Deep Learning Techniques for Oral Cancer Detection: Enhancing Clinical Diagnosis by ResNet and DenseNet Performance

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Abstract. This study aims to enhance the accuracy and efficiency of oral cancer diagnosis through the application of deep learning techniques in medical image analysis. The research employs convolutional neural networks (CNNs), specifically ResNet and DenseNet architectures, for the classification of oral cancer images into malignant and benign categories. Data preprocessing involves resizing, normalization, and augmentation to optimize model performance. Evaluation metrics including accuracy, loss, specificity, and sensitivity demonstrate varying performance across different CNN models. DenseNet architectures consistently outperform ResNet and conventional CNNs in terms of accuracy and sensitivity metrics. The results showed that DenseNet consistently outperformed ResNet, achieving higher accuracy and sensitivity, which are crucial for early cancer detection. The findings underscore the transformative potential of deep learning in augmenting clinical decision-making for oral cancer detection. Integration of these advanced technologies into healthcare workflows could significantly improve early detection rates and treatment outcomes, paving the way for personalized medicine approaches in oncology.

Keywords: Deep Learning · Oral Cancer Detection · Image Classification · Convolutional neural Network (CNN) · Oncology Diagnosis

1 Introduction

Oral cancer [18] is a significant health concern worldwide, with increasing incidence and mortality rates. Early detection and timely intervention are crucial

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for improving patient outcomes [28]. However, many individuals lack the necessary awareness and resources to recognize early symptoms and seek appropriate care. Traditional methods of patient education and support are often limited by accessibility and scalability, creating a need for innovative solutions that leverage modern technology [19]. Despite advancements in healthcare technology, there remains a gap in accessible and reliable tools for patient education and early symptom recognition specific to oral cancer [4]. Traditional diagnostic approaches, which rely on visual examination and biopsy, and these approaches are time-consuming, invasive, and often fail to detect cancer in its early stages. This study addresses the critical need for more accurate and efficient diagnostic tools by using deep learning techniques in medical image analysis.

This research addresses this gap by developing a novel oral cancer image classification framework using deep learning techniques. By employing two substantial datasets from Kaggle (https://www.kaggle.com/shi vam17299/oral-cancer-lips-and-tongue-images) and RoboFlow [25], this study maintains a balance between cancerous and non-cancerous samples and allows the development of methods to enhance diagnostic accuracy.

Artificial intelligence (AI) [5,11] and machine learning (ML) [1] have different applications across numerous domains, with medicine being no exception. In this context, this study presents an infrastructure that uses advanced Deep Learning (DL) [2] algorithms to enhance the detection of oral cancer. The techniques used are an spectrum of convolutional neural network (CNN) models, including ResNet 101, DenseNet 121, DenseNet 169, and DenseNet 201, are used to train and validate algorithms capable of classifying oral images into two categories: cancerous and non-cancerous [7].

This paper presents the design and implementation of a DL-based system for oral cancer image detection and classification. The primary objective aims to utilize image classification [12] to aid in the early recognition of oral cancer symptoms, facilitating timely intervention. The system also contributes to the field of medical image processing and analysis through the development and application of DL algorithms specifically tailored for early oral cancer detection. By integrating advanced AI technologies, the system seeks to improve diagnostic workflows and augment the precision of oral cancer diagnoses. By leveraging these advanced technologies, the system aims to enhance patient engagement in the diagnostic process and facilitate early detection with professional healthcare support [10].

This paper is organized into several key sections to systematically present the design and implementation of a deep learning-based system for oral cancer image detection and classification. The Sect. 1 section provides the background and motivation for the research. It also introduces the research question: "How can deep learning techniques be effectively utilized to enhance the accuracy and efficiency of oral cancer diagnosis through image classification?" The Sect. 2 covers existing studies and methodologies related to deep learning in medical image analysis, setting the stage for the current study's contributions. The Sect. 3 details the system's architecture, including data acquisition, preprocessing, and the specific deep learning models employed, such as ResNet and DenseNet. In the Sect. 4, the paper presents the outcomes of the system's performance, evaluated through metrics like accuracy and loss, and compares these with related work. The Sect. 5 explores the implications of these results, discusses limitations, and suggests potential areas for future research. Finally, the Sect. 6 summarizes the main findings, emphasizes the contributions to the field of medical image processing and oral cancer detection, and proposes recommendations for future research and practical applications.

2 Related Work

Oral cancer remains a significant global health challenge, prompting intensive research into advanced diagnostic techniques. Recent years have witnessed a paradigm shift towards leveraging deep learning methodologies for the automated classification of oral cancer images. This section explores the latest advancements, methodologies, and key findings in this burgeoning field [14].

2.1 Deep Learning in Medical Imaging

In [6] deep learning techniques are used to select features and classify MRI images by merging the techniques with machine learning algorithms. Additionally, in [24] deep learning and transfer learning are used for histopathological diagnosis of adenocarcinomas from biopsy needle images. In [8], CNN is used for image segmentation and machine learning techniques are used to extract features. In [3], deep learning techniques are used to make predictions about image regions.

2.2 Advancement in Oral Cancer Image Classification

Recent studies have demonstrated promising advancements in utilizing deep learning for oral cancer image classification. Researchers have increasingly adopted convolutional neural networks (CNNs) due to their ability to extract intricate features from complex imaging data. For instance, [26] have highlighted the effectiveness of CNN-based architectures such as ResNet and DenseNet in achieving high accuracy rates in distinguishing between malignant and benign oral lesions.

2.3 Deep Learning Models

Methodologically, researchers have focused on optimizing deep-learning models for oral cancer classification [9]. Preprocessing techniques play a crucial role in enhancing image quality and standardizing data inputs. Techniques such as image enhancement, noise reduction, and normalization have been employed to improve model robustness and accuracy. Moreover, transfer learning approaches, as demonstrated by [15], have shown promising results by leveraging pre-trained models on large-scale datasets to enhance model generalization capabilities.

The literature underscores the efficacy of deep learning models in enhancing diagnostic accuracy for oral cancer. Studies have reported significant improvements in sensitivity and specificity metrics, crucial for early detection and treatment planning. For instance, the work by [27] demonstrated good performance metrics in detecting oral cancer lesions using a tailored CNN architecture, highlighting the potential clinical utility of deep learning in augmenting traditional diagnostic methods.

2.4 Machine Learning in Oral Cancer

In the context of oral cancer, [13] reviewed various machine learning techniques for detection, prevention, prognosis, and treatment, including support vector machines, artificial neural networks, and logistic regression, are reviewed. On the other hand, in [21] a systematic review of machine learning techniques is conducted. The integration of deep learning techniques holds immense promise for revolutionizing oral cancer diagnosis through automated image classification. While challenges such as dataset variability and interpretability remain, ongoing research efforts continue to refine methodologies and expand the applicability of deep learning in improving healthcare outcomes for oral cancer patients.

3 Methodology

In this section, we outline the systematic approach employed to classify oral cancer images using deep learning techniques. The methodology is structured to provide a comprehensive overview of the steps involved, starting with the preprocessing of image data, followed by the splitting of data for training and evaluation, and concluding with the details of model training and performance assessment.

Oral cancer remains a significant global health issue, with early detection being crucial for effective treatment and improved survival rates. Traditional diagnostic methods often rely on visual inspection and biopsies, which can be subjective and time-consuming. Leveraging deep learning techniques for the classification of oral cancer images presents an opportunity to enhance diagnostic accuracy and efficiency.

In this study, we aim to classify oral cancer images into two primary categories: benign and malignant. We utilize a publicly available dataset of histopathology images, which provides a comprehensive collection of annotated images for training and evaluation purposes. Figure 1 illustrates the methodology employed divided into clear stages: data preprocessing, dataset preparation, and model training. It begins with preprocessing, where images are separated into cancerous and non-cancerous categories, involving the removal of duplicates. Following this step, the dataset is prepared for use with Deep Learning techniques.

First, the system's foundation relies on two robust datasets for training and evaluation: one from Kaggle with 500 oral cancer images and 450 non-cancerous

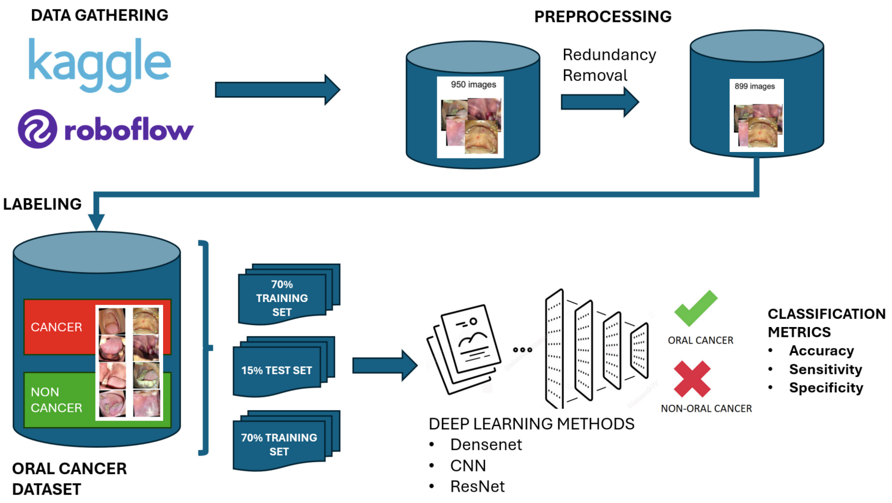


Fig. 1. Deep Learning Oral Cancer Images Detection Methodology

images, and a Roboflow, dataset with images evenly divided between cancer and control cases. Both datasets had preprocessing steps like resizing, normalization, and augmentation. The core of the system is a deep learning model using Convolutional Neural Networks (CNNs) to classify images accurately. Transfer learning techniques enhanced performance and reduced training time, improving generalization from limited medical imaging data. Examples of the images can be seen in Fig. 2.

3.1 Image Preprocessing and Resizing

Each dataset was prepared to ensure uniformity and readiness for machine learning. The preprocessing steps included:

1. **Importing Images:** We loaded two datasets from Kaggle and RoboFlow.
2. **Image Preprocessing:**
   - **Resizing Images:** We resized all images to 256×256 pixels so that they were all the same size.
   - **Adding Borders:** We added a 2-pixel black border around each image to handle edge effects better during processing.
   - **Applying Blur:** We applied a light blur with a 2×2 kernel to reduce noise and avoid focusing too much on small details that might not be important.
   - **Image Comparison:** We compared each image with others using root mean square (RMS) error to find duplicates.
   - **RMS Calculation:** We converted images to arrays with NumPy and calculated the RMS. If the RMS was below 3, the images were considered similar or identical.

Fig. 2. Samples from the Datasets

– **Similarity Verification:** We removed duplicate images from the dataset to avoid redundancy.

After preprocessing, the images were organized into two main folders. A new folder named "Processed" was created to store the resized images, ensuring they were appropriately prepared for the subsequent stages of model training and evaluation.

1. **Randomization and Splitting:** We listed and randomly shuffled the images to prevent biases. Using NumPy's `np.split` function, we divided the images into training, validation, and test sets. By default, 15% of images were used for validation, another 15% for testing, and 70% for training.

Table 1. Summary of Techniques and Descriptions

Technique	Description
ResNet 101	Deep convolutional neural network architecture known for training very deep networks effectively using residual connections.
DenseNet 121	Convolutional neural network architecture featuring dense connectivity, facilitating gradient flow and feature reuse.
DenseNet 169	Variant of DenseNet architecture with increased number of layers, providing greater model capacity and performance.
DenseNet 201	Variant of DenseNet architecture with even larger number of layers, offering greater model capacity and expressive power.
CNN	Class of deep neural networks are commonly used for various computer vision tasks, characterized by convolutional and pooling layers.

2. **Image Copying:** We copied the images from the source directory to the training, validation, and test directories to keep them separate.

A dedicated "Data-Splitting" folder was established, containing subfolders for Training, Testing, and Validation datasets. The images were organized into these subfolders to facilitate the systematic training, testing, and validation of the model.

3.2 Deep Learning Techniques

Convolutional neural networks were chosen because they are highly effective for image classification due to their ability to automatically detect and learn important features from images. The preprocessing techniques were selected to enhance image quality and ensure uniformity across the dataset, which is crucial for the model's performance. The chosen tools and libraries, like TensorFlow and Keras, are widely recognized in the deep learning community for their robustness and flexibility, allowing for efficient model development and testing. The use of GPUs in the experimental setup was essential to handle the computational demands of training deep learning models, significantly speeding up the process and enabling more complex model architectures.

The models are various deep-learning techniques employed for oral cancer image classification. ResNet-101 utilizes a pre-trained architecture with custom final layers and global average pooling for feature extraction, optimized through Adam optimizer with dynamic learning rate adjustment and early stopping. DenseNet models (121, 169, and 201) adapt pre trained structures with GlobalAveragePooling2D and dense layers, employing binary cross-entropy loss, Adam optimizer, and similar training strategies. The CNN architecture offers customization flexibility with task-specific convolutional and fully connected layers, supporting various optimizers and the potential for early stopping and learning rate adjustments based on validation metrics. A scheme of the techniques is shown in Fig. 3.

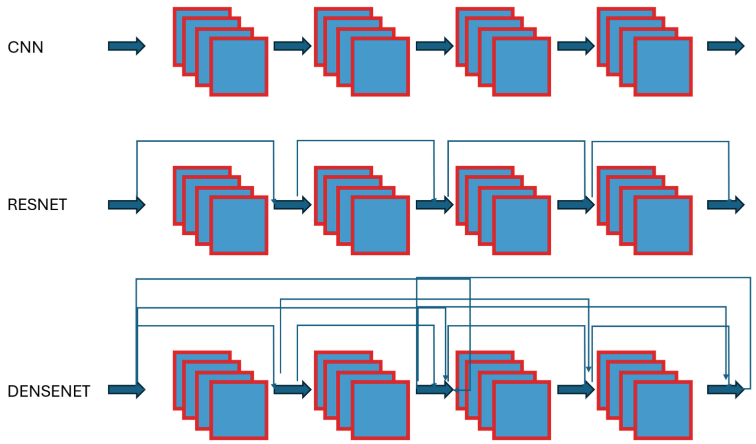


Fig. 3. Deep Learning Techniques

Deep learning models, such as DenseNet and ResNet, offer superior accuracy compared to traditional diagnostic methods, with improved sensitivity and specificity. These models analyze large volumes of images faster than manual inspection, enhancing efficiency. Although the initial cost for training and hardware is high, long-term savings may result from fewer repeat tests and diagnostic errors. Thus, while deep learning models promise advancements in accuracy and efficiency, their cost-effectiveness will be evaluated as they are integrated into clinical settings.

To assess the performance of our models, in Table 2 we show several evaluation metrics, summarized in the table below along with their respective equa-

Table 2. Summary of Evaluation Metrics and Equations

Metric	Equation
Confusion Matrix	**Predicted Positive Predicted Negative**
	Actual Positive TP (true positive) FN (false negative)
	Actual Negative FP (false positive) TN (true negative)
Accuracy	Accuracy $= \frac{TP+TN}{TP+TN+FP+FN}$
Cross-Entropy Loss	Loss $= -\frac{1}{N}\sum_{i=1}^{N}[y_i \cdot \log(\hat{y}_i) + (1-y_i)\cdot\log(1-\hat{y}_i)]$ where: N = Total number of samples y_i = True label for sample i $\hat{y}_i$ = Predicted probability for the positive class for sample i
Sensitivity (Recall)	Sensitivity $= \frac{TP}{TP+FN}$
Specificity	Specificity $= \frac{TN}{TN+FP}$

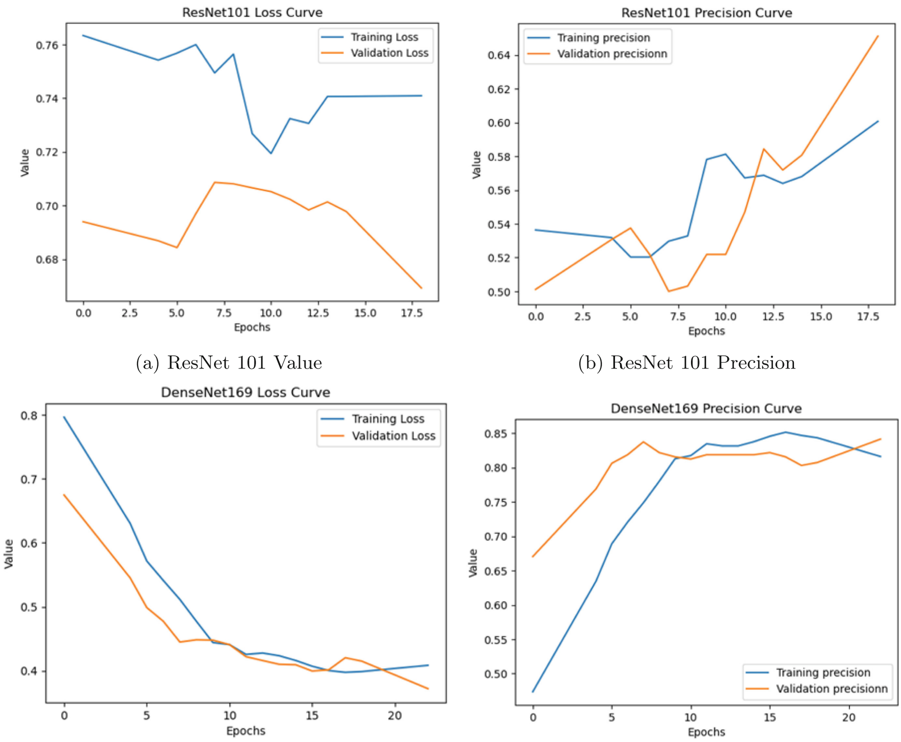
tions. The confusion matrix is also provided to illustrate the calculation of these metrics.

4 Results

The study evaluates multiple deep learning models for their performance in classifying oral cancer images. Figure 4 illustrates the loss and precision curves for ResNet101 and DenseNet 169. These curves track training progress and accuracy of positive predictions, aiding in comparative analysis and model selection.

Table 3 presents a detailed comparison of model performance metrics.

Accuracy varies notably across models, ranging from 52.25% for ResNet101 to approximately 85–88% for DenseNet models, with CNN achieving 58.54%. Higher accuracy values indicate better classification performance, highlighting DenseNet models' superior performance over ResNet101 and CNN. Loss, reflecting prediction error, also varies significantly, with ResNet101 showing higher loss (68.26%) compared to DenseNet models and CNN, which range between 29.92% and 66.65%. Specificity, measuring the ability to correctly identify negatives, is



(a) ResNet 101 Value (b) ResNet 101 Precision

(c) DenseNet 169 Value (d) DenseNet 169 Precision

Fig. 4. Performance Curves for Techniques

highest for ResNet101 (99.33%) and ranges from 49.71% to 60.46% for DenseNet models and CNN. Sensitivity, indicating the ability to correctly identify positives, ranges from 8.19% to 47.99%, showing variability across models in detecting cancerous lesions.

Overall, these results demonstrate the effectiveness of DenseNet architectures in accurately classifying oral cancer images, outperforming ResNet101 and CNN in accuracy and loss metrics. The findings guide the selection of appropriate models based on specific performance requirements, such as accuracy, error tolerance, and classification sensitivity.

Table 3. Model Performance Metrics

Model	Accuracy (%)	Loss (%)	Specificity (%)	Sensitivity (%)
ResNet101	52.25	68.26	99.33	8.19
DenseNet201	85.84	33.42	60.46	47.89
DenseNet169	87.81	29.92	49.71	47.99
DenseNet121	87.35	32.33	50.92	47.91
CNN	58.54	66.65	16.42	48.14

5 Discussion

The application of deep learning techniques in oral cancer detection offers significant implications for patient outcomes and healthcare accessibility. These methods facilitate precise and early detection through robust image classification models. By leveraging advanced convolutional neural networks (CNNs) like ResNet and DenseNet, this study demonstrates enhanced accuracy in distinguishing cancerous lesions from non-cancerous tissues. This capability not only aids in timely diagnosis but also supports clinicians in making informed treatment decisions, potentially improving survival rates and reducing treatment-related morbidity.

The reported metrics (accuracy, loss, specificity, and sensitivity) are essential for evaluating model performance in oral cancer detection. Accuracy represents the overall success rate of the model; however, in clinical practice, it is often less meaningful on its own, especially in cases with imbalanced datasets where the model might correctly classify non-cancerous cases while missing critical malignant ones. On the contrary, sensitivity is crucial for identifying true cancer cases early, while specificity helps reduce false positives, preventing unnecessary stress and procedures. In clinical practice, balancing sensitivity and specificity is vital to avoid overwhelming healthcare systems with false positives or missing early-stage cancers. DenseNet architectures, with their superior sensitivity, show promise in improving cancer detection rates and could enhance patient outcomes if integrated into clinical workflows.

The variance in specificity and sensitivity metrics across models is influenced by factors such as model architecture, training procedures, and data quality. Deep learning models like DenseNet often show higher sensitivity due to their advanced feature extraction capabilities, crucial for detecting subtle cancerous lesions. However, this can come at the cost of lower specificity, leading to potential false positives. The quality and diversity of the training data also affect these metrics; imbalanced or non-representative datasets can skew results, impacting clinical usability. For clinical practice, achieving a balance between high sensitivity and specificity is essential to ensure accurate cancer detection while minimizing unnecessary procedures.

Interpretability is crucial for clinical adoption of deep learning models. Techniques like Grad-CAM [23] provide visual explanations by highlighting key image areas influencing predictions, helping clinicians trust and validate the model's outputs. This transparency is essential for integrating deep learning models into clinical workflows and supporting informed decision-making.

In assessing our deep learning models for oral cancer detection, it is important to compare them with traditional diagnostic methods and simpler machine learning models. Traditional methods like visual inspection and biopsy are still the standard but can be subjective and inconsistent due to pathologist experience and sample quality [20]. Simpler machine learning models, such as Support Vector Machines and Random Forests, have shown varied performance in image classification due to their limitations in capturing complex patterns [16,22]. Our deep learning models, including DenseNet and ResNet, demonstrate good sensitivity and specificity, crucial for early cancer detection and minimizing false positives [17]. This indicates that deep learning can improve diagnostic accuracy significantly compared to both traditional and simpler methods, with DenseNet's performance particularly promising for clinical integration.

Comparison with related work underscores the effectiveness of deep learning models in oral cancer diagnostics. Our findings align with previous studies showing the superiority of pre-trained architectures like ResNet and DenseNet in handling complex medical imaging tasks. These models, fine-tuned for oral cancer classification, exhibit superior performance metrics such as accuracy and sensitivity compared to traditional methods.

Despite these advancements, several limitations must be addressed to optimize the deployment of deep learning in clinical practice. Challenges include the need for large, diverse datasets to enhance model generalization, as well as interpretability of model decisions in medical settings. Future research should focus on refining these models through data augmentation techniques, integrating multimodal data sources, and ensuring robust validation across diverse patient demographics.

6 Conclusion

In conclusion, this study underscores the pivotal role of deep learning techniques in advancing oral cancer diagnosis and management. Utilizing CNNs such as

ResNet and DenseNet, our research contributes to the evidence supporting their efficacy in medical image analysis. These techniques enhance diagnostic accuracy and offer potential for treatment strategies to individual patient profiles.

It is crucial to integrate deep learning models into clinical workflows, facilitating collaboration with healthcare providers. This includes leveraging telemedicine platforms for remote consultations and monitoring patient outcomes over time. Furthermore, improving model interpretability and transparency is essential to build trust among healthcare professionals and patients.

Several avenues for future research can be used to enhance the performance and applicability of deep learning models for oral cancer detection. First, the need of expanding the dataset to include more diverse and comprehensive samples from various sources and clinical settings will improve model generalizability. Integrating these models into clinical data is essential, requiring the development of user-friendly interfaces and validation in real-world environments. Additionally, a thorough comparison with traditional diagnostic methods and simpler machine learning models will provide valuable context for the deep learning models' performance, considering factors such as cost, speed, and accuracy. Improving model interpretability is crucial for clinical adoption, and future research should focus on techniques that make model predictions more transparent and understandable for clinicians. Finally, exploring advanced techniques, such as Transformer models or hybrid approaches, could lead to further improvements in classification accuracy and robustness.

While our study demonstrates promising results using the Kaggle and Robo Flow datasets for oral cancer image classification, we acknowledge the limitation regarding the representativeness of these datasets. The current datasets may not encompass the full spectrum of oral cancer cases, which could impact the generalizability of our models. To mitigate this limitation, future work will involve expanding our dataset with additional sources that cover a wider range of cancer stages, subtypes, and demographic variations. We will also employ advanced data augmentation techniques and validate our models on diverse external datasets to enhance their robustness and applicability. By addressing these aspects, we aim to improve the models' performance and ensure their effectiveness in real-world clinical settings. This approach will contribute to more accurate and reliable early detection of oral cancer, ultimately supporting better patient outcomes.

To improve model accuracy and usability, we will expand the dataset to include a broader range of cases, experiment with advanced architectures and hyperparameter tuning, and develop user-friendly interfaces for clinical integration. We will also conduct comparative studies with traditional methods and perform a cost-benefit analysis to evaluate the economic implications of adopting these models.

In summary, deep learning represents an support in oral cancer care, providing scalable solutions to enhance early detection, treatment planning, and patient outcomes. Embracing technological advancements and collaborative research efforts can pave the way for accessible precision medicine, reducing disparities and improving health equity in oral cancer management.

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References

1. Ajagbe, S.A., Adegun, A.A., Mudali, P., Adigun, M.O.: Performance of machine learning models for pandemic detection using COVID-19 dataset. In: 2023 IEEE AFRICON, pp. 1–6. IEEE (2023)
2. Ajagbe, S.A., Adigun, M.O.: Deep learning techniques for detection and prediction of pandemic diseases: a systematic literature review. Multimedia Tools Appl. **83**(2), 5893–5927 (2024)
3. Brockmoeller, S., et al.: Deep learning identifies inflamed fat as a risk factor for lymph node metastasis in early colorectal cancer. J. Pathol. **256**(3), 269–281 (2022)
4. Chakraborty, D., Natarajan, C., Mukherjee, A.: Advances in oral cancer detection. Adv. Clin. Chem. **91**, 181–200 (2019)
5. García-Pola, M., Pons-Fuster, E., Suárez-Fernández, C., Seoane-Romero, J., Romero-Méndez, A., López-Jornet, P.: Role of artificial intelligence in the early diagnosis of oral cancer. a scoping review. Cancers **13**(18), 4600 (2021)
6. Hassan, M.R., et al.: Prostate cancer classification from ultrasound and MRI images using deep learning based explainable artificial intelligence. Futur. Gener. Comput. Syst. **127**, 462–472 (2022)
7. Hegde, S., Ajila, V., Zhu, W., Zeng, C.: Artificial intelligence in early diagnosis and prevention of oral cancer. Asia Pac. J. Oncol. Nurs. **9**(12), 100133 (2022)
8. Ho, C., et al.: A promising deep learning-assistive algorithm for histopathological screening of colorectal cancer. Sci. Rep. **12**(1), 2222 (2022)
9. Huang, Q., Ding, H., Razmjooy, N.: Optimal deep learning neural network using ISSA for diagnosing the oral cancer. Biomed. Signal Process. Control **84**, 104749 (2023)
10. Ilhan, B., Lin, K., Guneri, P., Wilder-Smith, P.: Improving oral cancer outcomes with imaging and artificial intelligence. J. Dent. Res. **99**(3), 241–248 (2020)
11. Ilhan, B., Guneri, P., Wilder-Smith, P.: The contribution of artificial intelligence to reducing the diagnostic delay in oral cancer. Oral Oncol. **116**, 105254 (2021)
12. Jeyaraj, P.R., Samuel Nadar, E.R.: Computer-assisted medical image classification for early diagnosis of oral cancer employing deep learning algorithm. J. Cancer Res. Clin. Oncol. **145**, 829–837 (2019)
13. López-Cortés, X.A., Matamala, F., Venegas, B., Rivera, C.: Machine-learning applications in oral cancer: a systematic review. Appl. Sci. **12**(11), 5715 (2022)
14. Mira, E.S., et al.: Early diagnosis of oral cancer using image processing and artificial intelligence. Fusion: Pract. Appl. **14**(1), 293–308 (2024)
15. Palaskar, R., Vyas, R., Khedekar, V., Palaskar, S., Sahu, P.: Transfer learning for oral cancer detection using microscopic images. arXiv preprint arXiv:2011.11610 (2020)
16. Panigrahi, S., Swarnkar, T.: Machine learning techniques used for the histopathological image analysis of oral cancer-a review. The Open Bioinform. J. **13**(1) (2020)
17. Rai, H.M.: Cancer detection and segmentation using machine learning and deep learning techniques: a review. Multimedia Tools Appl. **83**(9), 27001–27035 (2024)
18. Rivera, C.: Essentials of oral cancer. Int. J. Clin. Exp. Pathol. **8**(9), 11884 (2015)

19. Seoane, J., Varela-Centelles, P., Tomas, I., Seoane-Romero, J., Diz, P., Takkouche, B.: Continuing education in oral cancer prevention for dentists in Spain. J. Dent. Educ. **76**(9), 1234–1240 (2012)
20. Sujir, N., Ahmed, J., Pai, K., Denny, C., Shenoy, N.: Challenges in early diagnosis of oral cancer: cases series. Acta Stomatol. Croat. **53**(2), 174 (2019)
21. Sulochana, C., Sumathi, M.: A systematic review on oral cancer diagnosis and prognosis using machine learning techniques. J. Algebraic Stat. **13**(3), 3542–3550 (2022)
22. Sultan, A.S., Elgharib, M.A., Tavares, T., Jessri, M., Basile, J.R.: The use of artificial intelligence, machine learning and deep learning in oncologic histopathology. J. Oral Pathol. Med. **49**(9), 849–856 (2020)
23. Magesh, T.R., Vionth Kumar, V., Guluwadi, S.: Enhancing brain tumor detection in MRI images through explainable AI using grad-cam with resnet 50. BMC Medical Imaging **24**(1), 107 (2024)
24. Tsuneki, M., Abe, M., Kanavati, F.: A deep learning model for prostate adenocarcinoma classification in needle biopsy whole-slide images using transfer learning. Diagnostics **12**(3), 768 (2022)
25. sagari vijay: oral cancer data dataset. https://universe.roboflow.com/sagari-vijay/oral-cancer-data (2021). https://universe.roboflow.com/sagari-vijay/oral-cancer-data, visited 08 Jul 2024
26. Warin, K., Limprasert, W., Suebnukarn, S., Jinaporntham, S., Jantana, P., Vicharueang, S.: Ai-based analysis of oral lesions using novel deep convolutional neural networks for early detection of oral cancer. PLoS ONE **17**(8), e0273508 (2022)
27. Warin, K., Suebnukarn, S.: Deep learning in oral cancer-a systematic review. BMC Oral Health **24**(1), 212 (2024)
28. Warnakulasuriya, S., Kerr, A.: Oral cancer screening: past, present, and future. J. Dent. Res. **100**(12), 1313–1320 (2021)