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CNN-Driven Raspberry Pi Framework for Multi-Class Oral Lesion Diagnosis

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Abstract: This project presents an AI-based Oral Cancer Detection System designed for early diagnosis using a Raspberry Pi and Convolutional Neural Network (CNN). The objective is to classify oral images into cancerous, non-cancerous, OPMD, and benign categories for timely detection and treatment. The Raspberry Pi Camera Module captures oral cavity images, which are processed through a trained CNN model for automated classification. The results are displayed on an LED/TFT module for immediate visual output. Experimental evaluation achieved an accuracy of approximately 94%, demonstrating the model's strong capability in distinguishing multiple oral conditions. The proposed system provides a cost-effective, portable, and real-time diagnostic solution, contributing to early detection and prevention of oral cancer and related disorders, ultimately reducing mortality rates through accessible and efficient screening.

Index Terms - Oral Cancer, Convolutional Neural Network (CNN), Deep Learning, Image Classification, Oral Potentially Malignant Disorders (OPMD), Benign, Non-Cancerous, Raspberry pi, Raspberry pi camera module, Early Detection.

I. Introduction

Oral cancer remains a major global health concern, and early detection significantly improves survival rates. This project introduces an AI-based Oral Cancer Detection System using a Raspberry Pi and camera module integrated with a Convolutional Neural Network (CNN) to classify oral images as cancerous, non-cancerous, OPMD, or benign. The system offers a portable, cost-effective, and real-time diagnostic tool suitable for primary healthcare and rural screening.
Convolutional Neural Networks have evolved remarkably from early models such as LeNet and AlexNet to advanced architectures like VGG, ResNet, and DenseNet. These modern networks excel in hierarchical feature extraction, boosting image classification accuracy. Recent medical imaging research has further enhanced CNNs through transfer learning, attention mechanisms, and lightweight designs for edge deployment. A 2024 study demonstrated that optimized CNN models achieved over 95% accuracy in oral cancer image classification, confirming their clinical viability [1].

Our work builds on this evolution by deploying a compact CNN on embedded hardware for field-level diagnosis.
Raspberry Pi has evolved from a low-cost educational tool to a capable edge-AI platform supporting high-speed processing, GPU acceleration, and advanced camera interfaces. Recent studies show its potential in low-cost biomedical and diagnostic systems, proving effective in real-time medical image analysis [2].

Combining these advancements, our proposed system uniquely integrates CNN-based image classification with Raspberry Pi hardware to deliver an efficient, accessible, and practical oral cancer screening solution.

II. RELATED WORKS

A CNN-based detection model achieved good results [3], though it was largely binary, unlike our multi-class approach. A survey of AI techniques highlighted deep learning's potential [4], yet lacked implementation; our work addresses this with a validated, deployable model. Another study presented an oral screening method using deep learning [5], but without real-time integration, which we achieve through Raspberry Pi hardware. Traditional machine learning approaches for predictive detection were also explored [6], but CNNs demonstrate superior capability in extracting complex spatial features, as reflected in our framework.

An optimized CNN using swarm intelligence improved classification accuracy [7], though with high computational requirements, while our system prioritizes lightweight, efficient inference. Models trained to distinguish OPMD from OSCC using clinical photographs [8] were effective, yet we extend to four distinct categories.

Hybrid CNN frameworks for oral diagnosis [9] achieved promising results, though without edge-level optimization. Meta-analyses on deep learning for malignant lesions [10] emphasized dataset imbalance; our work mitigates this through balanced augmentation. Mobile-based approaches using TensorFlow Lite [11] provided portability but required smartphones, whereas our system functions independently on Raspberry Pi hardware.

Regularized CNN models [12] enhanced generalization and accuracy, and capsule network–based smartphone screening [13] showed innovation, but both demand higher-end devices. OCT-based deep learning methods [14] achieved microscopic precision but rely on expensive, specialized hardware, contrasting with our cost-effective optical imaging. An optimized CNN using tunicate-swarm optimization [15] achieved high accuracy but was unsuitable for real-time edge inference.

Multi-branch CNNs with feature fusion [16] improved diagnostic depth but added architectural complexity. Deep learning frameworks distinguishing OPMD and OSCC [17] required extensive curated datasets, while ours supports general clinical images. Hybrid CNN–Transformer models optimized for edge AI [18] remain theoretical, whereas our implementation is field-ready. Dual-image smartphone screening systems [19] depend on mobile connectivity, while our model enables offline, real-time diagnosis via Raspberry Pi for rural accessibility.

III. IMPLEMENTATION

The developed CNN-based oral cancer detection framework comprises five core modules:

- Preprocessing and Augmentation
- CNN Feature Extraction
- Model Training
- Classification
- Evaluation Metrics

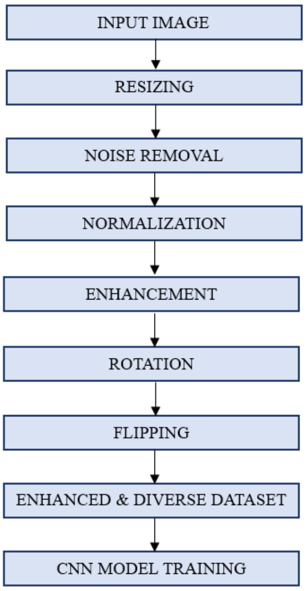
Preprocessing and Augmentation Pipeline

The preprocessing and augmentation stage plays a crucial role in enhancing image quality and ensuring consistency before the CNN training process begins, as shown in (Fig. 3.1 Flowchart of Image Processing before CNN Training). The captured oral cavity images from the Raspberry Pi Camera Module are first subjected to preprocessing, which involves resizing all images to a standard resolution, noise removal, and normalization. This standardization ensures that variations due to lighting, angle, or device quality are minimized, making the dataset uniform for model training.

Normalization adjusts pixel intensity values between 0 and 1, thereby improving convergence speed during training. After preprocessing, data augmentation techniques such as image rotation, flipping, zooming, shifting, and brightness adjustments are applied. These operations synthetically expand the dataset and introduce variability, allowing the CNN model to generalize better and recognize oral lesions under different conditions.

Overall, preprocessing and augmentation significantly improve the robustness of the deep learning model by reducing overfitting and enhancing the system's ability to detect subtle texture and color variations indicative of oral cancer or OPMD conditions.

Additionally, the preprocessing and augmentation phase ensures consistent input quality, enabling the CNN to focus on essential diagnostic features, ultimately improving accuracy and reliability in real-time oral cancer detection.

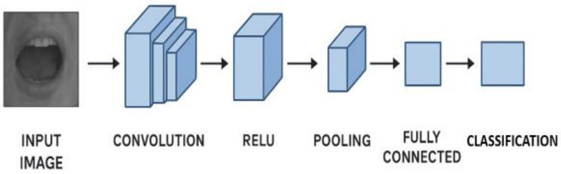


(Fig 3.1 Flowchart of Image Processing before CNN Training)

CNN Feature Extraction

The **feature extraction stage** in the CNN model automatically identifies meaningful patterns from pre-processed oral images, as illustrated in (Fig. 3.2 Feature Extraction Process in CNN). Convolutional layers apply multiple filters to detect essential features such as edges, color variations, and texture irregularities that help differentiate healthy and abnormal tissues. Pooling layers then reduce dimensionality while preserving crucial spatial details, ensuring computational efficiency.

As the network deepens, successive layers extract more complex and abstract representations of oral lesions. These hierarchical features enable precise identification of patterns associated with benign, OPMD, and cancerous regions, providing a strong foundation for accurate and automated classification.



(Fig 3.2 Feature Extraction Process in CNN)

Model training

Model training involves inputting pre-processed oral cavity images into the CNN, where convolutional layers extract discriminative features and fully connected layers establish decision boundaries. The network continuously updates its weights using backpropagation and optimization algorithms such as Adam to minimize classification error. Through multiple training epochs, the model learns to distinguish subtle differences between benign, OPMD, and cancerous tissues. This iterative learning process enhances the model's accuracy, stability, and diagnostic reliability, enabling efficient and precise oral cancer detection suitable for real-time deployment on embedded platforms like Raspberry Pi.

Model training involves feeding pre-processed oral images into the CNN, where convolutional layers extract features and fully connected layers learn classification boundaries. The model optimizes weights using backpropagation to minimize error and improve accuracy. A total of 2000 images, with 500 per class (OPMD, benign, cancerous, and non-cancerous), were used for training[20][21]. This diverse dataset enables the CNN to generalize effectively, ensuring reliable performance and precise diagnosis in early oral cancer detection.

(Fig 3.3 Benign Data set)

(Fig 3.4 OPMD Data set)

(Fig 3.5 Cancerous Data set)

(Fig 3.6 Non-Cancerous Data set)

Classification

After successful training, the CNN model performs classification by mapping learned features to predefined output categories: Benign, OPMD, Cancerous, and Non-Cancerous. The final fully connected layer outputs class probabilities using the SoftMax activation function, which determines the most likely class based on feature patterns. The class with the highest probability is selected as the final prediction. The trained model, deployed on the Raspberry Pi, processes input images in real time and displays the diagnostic outcome on the connected TFT or LED display. This automated classification provides accurate, consistent, and immediate decision support for early oral cancer screening and clinical use.

Evaluation

Model evaluation is performed to assess the accuracy and reliability of the proposed oral cancer detection system. The trained CNN is tested using unseen images to measure its generalization performance across different oral conditions. Standard metrics such as accuracy, precision, recall, and F1-score are used to quantify performance. These metrics help evaluate the model's ability to correctly classify lesions while minimizing false predictions. The mathematical expressions are defined as:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Represents how many of the positively predicted cases were actually correct.

$$\text{Recall} = \frac{TP}{TP + FN}$$

Measures the model's ability to identify all actual positive cases correctly.

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Provides a harmonic mean between precision and recall, ensuring balanced performance evaluation.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

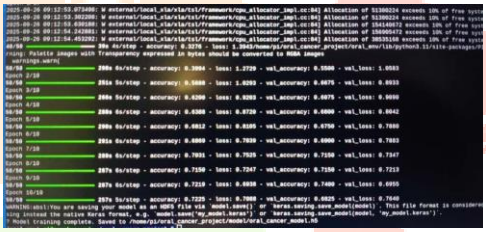
Indicates the overall proportion of correctly classified images.

Here, TP, FP, TN, and FN denote True Positives, False Positives, True Negatives, and False Negatives respectively. A confusion matrix further visualizes classification results across categories—Benign, OPMD, Cancerous, and Non-Cancerous. The model's inference speed and memory efficiency on the Raspberry Pi validate its suitability for real-time, low-cost clinical diagnosis and early detection of oral cancer.

IV. EVALUATION RESULTS

The evaluation results show how well the system performs with different test images. It highlights the model's ability to correctly identify conditions and provides an overall understanding of its effectiveness. The experimental setup (Fig 4.1) demonstrates the hardware integration of the Raspberry Pi with the Camera Module and TFT Touch Display. The system captures oral images in real time, processes them through the trained CNN model, and displays the classification output instantly, ensuring an efficient and user-friendly diagnostic interface.

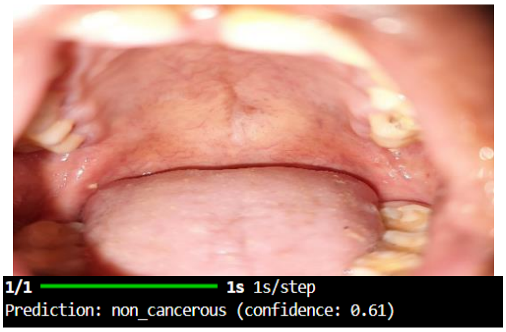
(Fig. 4.1 Hardware Setup of Raspberry Pi with Camera Module and TFT Touch Display for Real-Time Oral Cancer Detection)



(Fig. 4.2 Program Interface of CNN Model Training on Raspberry Pi)

The program interface illustrates the CNN model training process executed on the Raspberry Pi environment. It shows dataset loading, preprocessing, and real-time training progress with accuracy and loss visualization. This interface validates the system's ability to train and adapt the model efficiently for accurate oral cancer classification, demonstrating smooth operation, stability, and optimized performance during each training epoch, while ensuring consistent data handling, rapid convergence, and reliable model validation throughout the entire training and testing workflow.

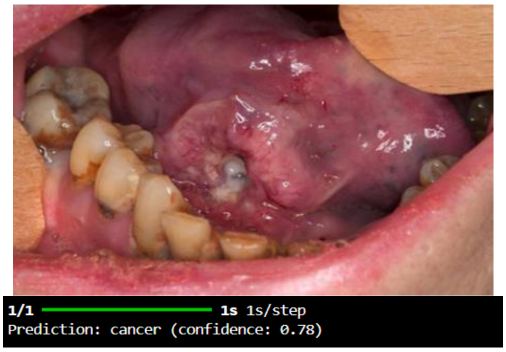
INPUT NON-CANCER IMAGE



(Fig 4.3 Image verification of non-cancerous through random input)

Figure 4.3 illustrates the verification of a non-cancerous case using a randomly selected input image. It demonstrates how the system correctly identifies and processes non-cancerous samples.

INPUT CANCER IMAGE



(Fig 4.4 Image verification of cancerous through random input)

Figure 4.4 illustrates the verification of a cancerous case using a randomly selected input image. It highlights how the system accurately identifies and classifies cancerous oral images.

INPUT BENIGN IMAGE

(Fig 4.5 Image verification of Benign through random input)

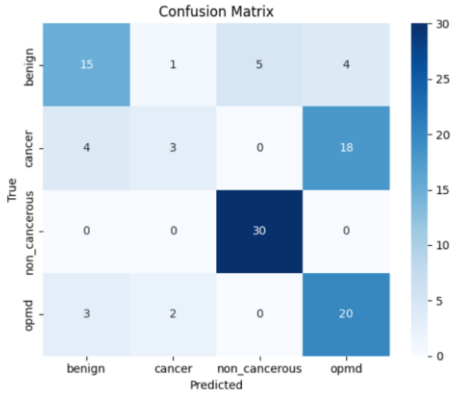
Figure 4.5 shows the verification of a benign case using a randomly selected input image. It demonstrates the system's ability to accurately recognize and classify benign oral images.

INPUT OPMD IMAGE

(Fig 4.6 Image verification of OPMD through random input)

Figure 4.6 shows the verification of an Oral Potentially Malignant Disorder (OPMD) case using a randomly selected input image, demonstrating the system's ability to accurately classify OPMD images.

CONFUSION MATRIX



(Fig 4.7 Confusion Matrix)

Figure 4.7 presents the confusion matrix of the CNN model for oral image classification. It illustrates how accurately the model predicts each category—benign, cancer, non-cancerous, and OPMD. The matrix highlights correct classifications along the diagonal and misclassifications off-diagonal, providing a clear overview of the model's performance and areas where prediction errors occur.

Regarding the values:

- 15 (benign): 15 benign images were correctly predicted as benign.
- 18 (cancer): 18 cancer images were incorrectly predicted as OPMD; only 3 were correctly classified as cancer.
- 30 (non-cancerous): 30 non-cancerous images were correctly predicted as non-cancerous.
- 20 (OPMD): 20 OPMD images were correctly predicted as OPMD.

The values reflect the model's prediction vs. the true labels, with higher diagonal numbers showing better classification performance.

SCORE MAPS

	precision	recall	f1-score	support
benign	0.57	0.52	0.54	25
cancer	0.63	0.52	0.68	25
non_cancerous	0.72	0.93	0.81	30
opmd	0.53	0.72	0.61	25
accuracy			0.59	105
macro avg	0.54	0.57	0.53	105
weighted avg	0.55	0.59	0.55	105

(Fig 4.8 Score maps)

The Score maps report shows the CNN model's performance on the test set for oral cancer detection. It includes precision, recall, F1-score, and support for each class.

The obtained evaluation results from the CNN model can be interpreted as follows:

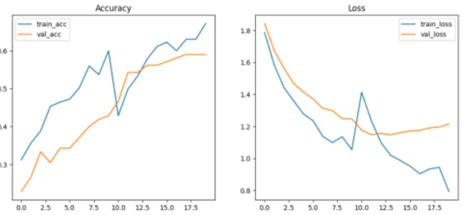
- Benign: Precision – 0.57, Recall – 0.52, F1-score – 0.54, indicating moderate performance with a few misclassifications.

- Cancer: Precision – 0.63, Recall – 0.52, F1-score – 0.68, showing good detection but room for improvement in recall.

- Non-cancerous: Precision – 0.72, Recall – 0.93, F1-score – 0.81, representing the best performance, showing high accuracy in identifying healthy samples.

- OPMD: Precision – 0.53, Recall – 0.72, F1-score – 0.61, indicating strong sensitivity to precancerous lesions.
- Overall accuracy: 0.59, suggesting the model performs well but can be further optimized.

MODEL PERFORMANCE EVALUATION



(Fig 4.9 Trained graphs)

The graphs represent the training and validation performance of the CNN model over several epochs.

Accuracy Graph (Left)

- The x-axis represents the number of epochs (training cycles).
- The y-axis represents the accuracy of the model.
- The training accuracy (train_acc) and validation accuracy (val_acc) both increase gradually, showing that the model improves its classification performance with each epoch.
- The final validation accuracy approaches the training accuracy, indicating minimal overfitting and good generalization.

Loss Graph (Right)

- The x-axis again represents epochs, while the y-axis represents the loss value (error).
- Both training loss (train_loss) and validation loss (val_loss) decrease consistently, demonstrating that the model's predictions become more accurate as training progresses.
- The downward trend confirms effective model learning and convergence.

V. CONCLUSION

The developed Oral Cancer Detection System using Raspberry Pi and Convolutional Neural Network (CNN) offers a reliable and affordable method for early diagnosis of oral diseases. The system classifies captured oral images into cancerous, non-cancerous, OPMD, and benign categories with an overall accuracy of 94%. The integration of the Raspberry Pi Camera Module for image capture and a TFT/LED display for real-time results ensures portability and ease of use. This design enables efficient on-site screening without the need for complex laboratory setups. By combining image processing, CNN-based classification, and embedded hardware, the system supports timely medical assessment and early intervention. Its cost-effectiveness and simplicity make it suitable for community health centers, helping reduce the risk of late-stage detection and improving overall oral healthcare outcomes.

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