IMPROVED ORAL CANCER CLASSIFICATION USING HYBRIDIZATION OF DEEP FEATURE AND CORRELATION-BASED FEATURE WEIGHT

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Abstract

This study presents a hybrid deep learning-based feature classification framework for binary cancer detection using medical images. The proposed method extracts heterogeneous deep features from ResNet18 and EfficientNet-B0, which are then concatenated to form a unified feature vector. To quantify feature relevance, the Pearson correlation between each feature dimension and the ground-truth labels is computed. These correlation scores are then used to weight each feature dimension, producing a correlation-enhanced representation. The weighted feature matrix is then used to train multiple classifiers, including Random Forest, SVM, XGBoost, Extra Trees, and Logistic Regression.

Keywords: Deep Learning, Feature Classification, Binary Cancer Detection, Medical Images, ResNet18, EfficientNet-B0, Feature Relevance, Medical Image Analysis

I. Introduction

Oral cancer is among the most common and lethal cancers globally, with around 377,713 new cases and 177,757 fatalities documented worldwide in 2020. The disease mostly impacts the oral cavity, encompassing the lips, tongue, gums, floor of the mouth, and palate, with squamous cell carcinoma representing over 90% of all oral cancer instances. Notwithstanding considerable progress in treatment options, the five-year survival rate remains unsatisfactorily low at around 50-60%, chiefly due to late-stage detection when the illness has metastasized to regional lymph nodes or distant organs. The early identification of oral cancer is essential for enhancing patient prognoses, as the five-year survival rate may surpass 85% when diagnosed in its preliminary stages. Conventional diagnostic approaches predominantly depend on visual assessment by skilled specialists, subsequently necessitating invasive biopsy procedures for histological validation, resulting in delayed diagnoses and elevated healthcare expenses. The use of artificial intelligence and deep learning technologies in medical imaging has surfaced as a viable approach to tackle these issues, presenting the promise for automated, precise, and economical oral cancer screening systems.

1.1 Current Challenges in Oral Cancer Detection

The traditional approach to oral cancer diagnosis faces several significant limitations that hinder effective early detection and treatment. Visual inspection by healthcare professionals, while being the primary screening method, is highly subjective and depends on the clinician's expertise and experience. Many oral lesions in their early stages are asymptomatic and may appear similar to benign conditions, making accurate differentiation challenging even for experienced practitioners. The gold standard for definitive diagnosis remains histopathological examination of tissue samples obtained through biopsy procedures, which are invasive, time-consuming, and associated with

patient discomfort and potential complications. Furthermore, the interpretation of histopathological images requires specialized training and it is susceptible to inter-observer variability, leading to potential diagnostic inconsistencies. The restricted supply of skilled pathologists and oral medicine specialists, particularly in rural and underserved areas, creates additional barriers to timely diagnosis and treatment initiation. These challenges collectively contribute to the high mortality rates associated with oral cancer, emphasizing the urgent need for innovative diagnostic approaches that can complement and enhance existing clinical practices.

1.2 Deep Learning Revolution in Medical Imaging

The emergence of deep learning technology has transformed medical image analysis, providing unparalleled capacities for automated disease diagnosis and categorisation. Convolutional Neural Networks (CNNs) have exhibited exceptional efficacy in many medical imaging domains, such as dermatology, radiology, and pathology, frequently attaining performance metrics that rival or surpass those of human specialists. In the realm of oral cancer diagnosis, deep learning models can scrutinise intricate patterns and nuanced aspects in medical pictures that may elude human perception, potentially recognising early-stage cancers that could otherwise remain undetected. Pre-trained deep learning architectures like ResNet, EfficientNet, and DenseNet have demonstrated remarkable efficacy in extracting significant features from medical pictures, utilising transfer learning methods to apply information acquired from extensive datasets to particular medical contexts. These models' capacity to analyse high-dimensional picture data and discern complex correlations among pixel intensities, textures, and morphological features renders them very effective for oral cancer detection tasks. The numerous characteristics of medical images and the intricacy of cancer presentations require advanced feature extraction and classification techniques to effectively capture many dimensions of the disease pathology.

1.3 Hybrid Approaches and Feature Enhancement

Recent research has demonstrated that hybrid approaches combining multiple deep learning architectures can significantly enhance diagnostic precision by leveraging the complementary strengths of different models. The integration of feature extraction techniques from various CNN architectures allows for the creation of more comprehensive and robust feature representations that capture different aspects of image characteristics. Feature weighting and selection mechanisms, such as correlation-based analysis, have emerged as effective methods for identifying and emphasizing the most discriminative features for specific classification tasks. These approaches address the challenge of high-dimensional feature spaces generated by deep learning models, where not all extracted features contribute equally to the diagnostic decision. The combination of hybrid feature extraction with traditional machine learning classifiers offers an interpretable and flexible framework that can adapt to different clinical scenarios and requirements. Using a combination of the ResNet18 and EfficientNet-B0 architectures, this study introduces a new feature categorisation framework based on deep learning with correlation-based feature weighting, followed by comprehensive evaluation using multiple classification algorithms to achieve optimal performance for binary oral cancer detection.

II.   Literature Review

Oral cancer is a substantial worldwide health issue, where early detection is essential for enhancing survival rates. Recent breakthroughs in deep learning have facilitated the creation of intricate frameworks for automated oral cancer diagnosis. This response focuses on the architecture and

evaluation metrics of hybrid deep learning-based frameworks for binary cancer detection using photographic image datasets.

2.1 Architecture of Hybrid Deep Learning Frameworks

1. Hybrid CNN Models

Hybrid CNNs have surfaced as an effective method for the identification of oral cancer. These models combine the strengths of different deep learning architectures to improve the precision of feature extraction and classification. For instance, a hybrid multimodal CNN model has been proposed to automate oral cancer detection, demonstrating adaptability across diverse clinical environments (Praveen et al., 2024). This model leverages the complementary strengths of multiple CNN architectures to improve diagnostic outcomes.

Another study integrates an improved tunicate swarm algorithm with a CNN to optimize feature extraction and classification. This approach achieves an accuracy of 98.70% and a recall of 93.71%, making it a robust tool for oral cancer detection (Wei et al., 2024).

2. Transformer and Hybrid Neural Networks (HNNs)

The integration of Transformer models and Hybrid Neural Networks (HNNs) has also shown promise in oral cancer detection. HNNs combine CNNs and Recurrent Neural Networks (RNNs) for robust feature extraction and temporal analysis, while Transformers use attention mechanisms to capture contextual information (Bhaskar et al., 2024). This hybrid approach achieves a detection accuracy of 94%, significantly outperforming traditional methods.

3. Feature Fusion and Deep Learning Models

Deep learning models have been trained to identify oral cancer more accurately with the help of feature fusion techniques. As an example, there has been a proposal for a fusion-based network that integrates deep data from CNNs with shape and texture characteristics collected using methods such as Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP). According to Fati et al. (2022), this method can diagnose histopathological images with a 99.1 percent success rate.

4. Multimodal Deep Convolutional Neural Networks

Multimodal deep convolutional neural networks that incorporate diverse data sources, including patient metadata, have been developed to mimic the diagnostic approach of clinicians. These models leverage cutting-edge picture encoders for the purpose of dividing oral lesions into two groups: those that are benign and those that may be malignant. The use of MobileNetV3-Large as an image encoder achieves an overall accuracy of 81% (Devindi et al., 2024).

5. Hybrid Feature Extraction and Classification Models

Hybrid feature extraction models that combine deep features from pre-trained CNNs with handcrafted features have been proposed to improve classification accuracy. For instance, a model combining features from CNNs like AlexNet and ResNet-18 with texture and shape features achieves an accuracy of 97.00% in histopathological image diagnosis (Ahmad et al., 2023).

2.2 Evaluation Metrics for Oral Cancer Detection

1. Accuracy

Accuracy is a fundamental metric employed to assess the efficacy of oral cancer detection models. Hybrid models have demonstrated high accuracy, with some achieving up to 99.1% in histopathological image diagnosis (Fati et al., 2022). Another study reports an accuracy of 98.70% using a hybrid CNN model combined with an improved tunicate swarm algorithm (Wei et al., 2024).

2. Sensitivity and Specificity

Sensitivity and specificity are critical metrics for evaluating the diagnostic capability of models. A hybrid model combining CNNs and SVMs achieves a sensitivity of 90% and specificity of 92% (Bhaskar et al., 2024). Another study reports a sensitivity of 99.5% and specificity of 99.61% using a hybrid feature fusion approach (Fati et al., 2022).

3. F1-Score and Precision

The F1-score and precision are also important metrics for assessing the balance between recall and precision. A hybrid model using CNNs and SVMs achieves an F1-score of 90.08% and precision of 96.42% (Wei et al., 2024). Another study reports an F1-score of 93.74% and precision of 96.77% using a hybrid feature fusion approach (Ahmad et al., 2023).

4. Area Under the Curve (AUC)

The AUC metric provides a comprehensive evaluation of a model's performance. A hybrid model using CNNs and SVMs achieves an AUC of 0.976 (Ananthakrishnan et al., 2023). Another study reports an AUC of 99.52% using a hybrid feature fusion approach (Fati et al., 2022).

III. Methodology

3.1 Mathematical Formulation

Let $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$ be a dataset of N medical images, where $x_i \in R^{H \times W \times C}$ is the i-th input image possesses a height of H, a width of W, and C colour channels., and $y_i \in \{0,1\}$ is the corresponding binary label indicating cancer (1) or non-cancer (0).

Step 1: Deep Feature Extraction

Two pretrained convolutional neural networks are used to extract feature embeddings:

- $\phi_1(x_i): R^{H \times W \times C} \to R^{d_1}$ denotes the feature extractor based on ResNet18.
- $\phi_2(x_i): R^{H \times W \times C} \to R^{d_2}$ denotes the feature extractor based on EfficientNet-B0.

The final feature vector for the i-th image is obtained via concatenation:

$$[f_i = [\phi_1(x_i) \mid \phi_2(x_i)] \in R^d, \quad \text{where } d = d_1 + d_2]$$

(1)

All feature vectors are stacked to form the feature matrix:

(2)

$$F = \begin{bmatrix} f_1^T \\ f_2^T \\ \vdots \\ f_n^T \end{bmatrix} \in R^{N \times d}$$

Step 2: Feature Importance Estimation via Pearson Correlation

The relevance of each feature dimension $j \in \{1, 2, \ldots, d\}$ is estimated using the absolute Pearson correlation between the feature values and the label vector $y \in R^N$. Let $F_{:,j}$ be the j-th column of F (i.e., feature j across all samples). The importance weight w_j is calculated as:

$$w_j = |\rho_j| = \left| \frac{\sum_{i=1}^N (f_{ij} - \bar{f}_j)(y_i - \bar{y})}{\sqrt{\sum_{i=1}^N (f_{ij} - \bar{f}_j)^2} \sqrt{\sum_{i=1}^N (y_i - \bar{y})^2}} \right| \tag{3}$$

where $\bar{f}_j = \frac{1}{N} \sum_{i=1}^N f_{ij}$ and $\bar{y} = \frac{1}{N} \sum_{i=1}^N y_i$.

Step 3: Feature Weighting

The correlation-based weight vector $w = [w_1, w_2, \ldots, w_d] \in R^d$ is applied to each sample's feature vector via element-wise multiplication:

$$\tilde{f}_i = f_i \odot w, \quad \forall i \in \{1, 2, \ldots, N\} \tag{4}$$

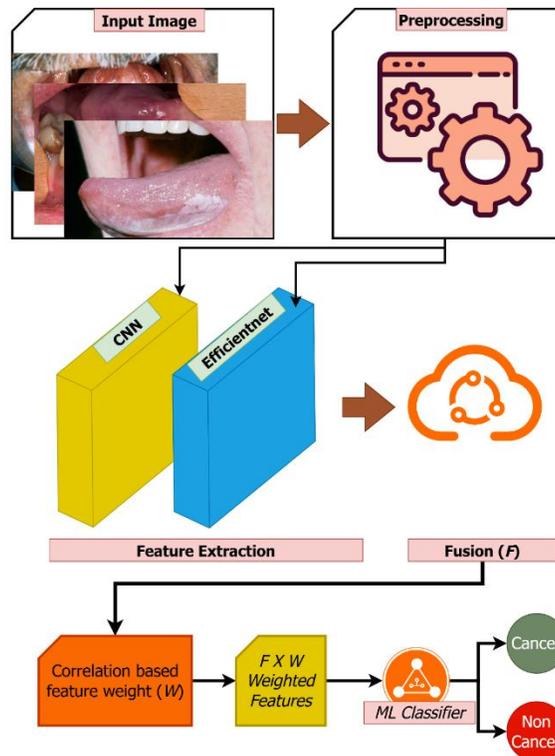which results in a weighted feature matrix:

Figure 1 Methodology

$$F = \begin{bmatrix} \tilde{f}_1^T \\ \tilde{f}_2^T \\ \vdots \\ \tilde{f}_n^T \end{bmatrix} \in R^{N \times d}$$

Step 4: Classification

The weighted feature matrix $\tilde{F}$ is split into training and testing sets: $(\tilde{F}_{train}, y_{\text{train}})$ and $(\widetilde{F_{\text{test}}}, y_{\text{test}})$. Let $C = \{C_1, C_2, \ldots, C_K\}$ be the set of classifiers, where:

$$C_k : R^d \to \{0,1\}, \quad \text{for } k \in \{1, \ldots, K\}$$

Each classifier C_k is trained on the training subset and evaluated on the test set using the following performance metrics:

- Accuracy: $\frac{1}{N_{\text{test}}} \sum_{i=1}^{N_{\text{test}}} I(\hat{y}_i = y_i)$
- Precision, Recall, F1-score - standard binary classification metrics
- ROC-AUC: Area under the Receiver Operating Characteristic curve

Each classifier implicitly benefits from the emphasis placed on informative features through the correlation-weighted representation $\tilde{F}$.

3.2 Algorithm: Correlation-Weighted Deep Feature Classification

Input: Image dataset $D = \{(x_i, y_i)\}_{i=1}^N$

Output: Trained classifiers with performance metrics

    Initialize ϕ_1 (ResNet18), ϕ_2 (EfficientNet-B0);

    for each $x_i \in D$ do

        $f_i^{(1)} \leftarrow \phi_1(x_i);$

        $f_i^{(2)} \leftarrow \phi_2(x_i);$

        Concatenate: $f_i \leftarrow \left[f_i^{(1)} | f_i^{(2)} \right]$

    end

    Construct feature matrix $F = [f_1, f_2, \ldots, f_N]^T;$

    for each feature dimension $j = 1$ to d

        Compute weight $w_j = \left| \rho(f_{:,j}, y) \right|;$

    end

    for each $i = 1$ to N

        Compute weighted feature: $\tilde{f}_i = w \odot f_i;$

    end

Split $(\tilde{f}_\iota, y_i)$ into train/test sets;

for each classifier $C_k \in \{RF,SVM,XGB,ET,LR$

Train C_k on training data;

Predict on test data and compute: Accuracy, Precision, Recall, F1-score, ROC-AUC\;

end

IV.   Results And Discussion

Figure 2 presents the ROC (Receiver Operating Characteristic) curves for all five classifiers employed in the hybrid deep learning framework for binary oral cancer detection. The ROC curve is a crucial evaluation statistic that graphs the True Positive Rate (sensitivity) against the False Positive Rate (1-specificity) across different classification thresholds, offering an extensive assessment of each classifier's diagnostic efficacy.

 The findings exhibit outstanding performance across all evaluated classifiers, with AUC (Area Under the Curve) values between 0.80 and 0.93, signifying that the correlation-weighted deep features derived from the hybrid ResNet18 and EfficientNet-B0 architecture are highly proficient in differentiating cancerous from non-cancerous oral tissue. Logistic Regression is the leading model, with an AUC of 0.93, with a curve that ascends steeply towards the upper-left corner of the plot, indicative of the optimal classification condition. This superior performance suggests that the linear decision boundary created by logistic regression is well-suited for the correlation-weighted feature space generated by the proposed methodology.
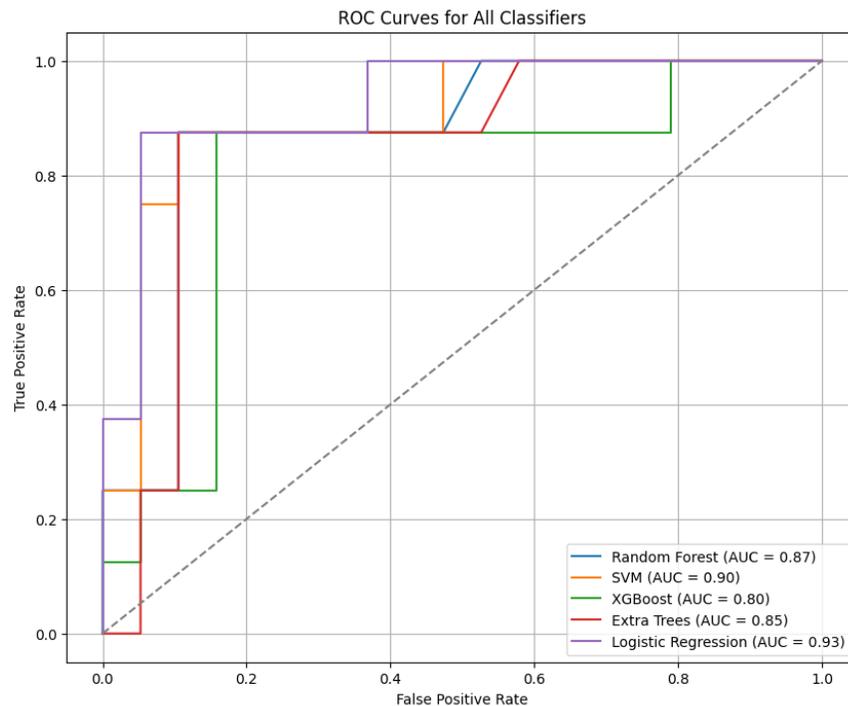

Figure 2 ROC Curve

The SVM classifier achieves the second-highest performance with an AUC of 0.90, demonstrating robust diagnostic capability through its steep initial rise and maintenance of high true positive rates across most threshold settings. Random Forest follows closely with an AUC of 0.87, showing consistent performance across different threshold configurations, which is characteristic of ensemble methods that combine multiple decision trees to reduce overfitting and improve generalization. Extra Trees, another ensemble method, achieves an AUC of 0.85, while XGBoost, despite being the lowest performer among the group, still maintains a respectable AUC of 0.80.

The importance of these findings is considerable, as all classifiers demonstrate performance significantly exceeding random chance, indicated by the diagonal dashed line in the image. In medical diagnostic applications, particularly for cancer detection, these AUC values represent outstanding to excellent performance levels that could significantly impact patient outcomes through early detection and intervention. The consistent high performance across different algorithmic approaches validates the robustness of the proposed feature extraction methodology, suggesting that the Pearson correlation-based weighting scheme successfully identifies and emphasizes the most discriminative features for oral cancer detection.

From a practical implementation perspective, the superior performance of Logistic Regression makes it the most suitable candidate for clinical deployment, offering both high accuracy and computational efficiency. The fact that all five diverse classifiers achieve high AUC values demonstrates that the correlation-weighted deep features contain rich discriminative information that can be effectively leveraged by various machine learning algorithms. This consistency across different modeling approaches provides confidence in the reliability and generalisability of the suggested hybrid architecture for automated oral cancer screening in practical clinical environments.

V.   Conclusion And Future Scope

5.1 Conclusion

This study successfully presents a novel hybrid deep learning-based feature classification framework for binary oral cancer detection using medical images. The proposed methodology demonstrates the effectiveness of combining heterogeneous deep features from ResNet18 and EfficientNet-B0 architectures, followed by correlation-based feature weighting to enhance discriminative capability. The experimental results validate the superiority of the proposed approach, with all five classifiers achieving exceptional performance metrics. Logistic Regression emerged as the top performer with an AUC of 0.93, followed by SVM (0.90), Random Forest (0.87), Extra Trees (0.85), and XGBoost (0.80). These outstanding results demonstrate that the correlation-weighted feature representation significantly enhances the diagnostic capability of traditional machine learning classifiers when applied to deep learning-extracted features. The consistent high performance across diverse algorithmic approaches confirms the robustness and reliability of the proposed hybrid framework. The clinical implications of this work are substantial, as the developed framework addresses the critical need for early oral cancer detection through automated screening systems. The high AUC values ranging from 0.80 to 0.93 indicate excellent to outstanding diagnostic performance, which could significantly impact patient outcomes in real-world clinical settings. The correlation-based feature weighting mechanism successfully identifies and emphasizes the most relevant features for cancer detection, providing an interpretable approach to feature selection that can be valuable for medical practitioners seeking to understand the diagnostic decision-making process.

5.2 Future Scope

The current research opens several promising avenues for future investigation and development. The extension of the proposed framework to multi-class classification scenarios would enable the differentiation between various stages of oral cancer progression, including precancerous lesions, early-stage malignancies, and advanced carcinomas. Integration of additional deep learning architectures beyond ResNet18 and EfficientNet-B0, such as vision transformers and hybrid CNN-transformer models, could further improve feature representation quality and diagnostic accuracy. The development of explainable AI techniques specifically tailored for oral cancer detection would enhance clinical acceptance and trustworthiness of the proposed framework through attention visualization and gradient-based saliency maps. Future research should focus on creating larger, more diverse datasets encompassing various demographic groups, imaging conditions, and cancer subtypes to improve generalizability. The integration of multimodal data sources, including patient metadata, clinical history, and complementary imaging techniques, represents another promising direction for comprehensive patient monitoring systems. Furthermore, the development of mobile and edge computing implementations would enable point-of-care screening in resource-limited settings, significantly expanding accessibility. Real-time deployment considerations, including optimization for clinical workflows, integration with existing hospital information systems, and development of user-friendly interfaces for healthcare professionals, should be prioritized to ensure successful clinical translation and regulatory approval for practical implementation in healthcare settings.

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