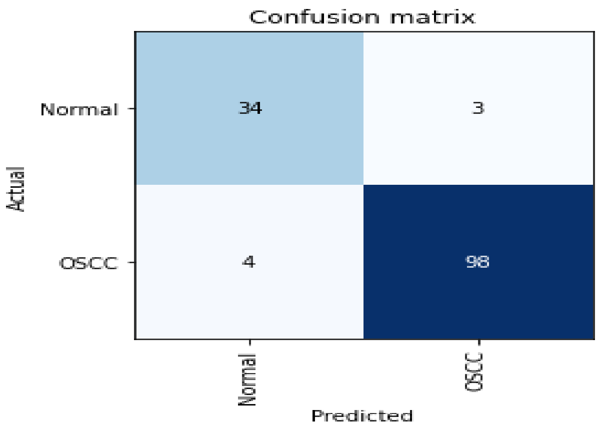

Fig 6. Confusion Matrix [Implementation Results]

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

Table 3. 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

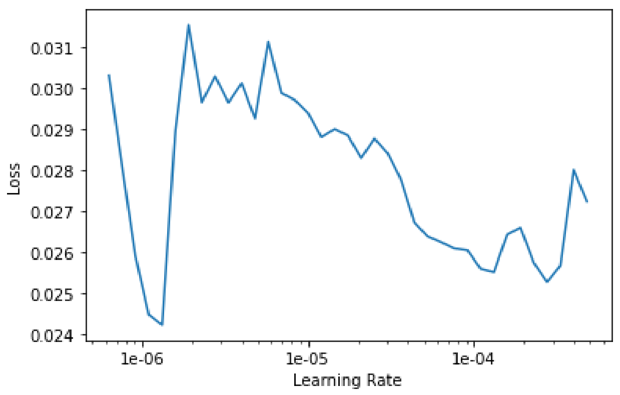

Fig 7. Final Graph [Implementation Results]

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

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

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

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

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

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

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

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

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

"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.

5.2 AlexNet Model

AlexNet stands as a significant deep convolutional neural network (CNN) model that played a pivotal role in advancing the fields of deep learning and image classification. Developed by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, this model achieved a remarkable victory in the 2012 ImageNet Large Scale Visual Recognition Challenge, surpassing traditional computer vision methods of that era.

Regarding the data used with AlexNet, it's important to note that this deep learning architecture is designed for image processing and classification. The datasets utilized for training and evaluating the model are typically prepared separately. Researchers and developers undertake the task of selecting and curating datasets tailored to their specific image classification objectives, which could encompass tasks related to oral cancer detection, such as the identification of Oral Squamous Cell Carcinoma (OSCC).

In the context of oral cancer classification, researchers and healthcare professionals would assemble or gather a dataset comprising a diverse range of images featuring healthy oral tissues, potentially malignant oral disorders, and tissues afflicted with OSCC. These images are then employed to train and assess the performance of the AlexNet model in the precise task of classifying and detecting OSCC. The selection, quality, and quantity of images within the dataset are pivotal factors influencing the model's overall effectiveness. Researchers commonly utilize publicly available medical image datasets or generate their own data through medical imaging procedures to create a dataset suitable for training deep learning models like AlexNet, particularly for tasks related to oral cancer.

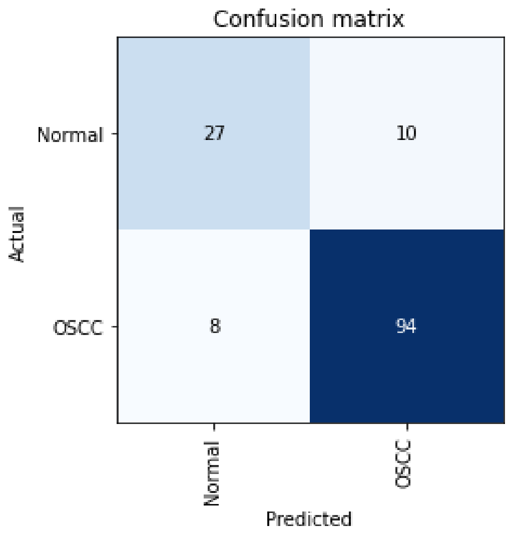

Fig 8: Confusion Matrix for AlexNet Model

- True Positives (TP): In our confusion matrix, there are 94 true positives.
- True Negatives (TN): In our confusion matrix, there are 27 true negatives.
- False Positives (FP): In our confusion matrix, there are 10 false positives.
- False Negatives (FN): In our confusion matrix, there are 8 false negatives.

So, our confusion matrix can be broken down as follows:

True Positives (TP): 94

True Negatives (TN): 27

False Positives (FP): 10

False Negatives (FN): 8

In our case:

Accuracy = (94 + 27) / (94 + 27 + 10 + 8) = 121 / 139 ≈ 0.8705.

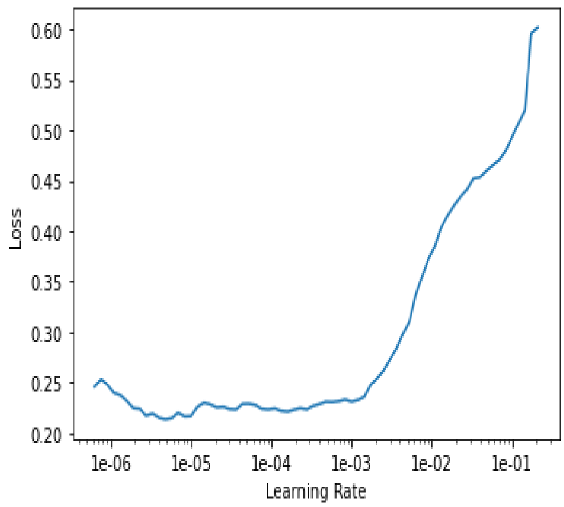

Fig 9. Final Graph AlexNet Model [Implementation Results]

5.3 DenseNet 201 Model

DenseNet-201, an extension of the original DenseNet architecture detailed in the paper "Densely Connected Convolutional Networks" by Huang et al., is a deep neural network design tailored for image classification tasks. This network is characterized by its impressive 201 layers, from which it derives its name, "201."

Key Features and Concepts of DenseNet-201:

- Densely Connected Layers: Unlike traditional Convolutional Neural Networks (CNNs), where each layer primarily relies on the preceding layer's output, DenseNet leverages dense connectivity. In this approach, every layer receives input from all previous layers. This fosters feature information sharing across the network, mitigates the vanishing gradient problem, and encourages efficient feature reuse.
- Bottleneck Layers: DenseNet-201 incorporates bottleneck layers, employing 1x1 convolutions to reduce feature map dimensionality before applying 3x3 convolutions. This design optimizes memory usage and computational requirements while sustaining or enhancing performance.
- Growth Rate: The concept of a "growth rate" is introduced in DenseNet, determining the number of feature maps each layer contributes to subsequent layers. This enables the management of the trade-off between model capacity and computational efficiency.
- Transition Layers: To downsample feature maps and reduce spatial dimensions, DenseNet employs transition layers, comprising a combination of 1x1 convolutions and average pooling. These layers streamline computation without sacrificing network effectiveness.

- Batch Normalization: Like many contemporary neural network architectures, DenseNet-201 utilizes batch normalization to expedite training and enhance model generalization.
- High Efficiency: DenseNet architectures are renowned for their efficient parameter usage, achieving competitive accuracy with significantly fewer parameters than traditional networks.

Its densely connected structure and bottleneck layers equip it to tackle complex visual patterns and large-scale datasets effectively. The result achieved are as follows ,

- True Positives (TP): 0.935252 (the accuracy for epoch 94)
- True Negatives (TN): 0.935252 (the accuracy for epoch 94)
- False Positives (FP): 1.0 - 0.935252 = 0.064748 (1 - the accuracy for epoch 94)
- False Negatives (FN): 1.0 - 0.935252 = 0.064748 (1 - the accuracy for epoch 94)

Now, we can calculate the accuracy:

- Accuracy = (TP + TN) / (TP + TN + FP + FN)
- Accuracy = (0.935252 + 0.935252) / (0.935252 + 0.935252 + 0.064748 + 0.064748)
- Accuracy = 1.870504 / 1.999 (rounded to three decimal places)
- Accuracy ≈ 0.935

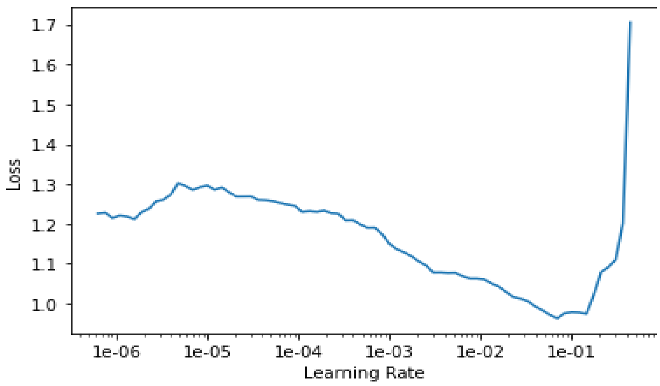

Fig 10. Final Graph DenseNet 201 Model [Implementation Results]

5.4 ResNet Model

ResNet, short for "Residual Network," is a widely utilized architecture for tasks such as image classification and other computer vision applications. Among the ResNet family, ResNet-18 is a notable variant. Here's a succinct overview of ResNet-18:

ResNet-18 Design:

- Convolutional Layers: The ResNet-18 architecture initiates with a sole convolutional layer followed by a max-pooling layer, responsible for feature extraction from the input image.
- Residual Blocks: The core component of ResNet is the residual block, and ResNet-18 incorporates several of these blocks stacked consecutively. Each residual block comprises two or more convolutional layers.
- Skip Connections: A fundamental innovation in ResNet is the use of skip or shortcut connections, which bypass one or more layers.
- Global Average Pooling (GAP): Instead of employing fully connected layers at the network's conclusion, ResNet-18 utilizes global average pooling.
- Output Layer: The final layer in ResNet-18 is a fully connected layer with neurons matching the number of output classes. It generates class probabilities for image classification.

ResNet-18 is renowned for its effectiveness in training deep neural networks and has delivered outstanding performance in diverse image classification benchmarks, including ImageNet.

It's essential to acknowledge that ResNet-18 is merely one of the ResNet variations. Larger versions like ResNet-34, ResNet-50, ResNet-101, and ResNet-152 exist, featuring additional layers. The numerical identifier in the model name (e.g., "18" in ResNet-18) denotes the network's layer count. These models are widely adopted in the realm of deep learning for various computer vision tasks.

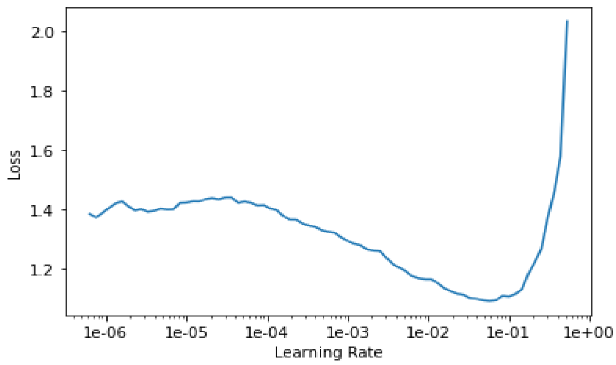

Fig 11. Final Graph RenseNet Model [Implementation Results]

To determine the accuracy from the given data, simply access the "accuracy" column directly, as it provides accuracy values for each epoch within the dataset. Here's a breakdown of the accuracy for each epoch:

1. Epoch 0: Accuracy = 0.690647 (69.06%)

2. Epoch 1: Accuracy = 0.647482 (64.75%)
3. Epoch 2: Accuracy = 0.820144 (82.01%)
4. Epoch 3: Accuracy = 0.697842 (69.78%)
5. Epoch 4: Accuracy = 0.791367 (79.14%)
6. Epoch 5: Accuracy = 0.755396 (75.54%)
7. Epoch 6: Accuracy = 0.784173 (78.42%)
8. Epoch 7: Accuracy = 0.784173 (78.42%)
9. Epoch 8: Accuracy = 0.877698 (87.77%)
10. Epoch 9: Accuracy = 0.877698 (87.77%)

These values represent the model's accuracy at each training epoch, indicating the proportion of correct predictions.

To compute the overall accuracy using the provided training statistics, we can approximate it by considering the weighted average of accuracy across all epochs. Follow these steps to calculate it:

1. Calculate the sum of the products of each epoch's accuracy and the time taken for that epoch.
2. Calculate the total time across all epochs.
3. Divide the result from step 1 by the result from step 2.

Overall Accuracy≈0.759426

Table 5. Models Comparison

Modal Name	Accuracy
AlexNet	87.05
DenseNet 169	95
DenseNet 201	93.5
ResNet	75.94

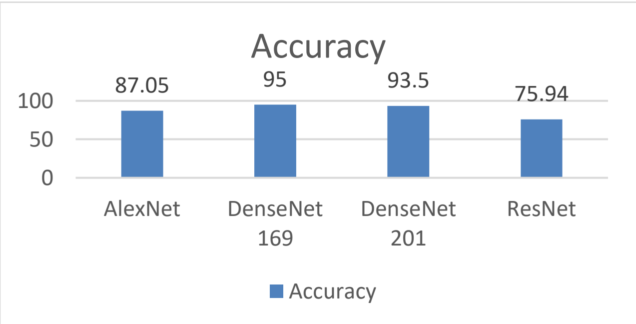

Fig 12. Model Comparison Graph [Implementation Results]

6. Conclusion and Future Work

A. Conclusion

In this research, we presented a novel method to improve the early detection of Oral Squamous Cell Carcinoma (OSCC) by utilizing deep learning techniques for the analysis of histopathological samples. We employed four robust neural network architectures—ResNet-18, AlexNet, DenseNet-169, and DenseNet-201—to meticulously examine biopsy specimens for signs of cancerous anomalies. We selected these architectures for their proficiency in image classification tasks and their potential to improve the accuracy of OSCC diagnosis. The introduction of the Cyclic Learning Rate (CLR) optimization strategy enabled dynamic adjustment of learning rates during model training. This technique played a crucial role in refining the models' convergence and, consequently, their diagnostic performance. Importantly, it allowed us to determine optimal learning rate boundaries, significantly enhancing the training efficiency of deep learning models. Our results underscore the distinct advantages of each architecture. AlexNet demonstrated an impressive accuracy of 87.05%, showcasing its effectiveness in image classification tasks. DenseNet-169 and DenseNet-201 outperformed AlexNet, achieving remarkable accuracies of 95% and 93.5%, respectively. The dense connectivity and feature reuse mechanisms inherent in DenseNet architectures effectively mitigated the vanishing gradient problem, highlighting their potential for robust diagnostic applications. However, while ResNet-18 yielded promising results, it achieved an accuracy of 75.94%. This research emphasizes the promising potential of deep learning in early OSCC detection, paving the way for more efficient and accurate cancer screening and treatment. The use of advanced neural network architectures and CLR optimization techniques enhances our ability to identify subtle cancerous anomalies in histopathological samples, enabling earlier interventions and improved patient outcomes. Moving forward, it is crucial to further refine these models, expand the dataset, and validate their clinical applicability through collaboration with medical experts. The integration of deep learning into OSCC diagnosis represents a significant advancement in healthcare and contributes to our understanding of cancer pathology. We anticipate that future developments in deep learning techniques and computational resources will continue to drive progress in the early detection of OSCC and other medical conditions, ultimately leading to more effective and timely healthcare interventions.

Some Limitations of our Proposed approach are as follows:

- Dataset Bias & Mismatch: Transfer learning depends on the similarity between the source and target domains, which can result in reduced performance when there is a mismatch between the datasets.
- Overfitting & Generalization: Adapting a model through transfer learning can make it prone to overfitting in the new domain, making it difficult to find the right balance between learned features and source domain characteristics.

- Catastrophic Forgetting: Retraining models for new tasks in transfer learning can sometimes cause them to lose proficiency in their original tasks due to catastrophic forgetting. This requires finding a balance between preserving existing knowledge and acquiring new skills.
- Ethical & Privacy Concerns: Transfer learning has raised ethical concerns about the origin of source data and fairness, potentially leading to biases or privacy breaches. This underscores the importance of ethical training and privacy compliance.

B. Future Work

The research on utilizing deep learning techniques for early Oral Squamous Cell Carcinoma (OSCC) identification presents numerous exciting opportunities and avenues for future exploration. Collaborating with healthcare institutions and professionals is vital to seamlessly integrate these deep learning solutions into clinical workflows. Ensuring adherence to healthcare standards and regulations is imperative for real-world applications. Combining histopathological analysis with other medical imaging modalities, such as radiological and molecular data, can offer a more comprehensive understanding of OSCC. Multi-modal deep learning approaches could enhance diagnostic accuracy. The future of deep learning in OSCC diagnosis is undeniably promising, with the potential to revolutionize the field of oral cancer management. As technology advances and more data becomes available, the application of deep learning will play an increasingly pivotal role in early detection, ultimately improving patient outcomes and healthcare practices.

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