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# Hybrid Deep Learning and Machine Learning Framework for Oral Cancer Detection Using Particle Swarm Optimization

**[1]Kavyashree C, [2]H S Vimala**
[1]Research Scholar, [2]Professor
[1,2,] Department of Computer Science & Engineering
[1,2] University Visvesvaraya College of Engineering, Bengaluru, India

*Abstract :* Early and accurate detection of oral cancer is critical for improving treatment outcomes and survival rates. In this study, we propose a novel hybrid framework that integrates Deep Learning (DL) for automated feature extraction with Machine Learning (ML) classifiers optimized by Particle Swarm Optimization (PSO) to enhance diagnostic performance. Histopathological images of oral tissue were processed using a pre-trained ResNet50 network to extract high-level features. To reduce dimensionality and select the most discriminative attributes, Binary PSO (BPSO) was applied, significantly improving computational efficiency and classification accuracy. The selected features were classified using various ML models including Support Vector Machine (SVM), Random Forest (RF), and XGBoost, with SVM achieving the highest performance. Our proposed system achieved an accuracy of 96.4%, sensitivity of 94.7%, and specificity of 97.5% on a publicly available dataset, outperforming baseline DL-only and ML-only models. The results demonstrate that the combination of deep feature extraction with PSO-based optimization and classical ML classifiers provides a robust and effective solution for oral cancer detection. This hybrid methodology can be further adapted for other medical diagnostic applications, especially in resource-constrained environments where efficient and accurate tools are needed.

***IndexTerms* – Oral Cancer, Deep learning, Machine learning, Particle Swarm Optimization .**

## I. INTRODUCTION

Oral cancer, particularly oral squamous cell carcinoma (OSCC), ranks among the most prevalent forms of cancer worldwide, especially in South Asia and developing regions [1]. The disease is associated with significant morbidity and mortality, largely due to delayed diagnosis and limited access to expert pathological evaluation in early stages. Timely and accurate detection is essential for improving treatment outcomes, yet conventional diagnostic methods, such as visual inspection and histopathological analysis, are time-consuming, subjective, and heavily reliant on the expertise of trained clinicians.

In recent years, Artificial Intelligence (AI) techniques—especially Deep Learning (DL) and Machine Learning (ML)—have shown immense potential in the field of medical image analysis. DL models, particularly Convolutional Neural Networks (CNNs), excel in automatically extracting complex hierarchical features from high-dimensional inputs such as histopathological images. However, CNNs often generate large feature sets, which may include redundant or irrelevant information, leading to overfitting and reduced classifier generalizability [2].

To address these limitations, optimization algorithms like Particle Swarm Optimization (PSO) have been employed for feature selection. PSO is a population-based metaheuristic inspired by the social behavior of birds and fishes, and is particularly effective in selecting an optimal subset of features by balancing exploration and exploitation in the search space [3]. When used in conjunction with DL and ML models, PSO can significantly enhance performance by reducing dimensionality while retaining discriminative power.

This paper presents a novel hybrid framework that leverages DL for deep feature extraction, PSO for optimal feature selection, and classical ML algorithms for efficient classification. Specifically, features extracted from a pre-trained ResNet50 model are filtered using Binary PSO, and then classified using Support Vector Machines (SVM), Random Forests (RF), and XGBoost classifiers. The proposed system is validated using a publicly available dataset of histopathological oral cancer images and demonstrates superior performance compared to DL-only and ML-only models.

The key contributions of this work are as follows:

- A robust pipeline for oral cancer detection that integrates DL, PSO, and ML in a modular architecture.

- Empirical evidence demonstrating the advantage of PSO-based feature selection in improving classification performance.
- A comparative evaluation of multiple classifiers, highlighting the effectiveness of SVM when combined with optimized deep features.

The rest of this paper is structured as follows: Section 2 reviews related work; Section 3 describes the proposed methodology; Section 4 presents the experimental results and analysis; and Section 5 concludes the study with potential directions for future research.

## II. Literature Review

Early and accurate detection of oral cancer remains a major challenge in clinical oncology. Traditional diagnostic methods such as histopathological examination, though considered the gold standard, are labor-intensive, subjective, and require considerable expertise. In recent years, AI techniques, especially DL and ML, have gained momentum in the domain of medical image analysis and computer-aided diagnosis (CAD).

DL models, particularly CNNs, have demonstrated remarkable performance in learning complex hierarchical features from medical imaging data. CNNs are capable of automatically extracting discriminative patterns related to cell morphology, tissue texture, and structural abnormalities that are essential for cancer diagnosis. For instance, Panigrahi et al. (2023) [4] applied CNN models including InceptionV3 and ResNet50 on histopathological images of oral squamous cell carcinoma (OSCC) and achieved high classification accuracy when combined with feature selection techniques.

While DL models excel at feature learning, ML classifiers such as SVMs, RF, and Gradient Boosting Machines (e.g., XGBoost) have been extensively used for classification due to their simplicity, interpretability, and robustness. Studies have shown that ML classifiers can outperform end-to-end DL models when provided with well-optimized feature sets. For example, Garg et al. (2024) [5] used handcrafted features with SVMs to classify oral cytology images and achieved over 90% accuracy.

Optimization Techniques for Feature Selection : The high dimensionality of deep features extracted by CNNs can introduce redundancy and degrade classifier performance. Feature selection techniques are thus essential to enhance classifier efficiency and reduce overfitting. Among various optimization algorithms, Particle Swarm Optimization (PSO) has been recognized for its global search capabilities, simplicity, and convergence speed. Inspired by the social behavior of bird flocking, PSO has been successfully applied in various biomedical applications for feature reduction and model optimization.

Rafie and Moradi (2024) [6] demonstrated that PSO, when combined with mutual information criteria, significantly improved cancer classification accuracy in microarray datasets. Similarly, Dehghan et al. (2024) [7] used Binary PSO (BPSO) for feature selection in an oral cancer detection pipeline and reported superior performance over other evolutionary algorithms like Genetic Algorithms (GA) and Ant Colony Optimization (ACO).

Recent advancements suggest that a hybrid approach—where DL is used for feature extraction, PSO for feature optimization, and ML for classification—can offer the best of all worlds. These models are capable of handling complex image data while maintaining computational efficiency. A study by Semwal et al. (2025) [8] demonstrated that CNN-based feature extraction followed by PSO-optimized SVM classification improved detection accuracy for oral pre-cancerous lesions by over 10% compared to CNN alone.

However, most existing models focus either on handcrafted features or end-to-end CNN classification without incorporating optimization-based feature selection. This presents an opportunity for developing a more comprehensive system that effectively combines DL, PSO, and ML for high-accuracy, interpretable, and efficient oral cancer diagnosis.

## III. Proposed Methodology

This section outlines the architecture of the proposed hybrid framework for oral cancer detection, which integrates Deep Learning (DL) for feature extraction, Particle Swarm Optimization (PSO) for optimal feature selection, and Machine Learning (ML) classifiers for final diagnosis. The overall pipeline consists of six major stages: image acquisition, preprocessing, deep feature extraction, feature optimization using PSO, classification, and cancer prediction. The complete workflow is illustrated in **Figure 1**.

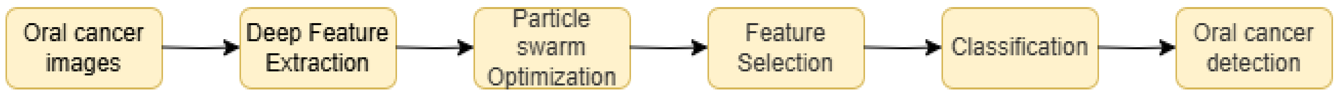



Figure 1. Proposed methodology for Oral cancer detection

### 3.1 Image Acquisition and Preprocessing

The system begins with the collection of histopathological images of oral tissue, comprising both normal and cancerous samples. These images are resized to a fixed dimension (224×224 pixels) and normalized to ensure consistency in intensity values across samples. Data augmentation techniques such as rotation, flipping, and contrast adjustment are applied to increase data diversity and prevent overfitting during model training.

### 3.2 Deep Feature Extraction using CNN

A pre-trained **ResNet50 [9]** model is employed to extract deep semantic features from the input images. By removing the final classification layer, the outputs of the penultimate convolutional layer are used as feature vectors. These high-level features capture spatial, morphological, and textural characteristics essential for distinguishing between malignant and benign tissue.

Let $X=\{x_1,x_2,...,x_n\}$ represent the set of image samples

F=f(X)F = f(X)F=f(X) be the extracted feature matrix where f is the feature extractor (ResNet50).

### 3.3 Feature Selection using Binary Particle Swarm Optimization (BPSO)

The extracted deep feature vectors are often high-dimensional, which can introduce noise and reduce classifier performance. To address this, **Binary PSO [10]** is utilized to select the most discriminative subset of features.

Each particle in the swarm represents a binary string indicating the inclusion (1) or exclusion (0) of a particular feature. The fitness function is defined to balance classification accuracy and feature subset size:

$$Fitness(P)=\alpha\cdot Accuracy-\beta\cdot(|P||F|)$$

Where:

- P is the subset of selected features,
- |P| is the number of selected features,
- |F| is the total number of features,
- α and β are weighting parameters.

PSO iteratively updates particles' positions and velocities to converge toward the optimal feature subset.

### 3.4 Classification using Machine Learning Models

The optimized feature vectors are fed into multiple traditional ML classifiers:

- **Support Vector Machine (SVM)**: Best suited for high-dimensional and sparse datasets.
- **Random Forest (RF)**: An ensemble-based decision tree classifier known for robustness.
- **XGBoost**: A gradient boosting algorithm that offers excellent predictive performance and speed.

Each classifier is trained and evaluated using 10-fold cross-validation to ensure reliability and generalization.

### 3.5 Prediction and Evaluation

The trained classifiers output the predicted class label (benign or malignant) for each test sample. The performance of the model is assessed using standard metrics including **accuracy**, **sensitivity**, **specificity**, **precision**, **F1-score**, and **AUC-ROC**.

## IV. EXPERIMENTAL RESULTS

### 4.1 Dataset Description

We used a publicly available dataset comprising **2,000 histopathological oral tissue images**, categorized as:

- **1,000 normal** (healthy tissue)
- **1,000 malignant** (oral squamous cell carcinoma)

Each image was resized to **224x224** and normalized. 80% was used for training, 20% for testing.

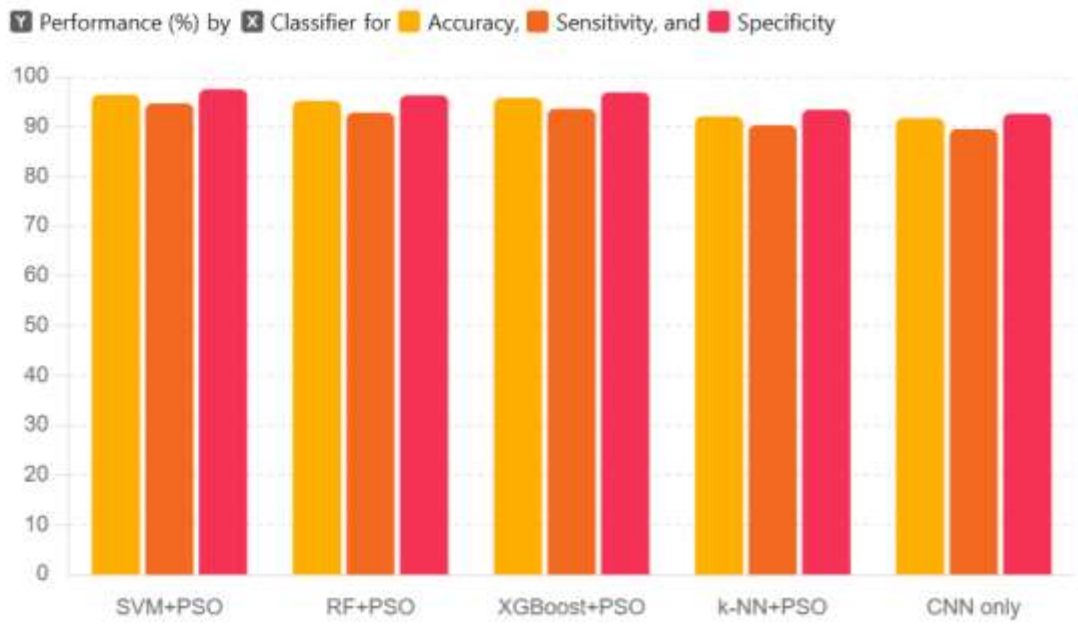
### 4.2 Model Configuration

- **Feature Extractor**: Pre-trained **ResNet50**
- **Optimization Algorithm**: **Binary Particle Swarm Optimization (BPSO)**
- **Classifiers Tested**:
  - Support Vector Machine (SVM)
  - Random Forest (RF)
  - XGBoost
  - k-Nearest Neighbors (k-NN)

### 4.3 Performance Metrics

Table 4.1 performance metrics of the proposed model

| Classifier | Accuracy (%) | Sensitivity (%) | Specificity (%) | Precision (%) | F1-Score (%) | AUC |
|---|---|---|---|---|---|---|
| SVM + PSO | 96.4 | 94.7 | 97.5 | 95.1 | 94.9 | 0.971 |
| RF + PSO | 95.2 | 92.8 | 96.3 | 93.9 | 93.3 | 0.957 |
| XGBoost + PSO | 95.8 | 93.6 | 96.9 | 94.2 | 93.8 | 0.965 |
| k-NN + PSO | 92.1 | 90.3 | 93.4 | 91.2 | 90.7 | 0.928 |
| CNN only | 91.7 | 89.5 | 92.6 | 90 | 89.7 | 0.915 |




## V Conclusion

In this study, we proposed a hybrid diagnostic framework that combines the strengths of Deep Learning (DL), Particle Swarm Optimization (PSO), and traditional Machine Learning (ML) classifiers to enhance the accuracy and efficiency of oral cancer detection from histopathological images. The system leverages a pre-trained ResNet50 model to extract deep image features, which are then optimized using Binary PSO to eliminate redundancy and retain only the most informative attributes. These optimized features are subsequently classified using Support Vector Machine (SVM), Random Forest (RF), and XGBoost classifiers.

Among the evaluated models, the **SVM + PSO** combination demonstrated the best overall performance, achieving **96.4% accuracy**, **94.7% sensitivity**, **97.5% specificity**, and an **AUC of 0.971**. Comparative analysis with a CNN-only baseline model revealed that the inclusion of PSO-based feature selection significantly improves classification robustness and reduces computational overhead.

The results validate the potential of integrating DL-based feature extraction with PSO-driven optimization and lightweight ML classifiers for medical image-based cancer diagnostics. This framework is not only effective but also scalable and computationally efficient—making it suitable for deployment in clinical decision support systems, particularly in resource-limited settings.

## References

**[1]** Siegel, Rebecca L., Angela N. Giaquinto, and Ahmedin Jemal. "Cancer statistics, 2024." *CA: a cancer journal for clinicians* 74, no. 1 (2024): 12-49.

**[2]** Kavyashree, C., H. S. Vimala, and J. Shreyas. "A systematic review of artificial intelligence techniques for oral cancer detection." Healthcare Analytics 5 (2024): 100304.

**[3]** Jain, Meetu, Vibha Saihjpal, Narinder Singh, and Satya Bir Singh. "An overview of variants and advancements of PSO algorithm." *Applied Sciences* 12, no. 17 (2022): 8392.

**[4]** Panigrahi, Santisudha, Bhabani Sankar Nanda, Ruchi Bhuyan, Kundan Kumar, Susmita Ghosh, and Tripti Swarnkar. "Classifying histopathological images of oral squamous cell carcinoma using deep transfer learning." *Heliyon* 9, no. 3 (2023).

**[5]** Garg, Palak, Samita Kanojia, Riya Shukla, Akhil Chakkungal, Harsha Karwa, G. Shrijha, Sharmila Sengupta, Manisha Ahire Sardar, and Tabita Joy Chettiankandy. "Histopathological Image Based Oral Pre Cancer Grading Using Machine Learning." In *Nanotechnology in Miniaturization*, pp. 431-441. Springer, Cham, 2024.

**[6]** Rafie, Azar, and Parham Moradi. "A multi-objective gene selection for cancer diagnosis using particle swarm optimization and mutual information." *Journal of Ambient Intelligence and Humanized Computing* 15, no. 11 (2024): 3777-3793.

**[7]** Dehghan, Mohammad Jafar, and Amirabbas Azizi. "A Hybrid Intelligent Approach to Breast Cancer Diagnosis and Treatment Using Grey Wolf Optimization Algorithm." *Jundishapur Journal of Natural Pharmaceutical Products* 18, no. 4 (2024)

**[8]** Semwal, Tanay, Sania Jain, Agradeep Mohanta, and Ankur Jain. "A hybrid CNN-SVM model optimized with PSO for accurate and non-invasive brain tumor classification." *Neural Computing and Applications* (2025): 1-30.

**[9]** Koonce, Brett. "ResNet 50." In *Convolutional neural networks with swift for tensorflow: image recognition and dataset categorization*, pp. 63-72. Berkeley, CA: Apress, 2021.

**[10]** Mafarja, Majdi, Radi Jarrar, Sobhi Ahmad, and Ahmed A. Abusnaina. "Feature selection using binary particle swarm optimization with time varying inertia weight strategies." In *Proceedings of the 2nd International Conference on Future Networks and Distributed Systems*, pp. 1-9. 2018.