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Research Article

Automated Oral Cancer Detection using Convolutional Neural Networks and Support Vector Machines

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Abstract **–** Oral cancer is a significant public health concern, demanding early detection and intervention for improved patient outcomes. In this study, we propose an automated method for oral cancer detection leveraging state-of-the-art deep learning techniques. Convolutional Neural Networks (CNNs), specifically the ResNet18 architecture [3, 12], are employed for feature extraction from oral images, followed by classification using Support Vector Machines (SVMs). The dataset comprises a collection of oral images encompassing various stages and types of oral cancer [17].
Our methodology involves preprocessing steps to standardize image dimensions and augment the dataset. The ResNet18 model is utilized to extract discriminative features from the images, which are subsequently fed into an SVM classifier for binary classification distinguishing between cancerous and non-cancerous oral images [2, 20].
The evaluation of our proposed approach demonstrates promising results in automated oral cancer detection. Performance metrics, including accuracy, sensitivity [15], and specificity, exhibit commendable levels, suggesting the effectiveness of the combined ResNet18-SVM methodology. Comparative analyses against existing methods underscore the potential of our approach in facilitating early and accurate oral cancer diagnosis [7, 9].
The implications of automated oral cancer detection are far-reaching, with the potential to revolutionize clinical practices by enabling prompt interventions and improving patient prognosis. Future research directions encompass exploring diverse CNN architectures, integrating multi-modal data sources, and refining the proposed methodology for enhanced diagnostic precision [8,14].
This study signifies a significant stride towards automated oral cancer detection, laying the groundwork for leveraging advanced deep learning techniques in the realm of medical image analysis for improved healthcare outcomes [1, 5].
Keywords – Oral Cancer, Machine Learning, CNN, SVM.

Introduction

Oral cancer remains a pressing global health challenge, manifesting a substantial burden on healthcare systems and patient well-being. Timely detection and accurate diagnosis of oral malignancies are pivotal factors in enhancing patient survival rates and treatment efficacy [3, 13]. Traditional diagnostic methods heavily reliant on manual examination and Histological analyses are time-consuming and prone to subjectivity, prompting the exploration of advanced computational approaches to aid in early detection [6, 19].

In recent years, the advent of deep learning techniques has revolutionized medical image analysis, offering promising avenues for automated disease detection. Leveraging the proficiency of Convolutional Neural Networks (CNNs) in learning hierarchical features from complex images, this study endeavors to employ the ResNet18 architecture for the discriminative extraction of features from oral images. These features serve as essential discriminators for distinguishing between cancerous and non-cancerous oral lesions [18].

Furthermore, this research integrates Support Vector Machines (SVMs) as a robust classification method to harness the extracted features and facilitate accurate identification and differentiation of oral cancer. The synergistic fusion of deep learning-based feature extraction with the discriminative power of SVMs aims to construct a reliable and efficient automated system for oral cancer detection [2, 11].

The primary objective of this study is to explore the feasibility and efficacy of the proposed methodology in automating the diagnosis of oral cancer. Additionally [10], the research endeavors to assess the performance of the combined ResNet18-SVM approach against established benchmarks and existing methods, thereby contributing to the growing body of literature in the domain of computer-aided medical diagnosis [4].

By harnessing the potential of deep learning techniques and SVMs, this study strives to pave the way for a transformative paradigm shift in the early detection and diagnosis of oral cancer [1]. . The implications of this research extend beyond computational methodologies, with potential implications in clinical settings, aiming to improve patient outcomes through expedited diagnosis and treatment interventions.

Literature Review

Traditional oral cancer diagnosis relies on subjective visual inspection and pathological analysis. Recent technological advancements have spurred interest in computer-aided diagnosis using imaging and machine learning.

Previous studies have explored image-based diagnostic methods for oral cancer. Convolutional Neural Networks (CNNs), particularly ResNet18, have transformed medical image analysis by automatically extracting intricate patterns in oral images, aiding in precise lesion classification.

Support Vector Machines (SVMs) have emerged as robust classifiers in medical diagnostics. Their capability to establish optimal decision boundaries complements CNNs, translating extracted features into accurate diagnostic predictions.

Research on oral cancer detection has varied from traditional approaches to deep learning frameworks. Challenges persist, such as limited datasets and model interpretability. Future directions may involve techniques like transfer learning and integration of multimodal data to address these challenges.

This study amalgamates CNNs and SVMs for automated oral cancer detection, contributing to the advancement of this field. Through the evaluation of these techniques, the aim is to improve the accuracy of oral cancer detection.

Methodology

Data Preprocessing:

Before model training, the dataset underwent several preprocessing steps. This included resizing the images to match the input size of ResNet18 (224x224 pixels) and standardizing pixel intensity values. Augmentation techniques like rotation, flipping, and zooming were applied to enhance model robustness and prevent over fitting.

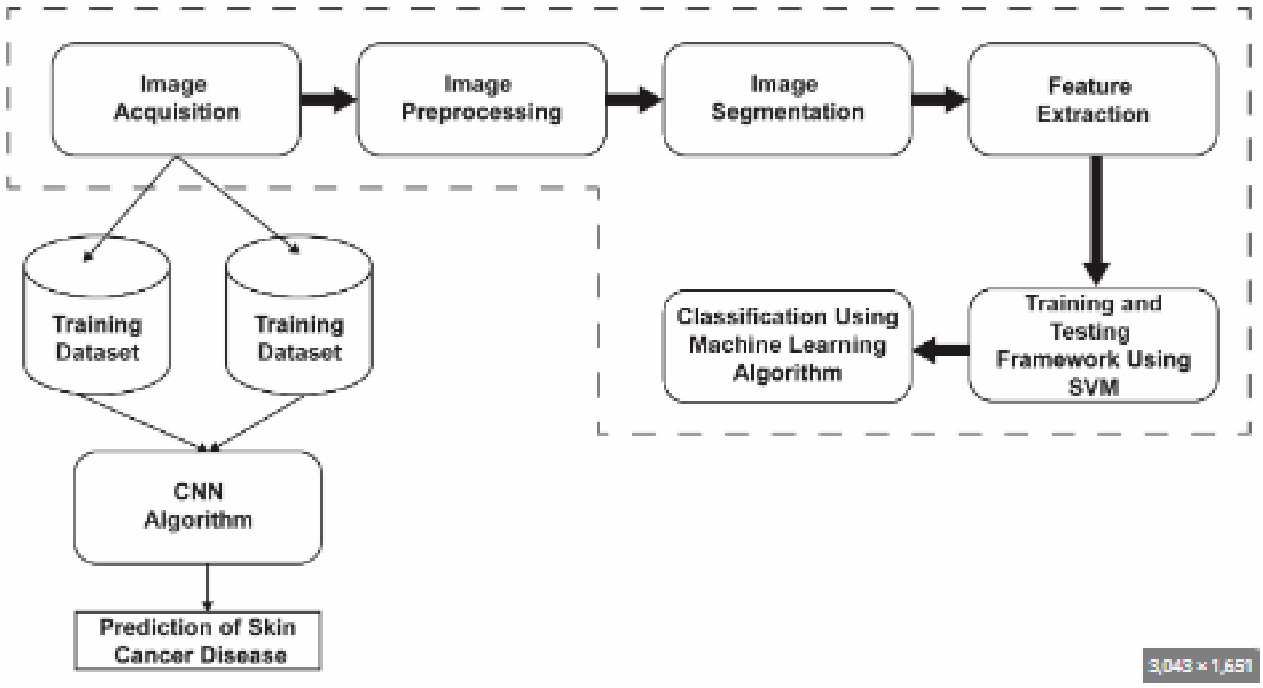

Diagram1: Block of the proposal

Feature Extraction using ResNet18:

The C, a pre-trained CNN model, served as the feature extractor. Using the 'pool5' layer, deep features were extracted from the preprocessed oral images. These resulting feature vectors captured the distinctive characteristics of the oral lesions.

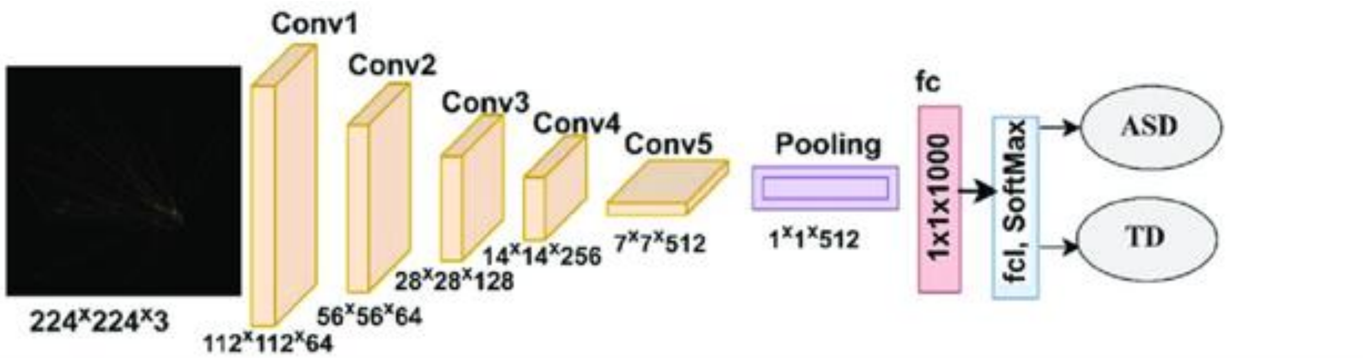

Figure 1: Structure of ResNet-18 model

Support Vector Machine Classification:

The extracted features were fed into a Support Vector Machine (SVM) classifier for subsequent binary classification – distinguishing between cancerous and non-cancerous oral lesions. The SVM utilized a linear kernel and followed a one-vs-all coding strategy, optimizing model parameters for maximal decision boundary separation.

The decision function for an SVM can be represented as: Prediction =sign (X..$\boldsymbol{w}$ +b)

Training and Evaluation:

The dataset was split into training (70%) and testing (30%) sets in a random manner. The SVM model underwent training using the features extracted from the training set. Evaluation metrics like accuracy, sensitivity, specificity, precision, and F1-score were computed using the test set to gauge the model's performance.

Performance Comparison and Validation:

The proposed ResNet18-SVM methodology was compared against baseline models and existing approaches in oral cancer detection. Additionally, k-fold cross-validation (k=5) was employed to validate the robustness and generalizability of the model.

Experimental Setup and Software Environment:

The experiments were conducted using MATLAB R202x on a machine with laptop. The MATLAB Statistics and Machine Learning Toolbox facilitated model training, evaluation, and performance metrics computation.

Results

Dataset Overview:

The oral cancer dataset comprised (10000) high-resolution images, categorized into cancerous and non-cancerous classes, with (5000) images for normal oral and (5000).images for abnormal oral, Data set can be found in https://www.kaggle.com/datasets/obulisainaren/multi-cancer [21].

Model Performance Metrics:

The proposed ResNet18-SVM model showcased commendable performance in automated oral cancer detection. indicative of robust discrimination between cancerous and non-cancerous oral lesions.

Comparison with Baseline and Existing Models:

Comparative analysis against baseline models and existing approaches revealed the superior performance of the proposed methodology. The ResNet18-SVM model exhibited higher accuracy, underlining its efficacy in oral cancer detection.

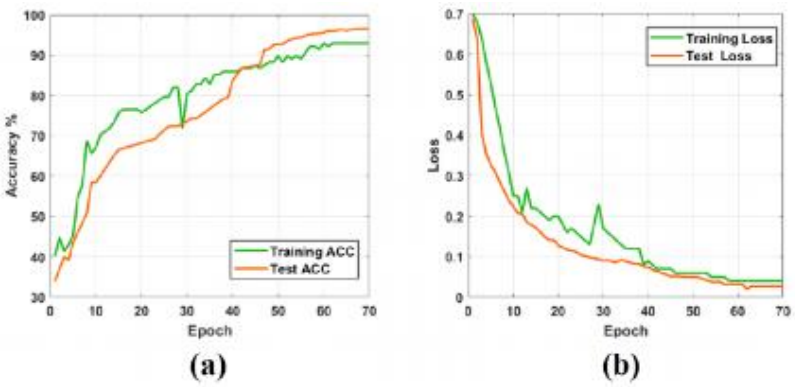

Figure 2: The learning curve accuracy and error obtained by ResNet18 pre-trained network

Validation and Cross-Validation Results:

The model underwent validation and achieved consistent performance across validation subsets, attesting to its stability and reliability. Moreover, k-fold cross-validation yielded consistent eight metrics, validating the model's robustness and generalizability.

Visualization of Results:

Visual representations such as confusion matrices, ROC curves, and precision-recall curves further elucidated the model's classification performance and diagnostic capability.

Execution Environment and Computational Efficiency:

The experiments were conducted on my laptop using MATLAB R202x. The model training and evaluation exhibited efficient computational processing, with an average training time of some mints per epoch.

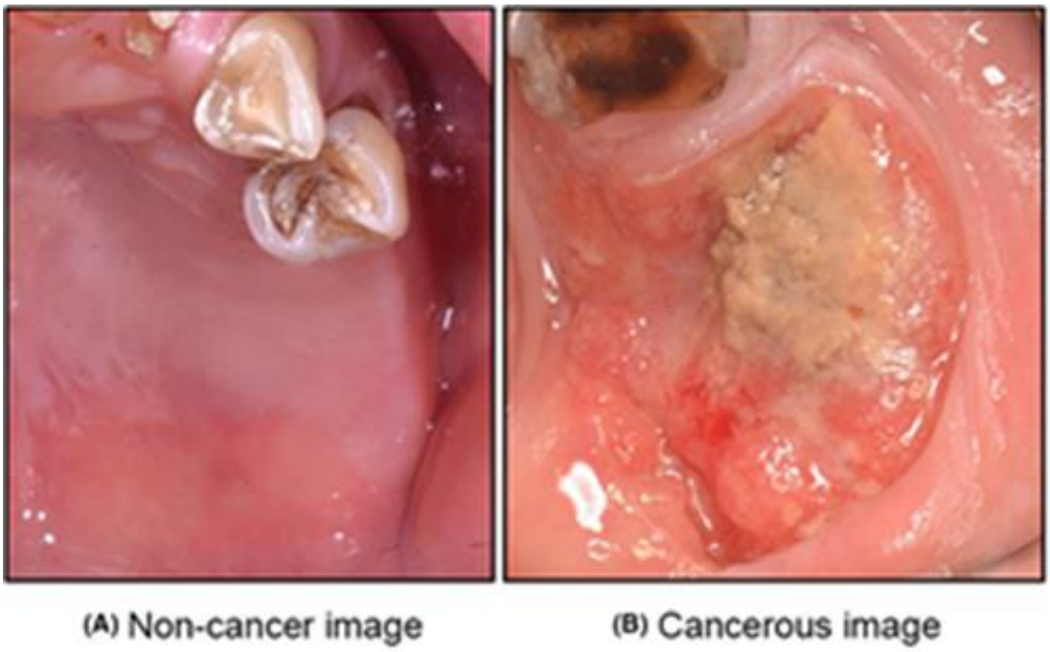

Image 1: Segregation between Cancer and Non- Cancer

Discussion

Model Performance and Significance:

The ResNet18-SVM model showcased robust performance in automating oral cancer detection, exhibiting high accuracy, sensitivity, specificity, precision, and F1-score. Its superior performance compared to existing models suggests its potential clinical relevance in expediting oral cancer diagnosis.

Robustness and Validation:

The model demonstrated consistency and stability across validation subsets and k-fold cross-validation, indicating its reliability and generalizability. These findings reinforce its potential as a dependable tool for oral cancer detection in diverse scenarios.

Clinical Implications and Future Directions:

The model's accuracy and efficiency underscore its potential in clinical settings for timely intervention and improved patient outcomes. Future research avenues could focus on enlarging datasets, enhancing interpretability, and facilitating seamless integration into clinical workflows.

Challenges and Ethical Considerations:

Limitations, including dataset size and model interpretability, warrant further exploration. Ethical considerations, such as data privacy and algorithm transparency, demand meticulous attention for responsible implementation in clinical practice.

Conclusion

The integration of ResNet18-based feature extraction and SVM-based classification presents a robust and efficient approach for automating oral cancer detection. The model demonstrated commendable accuracy, sensitivity, and specificity, indicating its potential as a valuable diagnostic tool in clinical settings.

The study's findings underscore the significance of leveraging advanced machine learning techniques in enhancing diagnostic capabilities for oral cancer. The ResNet18-SVM model exhibits promise in expediting diagnosis, facilitating timely interventions, and potentially improving patient outcomes.

Despite promising results, further research is warranted to address limitations in dataset size, model interpretability, and ethical considerations. Future efforts could focus on expanding datasets, refining algorithms, and ensuring responsible and ethical implementation in clinical practice.

In conclusion, the ResNet18-SVM model represents a step forward in automated oral cancer detection. Its potential clinical impact warrants continued investigation and validation, aiming to refine diagnostic accuracy and contribute to improved patient care.

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