International Journal of Advanced Trends in Engineering and Management
(ISSN 2583-7052)

pp. 167-172, April

Interpretable AI in OSCC Pathology Imaging

[1]Sathiyavathi. V, [2]S. Dineshkumar, [3]R. Gopinath, [4]S. Stephen Raj, [5]B. Anandha Padmanaban

[1]Assistant Professor, Department of Bio Medical Engineering, Arasu Engineering College, Kumbakonam.
[2,3,4,5]Student, Department of Bio Medical Engineering, Arasu Engineering College, Kumbakonam.

Corresponding Author E-mail: gopinath233343@gmail.com

ABSTRACT: An ensemble deep learning model for the detection of Oral Squamous Cell Carcinoma (OSCC) using histopathological images. To improve the early detection and diagnosis of oral cancer through advanced image analysis techniques. The basic methods of the convolutional neural network (CNN) and long short-term memory (LSTM) neural network are combine the convolutional neural network (CNN) and long short-term memory (LSTM) neural network to design an open oral scoring model based on CNN + LSTM. An experimental environment is then built to preprocess the data, and finally the model built in this study is trained and simulated. Evaluation metrics demonstrate the effectiveness of the model in diagnosing OSCC with high precision, preprocess the data, offering a potential tool for clinical decision support. Final outcome an oral cancer data analysis based cancer detection for cancer or non-cancer classification.

Objective

To develop a deep learning model proposes that the neural network can solve the analysis of oral cancer detection. The goal is to enhance diagnostic accuracy and efficiency, enabling early detection and improving patient outcomes through advanced image analysis techniques. CNN-LSTM model proposed in this paper has the highest evaluation accuracy. This aim to the project in oral cancer classification is to accurately detect and classify oral lesions as either cancerous or noncancerous, enabling early and reliable diagnosis.

1. Introduction

Oral cancer is a significant global health concern, accounting for substantial morbidity and mortality. Early detection and accurate diagnosis are crucial for effective treatment and improved survival rates.

Traditional diagnostic methods often rely on visual examinations and biopsies, which can be subjective and time-consuming. With advancements in medical imaging and machine learning, there is a growing interest in leveraging deep learning techniques for automated and precise detection of oral cancer.

However, many solutions are based on machine learning or algorithms, which have low effect, do not realize intelligent processing, and cannot meet the requirements of oral evaluation.

2. Literature Survey

Title	Author	Year	Description

Oral Cancer Detection Using Convolutional Neural Networks	T.Jagadesh; Kam alesh P	2024	Convolutional Neural Networks with Effective enhancement of oral cancer images, improving visibility
Enhancing Oral Cancer Diagnosis: IAWMF based Preprocessing in RGB and CT Images	C. Sulochana; M. Sumathi	2024	Adaptive Weighted Median Filter (IAWMF) with Early Detection Facilitation
Oral Cancer Analysis for Early Detection using Deep Learning	K M Shaheer; E. Bijolin Edwin	2024	CNN and EfficientNet models Challenging to understand the exact features

3. Existing System

Detecting oral cancer in medical images with higher accuracy. In this work, a novel and robust oral cancer detection based on a convolutional neural network (CNN) and optimized deep belief network (DBN).

The design parameters of CNN and DBN are optimized using a new optimization algorithm, which is developed as a hybrid of Particle Swarm Optimization (PSO) and Al-Biruni Earth Radius (BER) Optimization algorithms and is denoted by (PSOBER).

4. Existing Drawback

Time-Consuming: Experts struggle to keep up with the volume of queries.

Generic Responses: Chatbots and automated systems provide generalized answers that may not be relevant to specific questions.

Lack of Scalability: Existing systems are not built to handle thousands or millions of simultaneous user queries.

Out-dated Information: Traditional systems are based on static data, making them less useful over time.

Manual Effort: Experts must dedicate significant time to respond individually, leading to delays.

5. Proposed System

The proposed system integrates Convolutional neural network (CNN) is a representative algorithm of deep learning with LSTM to create a deep learning model for oral cancer detection.

CNN optimizes LSTM parameters to enhance its ability to analyze oral images accurately.

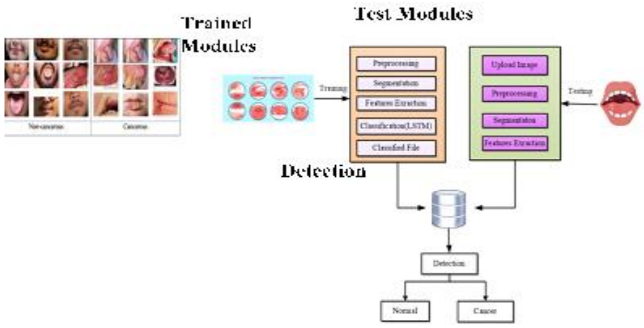
This system aims to provide a reliable and efficient tool for early detection of oral cancer, potentially improving patient outcomes through timely intervention.

The proposed method for oral cancer classification aims to accurately differentiate between cancerous and noncancerous cases using an automated system that combines image preprocessing, feature extraction, and deep learning classification techniques.

This approach leverages advancements in medical imaging and machine learning to aid in early detection, enhancing diagnostic accuracy and potentially improving patient outcomes

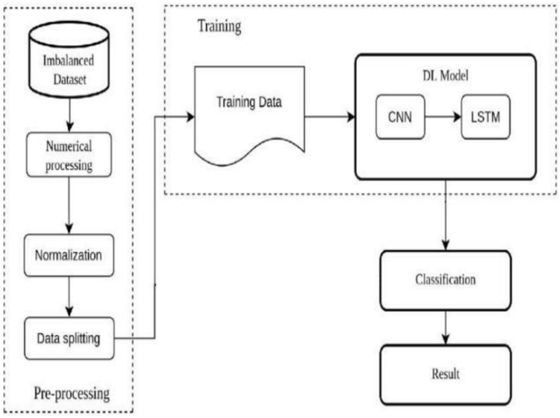
6. Proposed Block Diagram

6.1 Proposed Block Description



- Training an LSTM (Long Short-Term Memory) network for image classification is not typical, as LSTMs are primarily designed for sequence data, like time-series or text.
- However, in the context of image classification, you can use LSTMs if the images have sequential or temporal relationships.
- For example, in video frame classification or sequential image data (like in the case of gesture recognition or moving object tracking), an LSTM can be combined with CNN (Convolutional Neural Networks) for feature extraction from each frame and sequence processing.

6.2 Image Classification Training using LSTM



Proposed Modules List

► Data Collection

► Data Preprocessing

► Model Selection

► Training Module

► Testing Module

► Cancer Classification

Cancer detection

Non Cancer

Performance Evaluation

6.3 Modules Description

6.3.1 Data Collection

Collect Dataset: Gather a dataset of oral cancer images (e.g., from medical databases, hospitals, or research studies).

The dataset should contain labeled images with both cancerous and non-cancerous categories.

Data Augmentation: Apply transformations (e.g., rotations, flipping, cropping) to increase the size and diversity of the dataset.

6.3.2 Data Preprocessing

Resize Images: Standardize image sizes for model input (e.g., resize to 224x224 pixels).

Normalization: Normalize pixel values (e.g., scale between 0 and 1, or mean subtraction).

Preprocess image to resize, normalize and augument them for training.

6.3.3 Model Selection

Choose Architecture: Select a deep learning architecture, such as CNN (Convolutional Neural Network) or pre-trained models (e.g., VGG16, ResNet50, InceptionV3). Transfer Learning: Optionally use a pre-trained model on large image datasets (e.g., ImageNet) and fine-tune it on oral cancer images.

6.3.4 Training Module

The Training Module prepares the deep learning model by using the acquired dataset to learn distinguishing features of cancerous versus noncancerous tissues.

This involves preprocessing images (e.g., noise reduction, contrast enhancement) and then feeding the data into a deep learning architecture such as ResNet or a CNN model.

The model undergoes several iterations, adjusting its parameters to minimize classification errors. During training, techniques like data augmentation and regularization may be applied to improve the model's ability to generalize and handle various image variations, lighting conditions, and noise.

6.3.5 Testing Module

After training, the Testing Module assesses the model’s performance on a separate set of images not seen during training. This helps evaluate the model's real-world accuracy and robustness in correctly classifying cancerous and noncancerous cases.

The testing results offer insights into any weaknesses in the model, highlighting areas where it may need further tuning. This step is essential for verifying the system’s reliability before it is deployed in actual diagnostic settings.

6.4 Modules Description

Cancer Classification

The Cancer Classification module is the core functionality of the system, responsible for predicting whether a given input image indicates cancer or non-cancer. This module is split into two main components

Cancer Detection: If the system detects characteristics consistent with cancer, it flags the case as "Cancer." This result is based on features such as abnormal textures, patterns, or shapes identified in the processed image.

Non Cancer: For images where no cancerous traits are detected, the system classifies the case as "Non Cancer," giving healthcare providers confidence in cases where no signs of oral cancer are found.

6.5 Modules Description

Performance Evaluation

The Performance Evaluation module continuously monitors and assesses the system’s accuracy and efficiency by tracking key metrics, such as accuracy, sensitivity, specificity, and F1-score.

This evaluation provides insights into the model’s diagnostic reliability and is crucial for ongoing system improvements.

It helps ensure that the cancer classification model maintains high standards for both precision and recall, minimizing false positives and false negatives to offer dependable results in oral cancer detection.

6.6 System Requirements

► **Software Requirements**

• Operating System:	Windows 10/11
• Software Tool:	MATLAB R2018a
• Processor:	Any Intel or AMD x86/x64 processor
• RAM:	16GB (At least 8GB recommended)
• Disk Space:	40 GB for a MATLAB typical installation
• Graphics:	No specific graphics card is required.

7. Results and Discussion

The present research used the “Oral Cancer (Tongue and Lips) images” dataset for analyzing the suggested approach.

This dataset contains images that were recorded of three groups: carcinogenic with 87 series of oral cancer pictures, non-cancerous lesions with 44 series of oral non-cancerous lesions images (no diseases or benign lesions), and normal with 50 series of normal oral images.

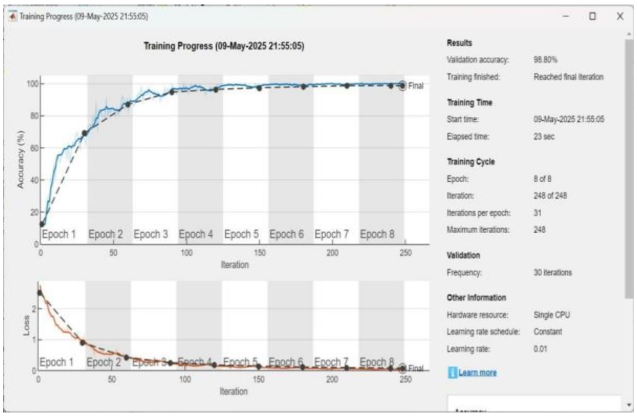
The photographs that are taken are stored in the “*.jpg” format.

7.1 Result Output

Output: Phase 1.1 Preprocessing

7.2 Input Image Gray Scale

Output: Phase 2.1 Segmented Feature



7.3 Output: Phase 3

Accuracy Graph (Cancer)

Accuracy Graph (Non Cancer)

8. Conclusion

The project demonstrates the potential of integrating Long SSS CNN for effective oral cancer detection.

The approach successfully improves classification accuracy by optimizing the LSTM model's parameters, providing a reliable tool for early diagnosis and intervention in oral cancer detection.

Rigorous training ensured the model's ability to generalize across diverse cases, while extensive testing validated its accuracy and robustness.

The results demonstrated the model's high precision in identifying cancerous and non-cancerous cases, making it a promising tool for early diagnosis and improving patient outcomes.

References

1. Karageorgos GM, Zhang J, Peters N, Xia W, Niu C, Paganetti H, Wang G, De Man B. A denoising diffusion probabilistic model for metal artifact reduction in CT. IEEE Trans Med Imaging. 2024 Jul 4;PP. doi: 10.1109/TMI.2024.3416398. Epub ahead of print. PMID: 38963746.
2. C. Li, "Research on Image Denoising Method Based on Dual Frequency Domain Transform," 2024 IEEE 6th Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC), Chongqing, China, 2024, pp. 861-864, doi: 10.1109/IMCEC59810.2024.10575759.

3. Y. Chen et al., "Research on radar image change detection based on weight denoising and discrete coefficient k-means clustering," IET International Radar Conference (IRC 2023), Chongqing, China, 2023, pp. 4017-4024, doi: 10.1049/icp.2024.1756.
4. Y. Huang, Y. Ren, Y. Du and X. Yang, "Assessment of thermal noise impact on sea ice classification using Sentinel-1 images and U-Net," IET International Radar Conference (IRC 2023), Chongqing, China, 2023, pp. 3142-3145, doi: 10.1049/icp.2024.1598.
5. P. Bhasuthkar, J. D. Kumar and T. Nagpal, "Efficient Edge Preserving Image Denoising using Non-Local Algorithms," 2023 5th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N), Greater Noida, India, 2023, pp. 246-250, doi: 10.1109/ICAC3N60023.2023.10541597.
6. SINGH P, DIWAKAR M, SHANKAR A, et al A review on SAR image and its despeckling[J]. Archives of Computational Methods in Engineering, 2021
7. Li Chunyan, Ren Zemin, Tang Liming. Multiplicative noise removal via using nonconvex regularizers based on total variation and wavelet frame[J]. Journal of Computational and Applied Mathematics, 2020
8. L Fan, F Zhang, H Fan et al., "Brief review of image denoising techniques[J]", Visual Computing for Industry Biomedicine and Art, vol. 2, pp. 112, 2019.
9. B Goyal, A Dogra, S Agrawal et al., "Image denoising review: From classical to state-of-the-art approaches[J]", Information fusion, vol. 55, pp. 220-244, 2020.
10. A Prasetio and P M Hasugian, "Improving the quality of digital images using the median filter technique to reduce noise[J]", Sinkron: jurnal dan penelitian teknik informatika, vol. 4, no. 1, pp. 143-148, 2019.