Oral, Lip and Tongue Cancer Prediction Using Deep Learning

AG Trishala [1], CT Vidhya [2], G Gokilavani [3], M.Anitha[4]
[1,2,3,4] Department of Computer Science and Engineering, Avinashilingam Institute for Home Science and Higher Education for Women, School of Engineering
E-Mail-ID: vidhya_cse@avinuty.ac.in, gokilavani_cse@avinuty.ac.in, anitha_cse@avinuty.ac.in , 24pea001@avinuty.ac.in

ABSTRACT

This paper presents a deep learning-based approach for the early prediction of oral, lip, and tongue cancer using medical imaging techniques. These cancers are aggressive and debilitating, contributing to high global mortality rates. The proposed method aims to address the limitations of manual examination, which is often time-consuming, subjective, and error-prone. A convolutional neural network (CNN) model, specifically ResNet50, is fine-tuned and trained on a diverse dataset of oral, lip, and tongue images. Key techniques such as transfer learning, data augmentation, and batch normalization are employed to optimize the model's accuracy and robustness. Experimental results demonstrate the effectiveness of the proposed system in achieving high accuracy for cancer prediction. This approach holds significant potential for assisting clinicians in the early detection and diagnosis of these cancers, improving patient outcomes and reducing mortality rates. Furthermore, the methodology can be extended to other medical imaging applications, representing a valuable contribution to the fields of medical imaging and diagnostics.

Keywords: Preprocessing, Transfer learning, Data augmentation.

INTRODUCTION

Oral cancer is a major global health concern, with over 300,000 new cases reported annually and a five-year survival rate of approximately 50%. Early detection is crucial for improving patient outcomes, yet traditional diagnostic methods are often invasive, time-consuming, and limited in accuracy. This study explores the application of ResNet50, a deep learning-based convolutional neural network (CNN), to develop an automated predictive model for the early detection of oral, lip, and tongue cancer. By leveraging medical imaging data, the model aims to enhance diagnostic precision, reduce detection time, and provide a non-invasive, efficient tool for healthcare professionals. The system will be evaluated using key performance metrics, including accuracy, sensitivity, and specificity, to ensure its reliability in real-world applications. Additionally, this research investigates the adaptability of the model to other medical imaging applications, further expanding its impact. By harnessing the power of deep learning, this study seeks to revolutionize early cancer detection, improve patient care, and contribute significantly to the field of medical diagnostics, ultimately saving lives.

LITERATURE SURVEY

Nagamani Tenali et al. [1] (2023) presented "Oral Cancer Detection using Deep Learning Techniques" aiming to facilitate early detection and prevention of oral cancer. The study focused on employing deep learning techniques for early detection of oral cancer, enabling precision medicine. According to recent research reports, this method has significantly advanced the extraction of data and interpretation of crucial information related to medical imaging. M. E. Paramasivam et al. [2] (2024) addressed the challenge of human error in physical examinations by developing a Convolutional Neural Network (CNN) approach for oral cancer detection. The study modified three CNN architectures, including two based on DENSENET-121, to discern photos containing both oral cancer and healthy cells. The experiment focused on two classes: normal and malignant cells, achieving a notable accuracy rate. Ram Kumar Yadav et al. [3] (2023) proposed a deep learning approach for early detection and categorization of oral cancer. Using wavelet features, Zernike moment, and bagged histogram of oriented gradients, along with fuzzy particle swarm

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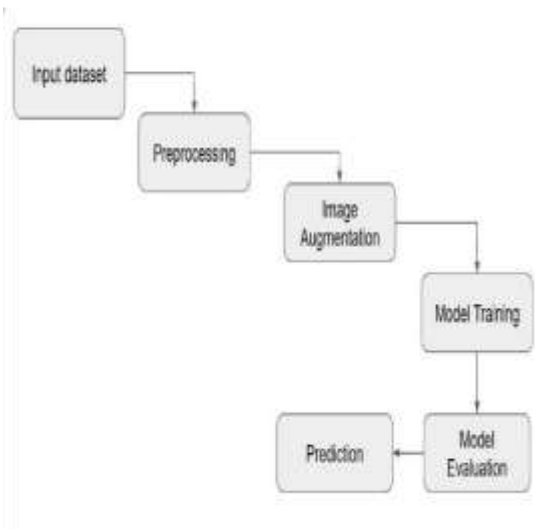
optimization (FPSO) and CNN classification, the proposed method achieved high accuracy. Results showed that combining Artificial Bee Colony (ABC), FPSO, and CNN optimized oral cancer identification. Amit Kumar et al. [4] (2023) explored the integration of vision-based supplemental technologies in oral cancer screening, presenting a novel avenue for early detection and intervention. The study proposed a machine learning-based approach for detecting and classifying oral cancer, utilizing a dataset sourced from Kaggle. C. Kavyashree et al. [5] (2022) improved oral cancer detection using a pre trained model, achieving a good improvement in detection accuracy with 85% and significantly reducing the loss. The study compared the performance of a CNN-based approach with pre trained DenseNet201, DenseNet169, and DenseNet121 models. Roshan Alex Welikala et al. [6] proposed an automated detection and classification system using deep learning for early detection of oral cancer. The study employed CNNs to analyze images of oral lesions, achieving promising results. S. Hemalatha et al. [7] (2022) evaluated the performance of a deep learning approach for oral cancer detection and classification. The study proposed a Fragment Jaya Whale Optimizer with Deep Convolutional Neural Network (FJWO-DCNN) to segment and classify oral cancer images, achieving a high recognition rate. Pradeep Singh S M et al. [8] (2023) presented a real-time oral cavity detection approach using CNN for oral cancer prediction. The study integrated patient questionnaires and oral cavity images, enhancing accuracy and reliability.

PROPOSED METHODOLOGY

Oral, lip, and tongue cancer prediction leverages deep learning techniques, specifically the ResNet50 convolutional neural network (CNN), to enhance early detection and diagnostic accuracy. The approach begins with data collection, where a labeled dataset comprising cancerous and non-cancerous medical images is gathered. These images undergo preprocessing, including resizing, normalization, and augmentation, to improve model performance and generalization. Image augmentation techniques such as rotation, flipping, zooming, and shifting are applied to diversify the dataset and prevent over fitting. The model development phase involves employing the pre-trained ResNet50 architecture through transfer learning, wherein the initial layers are frozen to retain learned features while deeper layers are fine-tuned to adapt to the specific classification task. Additional layers such as Global Average Pooling, Dropout, and Dense layers are integrated to enhance the model's capability for binary classification. The model training process is conducted using optimized hyper parameters, ensuring an efficient learning process that minimizes errors while improving classification accuracy. Once trained, the model undergoes evaluation using key performance metrics, including accuracy, precision, recall, and F1-score, to assess its reliability. The final system is then deployed as a web-based platform, allowing users, particularly healthcare professionals, to upload medical images and receive real-time predictions with confidence scores. The platform provides actionable insights, such as recommendations for medical consultation or further screening. By implementing this deep learning-based methodology, the project aims to assist in the early detection of oral cancer, thereby improving patient outcomes and facilitating timely medical interventions.

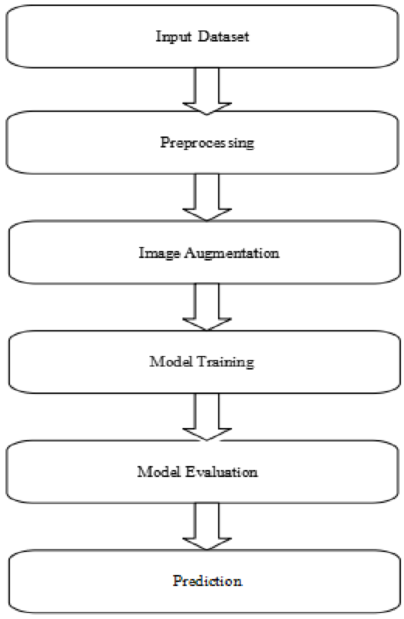
WORKFLOW DIAGRAM



SYSTEM IMPLEMENTATION

The implementation of the oral, lip, and tongue cancer detection system consists of several critical modules that collectively deliver an efficient and accurate predictive platform. The system leverages the ResNet50 architecture, a deep learning model optimized for image classification tasks. The following sections outline the key stages of system implementation:

1. Data Collection and Preprocessing**:** Labeled medical images of oral, lip, and tongue cancer were collected to form the dataset. Images were resized to a uniform dimension (240x240 pixels) and normalized to ensure consistent input. Preprocessing also included visualization of cancerous and non-cancerous image distributions.
2. Image Augmentation: To prevent over fitting and improve model generalization, augmentation techniques were applied. Transformations like rotation, flipping, zooming, and shifting increased the dataset's size and variability.
3. Model Development and Training: The ResNet50 pre-trained model was adapted for binary classification using transfer learning. Layers of the ResNet50 were selectively frozen to retain learned features, and custom layers were added for the specific task. Techniques such as Global Average Pooling, Dropout, and Dense layers were integrated to enhance performance. Hyper parameter tuning was conducted to optimize model settings.
4. Model Evaluation: Performance metrics, including accuracy, precision, recall, F1-score, and a confusion matrix, were computed to assess the model. Evaluation ensured the model’s robustness in classifying cancerous and non-cancerous images.
5. Prediction and Classification: A user-friendly web interface was developed to allow healthcare professionals to upload images and obtain real-time predictions. Predictions were displayed with confidence scores and visualizations to aid in clinical decision-making.



EMPLOYMENT OF RESNET50 IN ORAL, LIP AND TONGUE CANCER PREDICTION

ResNet50, a deep learning-based convolutional neural network (CNN), is employed in this study to address the challenges of early detection and accurate prediction of oral, lip, and tongue cancer. The deployment of ResNet50 within the system is outlined as follows:

1. Transfer Learning: The pre-trained ResNet50 model is utilized, which has been trained on a large-scale image dataset. This allows the system to leverage pre-learned features, accelerating the training process and enhancing model performance. Transfer learning enables the adaptation of ResNet50's general feature extraction capabilities to the specific task of detecting oral cancer.
2. Customization of ResNet50: Layers of the pre-trained ResNet50 model are frozen to retain learned weights and prevent over fitting during training. Additional custom

layers, such as Global Average Pooling, Dropout, and Dense layers, are integrated to refine the model for binary classification (cancerous vs. non-cancerous).

3. Fine-tuning: The frozen layers are selectively unfrozen and fine-tuned on the oral cancer dataset to improve feature representation specific to the task. Hyper parameter optimization is conducted to enhance the overall training process and ensure robustness.
4. Data Augmentation and Regularization**:** Image augmentation techniques are employed to expose the ResNet50 model to a variety of input conditions, improving its ability to generalize. Regularization methods, such as Dropout, are incorporated to reduce over fitting and improve model stability.
5. Prediction and Classification: The fine-tuned ResNet50 model is integrated into the platform to classify user-uploaded images as cancerous or non-cancerous. The system provides predictions with a confidence score, aiding clinicians in their decision making process.
6. Performance Metrics**:** The ResNet50-based system is evaluated using key metrics, such as accuracy, precision, recall, and F1-score, demonstrating its effectiveness in distinguishing between cancerous and non-cancerous images.

By employing ResNet50, the platform effectively harnesses deep learning to deliver accurate and reliable cancer predictions, significantly improving the diagnostic process and enabling early interventions. This approach represents a critical step forward in leveraging advanced AI technologies for medical applications.

CONCLUSION

In the realm of oral, lip, and tongue cancer detection, significant advancements have been made in leveraging deep learning techniques to improve early diagnosis and patient outcomes. The integration of the ResNet algorithm into a web-based platform exemplifies the potential of artificial intelligence in transforming medical diagnostics by providing accurate predictions and actionable insights. This progress represents a pivotal step forward in addressing the challenges of timely and reliable cancer detection, ultimately contributing to reduced mortality rates and enhanced preventive care. However, while these advancements are promising, it is essential to acknowledge the need for ongoing research to refine model performance, expand datasets, and ensure accessibility for diverse populations. By addressing these challenges, the platform can continue to evolve and make a lasting impact in the field of medical imaging and diagnostics.

FUTURE ENHANCEMENT

The proposed deep learning-based oral, lip, and tongue cancer detection system has demonstrated high accuracy and potential in aiding early diagnosis. However, there are several areas for future enhancements that can further improve its performance, accessibility, and clinical applicability.

1. Expansion of Dataset: Increasing the dataset size by incorporating more diverse medical images from different demographics, age groups, and ethnicities to improve model generalization. Integrating multi-source data, including histropathological and radiological images, to enhance diagnostic accuracy.
2. Real-Time Mobile Application Development: Deploying the model as a mobile application for wider accessibility, enabling individuals to upload images for preliminary screening. Implementing cloud-based AI processing to ensure efficient performance on mobile devices with limited computational power.
3. Integration with Clinical Workflows: Developing an API for seamless integration with hospital management systems and telemedicine platforms to assist healthcare professionals in real-time diagnosis. Enabling automated reporting features to

generate structured diagnostic summaries based on model predictions.

4. Improved User Experience and Accessibility: Enhancing the web platform with an intuitive user interface, voice commands, and multi-language support for wider adoption. Implementing federated learning techniques to allow multiple hospitals to train the model collaboratively without sharing patient data, ensuring privacy and security.

By implementing these enhancements, the proposed system can evolve into a more comprehensive, accurate, and accessible tool for oral cancer detection, ultimately contributing to better healthcare outcomes and early intervention strategies.

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