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Oral Cancer Detection Using Deep Learning

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Abstract: *The main aim is to examine the application of deep learning technique in detecting oral cancer at an early stage. The focus is on evaluating the performance of various optimization techniques to deep learning technique through analyzing images of the mouth and throat for oral cancer detection. The goal is to determine the most effective method for identifying oral cancer and gain insights into potential improvements. The importance of early detection of oral cancer cannot be overstated, as it plays a crucial role in improving patient outcomes through earlier treatment and higher survival rates. The findings have the potential to contribute to the development of more accurate and efficient methods for oral cancer diagnosis and make a positive impact in the field.*

Keywords: Deep Learning, Oral Cancer Detection, Optimization Techniques, Convolutional Neural Network, Transform Techniques

I. INTRODUCTION

Oral cancer, also known as Oral Squamous Cell Carcinoma (OSCC), represents a serious global public health issue, with millions of new cases diagnosed annually. Early identification is essential for improving patient survival rates, as the disease is significantly more treatable in its initial stages.

In recent years, deep learning has emerged as a powerful tool in the domain of medical image analysis. Numerous studies have demonstrated its effectiveness in accurately and efficiently identifying various diseases, including cancer.

This project aims to explore deep learning-based optimization methods for the detection of oral cancer [1].

The study focuses on integrating Transform Techniques into Convolutional Neural Networks (CNNs) to assess their efficiency in diagnosing oral cancer. Moreover, it will evaluate and compare different optimization strategies to identify the most effective approach for enhancing model performance in this specific medical context [2].

Oral cancer primarily affects the mouth and throat. According to the World Health Organization (WHO), there were an estimated 377,000 new cases and 177,000 deaths globally in 2020. Given that early-stage oral cancer is highly curable, early detection remains a crucial goal. This has led to an increasing demand for accurate and effective diagnostic methods.

Deep learning, a subfield of Artificial Intelligence (AI), has shown significant promise in medical imaging applications [3]. These models can autonomously learn from and extract features within medical images, making them invaluable in detecting diseases with high precision. Interest in applying deep learning for oral cancer detection has grown substantially in recent years.

Detecting oral cancer using deep learning involves training neural networks on large datasets of labeled oral cancer images. These models are designed to identify patterns and visual indicators associated with the disease. Once trained, they can analyze new images and detect cancer with high accuracy.

There are several advantages to using deep learning in this field. First, these models can process vast amounts of data rapidly and accurately, which helps alleviate the burden on healthcare providers and allows for quicker diagnoses.

Second, deep learning algorithms are adaptable to various imaging formats, including X-rays, CT scans, and MRIs, making them versatile diagnostic tools. Finally, these models can enhance diagnostic precision, reduce the chances of misdiagnosis, and ultimately improve patient outcomes [4].

However, despite these benefits, some challenges must be addressed. One major obstacle is the requirement for large, high-quality datasets to effectively train these models.

Additionally, developing and implementing deep learning solutions requires expertise in both artificial intelligence and oral cancer diagnostics.

Convolutional Neural Networks (CNNs) are particularly valuable in this context. They are widely used in tasks such as image segmentation, object localization, video analysis, autonomous vehicle navigation, and even speech recognition in natural language processing [5].

Convolutional Neural Networks (CNNs) play a crucial role in modern, rapidly advancing fields and are widely recognized in deep learning applications. Within deep learning, CNNs are a specialized class of deep neural networks most frequently utilized for image classification tasks. While traditional neural networks rely heavily on matrix multiplication, CNNs operate using a distinct technique known as convolution, which sets them apart from standard neural architectures [6].

Building upon the previously discussed concepts, the primary objective of this study is to determine the most effective model for oral cancer detection by evaluating models that combine CNN architectures with various optimization techniques.

The remainder of this study is organized as follows:

• Section 2 presents the oral cancer dataset used in this research.
• Section 3 outlines the methodology and includes a block diagram of the proposed approach.
• Section 4 discusses the results obtained.
• Section 5 concludes the study by summarizing the key findings.

II. ORAL CANCER HISTOPATHOLOGICAL IMAGE DATASET

This section presents a brief overview of the dataset used for oral cancer detection based on histopathological images. Histopathological imaging refers to the microscopic examination of tissue samples—typically obtained through biopsies or surgeries—that are processed and mounted on glass slides for analysis. This method is crucial for identifying signs of disease at the cellular level.

The dataset contains a total of 5,192 images, which are categorized into two classes: Normal and OSCC (Oral Squamous Cell Carcinoma). The Normal class consists of images depicting healthy tissue, while the OSCC class includes microscopic images of tissues affected by cancer.

III. PROPOSED MODEL

This section outlines the methodology employed to preprocess and train histopathological images for oral cancer detection using Transform Techniques, Optimization Techniques, and a Convolutional Neural Network (CNN) model.

In this approach, Transform and Optimization techniques are utilized for effective feature extraction, while the CNN serves as the primary model for classification. The key goal is to accurately categorize the images into two classes: cancer-affected and normal tissues.

The motivation for the proposed method arises from previous research that applied basic CNN architectures for oral cancer detection. Although these models achieved moderate success, recent findings suggest that integrating Transform and Optimization techniques with CNNs can significantly enhance overall performance. Based on this insight, our study focuses on incorporating these additional methods to improve classification accuracy [7].

The proposed model is structured in the following stages:

1. Preprocessing Phase – Involves preparing the raw histopathological images for analysis.
2. Feature Extraction Phase – Utilizes Transform and Optimization techniques to extract relevant features from the input data.
3. Classification Phase – Employs a CNN model to classify the images based on the extracted features.

To facilitate model training and evaluation, the dataset has been divided into three subsets:

• Training Set: 4,946 images
• Testing Set: 126 images
• Validation Set: 120 images

These subsets are used appropriately throughout the model development process, where the training set is used for learning, the validation set for tuning hyper parameters, and the testing set for evaluating the final model's performance.

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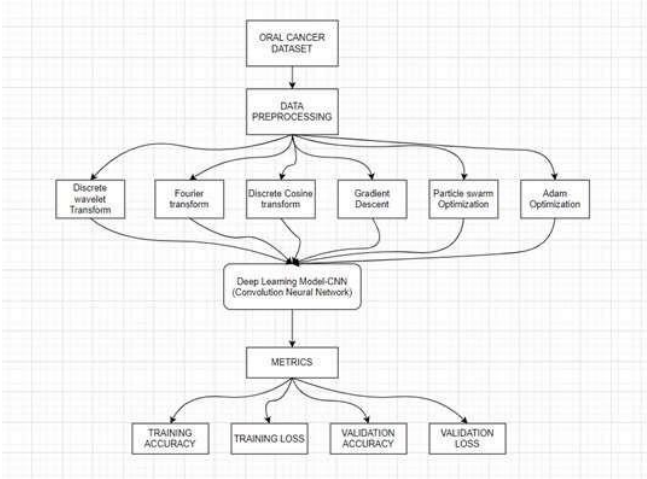

Fig.1.Block Diagram of the Model

A. Pre-processing Phase

The pre-processing phase is the initial and essential step in preparing the oral cancer histopathological image dataset for training. During this stage, several techniques are applied to standardize and enhance the quality of the input images.

1. Data Cleaning:

The process begins with data cleaning, where any corrupted or mislabelled images—such as those with missing pixels or incorrect classifications—are removed. This ensures that the dataset is accurate and reliable, which is critical for achieving valid machine learning results.

2. Image Rescaling:

Following cleaning, all images are resized to a uniform dimension of 224×224 pixels. This rescaling ensures consistency in input size, as variations in image dimensions and aspect ratios can negatively impact model performance. Uniform sizing is essential for effective training and inference in deep learning models.

3. Image Conversion:

For techniques like Fourier Transform, the images are converted to grayscale. This step simplifies the image data and reduces computational complexity. However, other techniques used in this study do not require grayscale images and thus operate directly on colored images.

4. Image Normalization:

Normalization adjusts the pixel intensity values to a fixed range, typically [0, 1] or [-1, 1], depending on the model requirements. This step ensures uniformity in pixel value distribution across all images, which helps stabilize and speed up the training process.

Notably, the dataset selected for this study was found to contain high-quality, noise-free images after rescaling. As a result, additional noise reduction or image enhancement procedures were not necessary.

The main features targeted in the images—cell boundaries and cell sizes—are preserved and enhanced through this pre-processing phase, preparing them for the next step: feature extraction.

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B. Feature Extraction Phase

Feature extraction is a vital step in preparing the dataset for training machine learning models. The primary objective is to isolate and extract meaningful features—specifically cell boundaries and cell sizes—from each image. In this study, color is not considered a feature.

There are generally two types of feature extraction approaches:

• Hand-crafted features

• Deep learning-based features

In our methodology, feature extraction is performed using a combination of Transform Techniques and Optimization Techniques.

1) Transform Techniques:

Transform techniques are fundamental in medical image processing, especially for histopathological analysis. These methods extract critical frequency-based features that reveal structures such as edges, contours, and texture, which are essential for accurate diagnosis and classification.

The transform methods applied in this study include:

• Fourier Transform (FT)

• Wavelet Transform (WT)

• Discrete Cosine Transform (DCT)

These techniques are used to extract high-frequency components that correspond to key visual features, such as edges and cell boundaries. By applying thresholds to wavelet coefficients, for instance, it becomes possible to isolate sharp transitions, which are then used to detect cell structures through operations such as contour detection or morphological analysis.

A) FOURIER TRANSFORM:

The Fourier Transform is a widely used method for feature extraction. It converts an image from the spatial domain to the frequency domain, representing it as a sum of sinusoidal components with varying amplitudes and frequencies [8], [9]. The resulting frequency spectrum highlights image features such as texture, shape, and contrast, which are instrumental for identifying cancerous patterns in histopathological images.

The mathematical formulation of the Fourier Transform is typically expressed as:

$$f(t)=\int^{-\infty} (\ ) \ ^{-iwt}dt$$

b) Discrete Wavelet Transform

Another widely adopted transform technique for image analysis is the Wavelet Transform. Unlike the Fourier Transform, which analyzes frequency components globally, the Wavelet Transform provides a multi-resolution analysis by decomposing an image into various levels of frequency and scale.

This decomposition results in wavelet coefficients that represent image features at different levels of detail. These coefficients can be used to identify important image structures such as edges, textures, and patterns, which are particularly useful in histopathological image analysis for detecting cancerous tissues [10].

The Discrete Wavelet Transform (DWT) is a specific implementation used in this study. DWT enables localized analysis of both spatial and frequency domains by applying a series of filters to the image. This allows for the detection of fine-grained details such as cell boundaries or irregular patterns that may indicate malignancy.

The mathematical representation of the Discrete Wavelet Transform is:

DWTj,k= ∫ −∞ ∞f(t) ψj,k(t) dtDWT_{j,k} = \int_{-\infty}^{\infty} f(t) \, \psi_{j,k}(t) \, dtDWTj,k= ∫ −∞ ∞f(t)ψj,k (t)dt

This property is particularly beneficial in medical imaging, where large volumes of high-resolution images must be stored or transmitted. By reducing the data size without compromising essential features, the DCT helps in improving storage efficiency and transmission speed.

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2) Optimization Techniques

Where:

- f(t)f(t)f(t) is the input signal (or image),
- ψj,k(t)\psi_{j,k}(t)ψj,k(t) is the wavelet function scaled by jjj and translated by kkk,
- jjj and kkk are the scale and translation parameters.

In practical applications, 2D DWT is used for image data, which decomposes the image into four sub-bands at each level: approximation, horizontal detail, vertical detail, and diagonal detail. These sub-bands are then analyzed to extract significant visual features.

The figure 2 shows the difference between Images from dataset before pre-processing and after applying Transform Techniques.

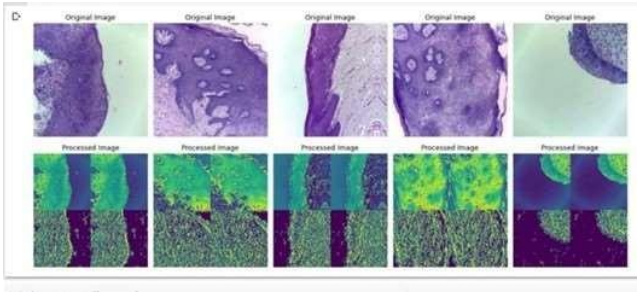

Fig.2.Images from Data set after applying Transform Techniques

C) DISCRETE COSINE TRANSFORM (DCT):

The Discrete Cosine Transform (DCT) is a widely used transform technique that is conceptually similar to the Fourier Transform. However, unlike the Fourier Transform, which uses both sine and cosine functions, the DCT employs only cosine functions as its basis. This results in a more compact representation of image features, especially at lower frequencies.

The DCT decomposes an image into components of varying frequency and scale, making it suitable for identifying significant patterns, textures, and structural features. It can be applied either to the entire image or to specific regions of interest, such as suspected tumor areas, to extract localized features relevant to disease detection.

One of the primary advantages of using DCT in feature extraction is its computational efficiency. Compared to other transform techniques, DCT requires less processing time, making it suitable for applications that involve large datasets or require real-time processing. Additionally, the DCT is known for its lossy compression capability, which allows for reducing the size of image data while still preserving critical diagnostic features [11].

Optimization techniques play a vital role in enhancing feature extraction by refining the learning process of machine learning models. These techniques help the models identify the most relevant and informative features from the input data. In the context of oral cancer histopathological image analysis, the following optimization methods are employed to improve classification performance and diagnostic accuracy.

a) Gradient Descent

Gradient Descent is a fundamental optimization algorithm that iteratively adjusts model parameters to minimize the error between predicted and actual outputs. In the context of feature extraction, this technique aids in identifying the most relevant numerical attributes by minimizing a predefined loss function.

One of the major benefits of Gradient Descent is its ability to automatically discover important features, eliminating the need for manual feature selection. However, it can be computationally intensive, especially with large datasets, and may require careful tuning of hyperparameters such as the learning rate and the number of iterations to achieve optimal results [13], [14].

Despite these challenges, Gradient Descent remains a powerful method for feature extraction when paired with robust pre-processing, quality control, and validation procedures.

b) Adam Optimization

Adam (Adaptive Moment Estimation) is one of the most popular and effective optimization algorithms used in deep learning. It combines the advantages of Momentum and RMSprop by computing adaptive learning rates for each parameter. Adam uses moving averages of both the first moment (mean) and second moment (variance) of the gradients, which allows it to converge quickly and handle sparse gradients efficiently.

In this study, Adam is used to extract relevant features from pre-processed histopathological images. A neural network with multiple layers is trained using Adam to learn patterns that are critical for distinguishing between normal and cancer-affected tissues [15]. The algorithm's performance can be further enhanced by fine-tuning hyperparameters or incorporating alternative optimization strategies like Stochastic Gradient Descent (SGD).

c) Stochastic Gradient Descent (SGD)

Stochastic Gradient Descent (SGD) is a variant of traditional gradient descent that updates model parameters using a randomly selected subset (mini-batch) of the training data at each iteration. This makes it highly efficient, especially for large datasets such as histopathological image collections.

In oral cancer analysis, SGD optimizes a loss function that quantifies the discrepancy between predicted labels (cancerous or non-cancerous) and actual labels. The model iteratively learns to focus on the features most relevant for identifying cancer cells in biopsy samples [16]. While effective, SGD should be applied alongside other diagnostic tools and expert interpretation to ensure reliable outcomes.

d) RMSprop Optimization

RMSprop (Root Mean Square Propagation) is another widely used optimization algorithm designed to improve convergence in neural networks. It dynamically adjusts the learning rate of each parameter based on the exponentially weighted average of squared gradients, thereby preventing the learning rate from becoming too large and helping avoid local minima.

In the context of oral cancer image analysis, RMSprop can efficiently extract critical features by stabilizing the training process. It helps models converge more reliably when identifying cancerous patterns in biopsy images. As with other methods, RMSprop should be integrated within a broader diagnostic framework that includes clinical assessments, imaging, and laboratory tests to support accurate medical decisions.

e) Adadelta Optimization

Adadelta is an adaptive learning rate optimization algorithm designed to improve upon the limitations of the Adagrad method, particularly its tendency to rapidly diminish learning rates during training. Unlike Adagrad, which accumulates all past squared gradients, Adadelta maintains a decaying average of past gradients, enabling it to adjust learning rates more dynamically over time.

In the context of oral cancer image analysis, Adadelta is applied to facilitate the extraction of features that are most relevant for the accurate classification of biopsy samples. By focusing on the most informative patterns—such as variations in cell size, shape, and boundary irregularities— Adadelta helps improve the model's ability to distinguish between cancerous and non-cancerous tissues.

One of the notable advantages of Adadelta is its low memory consumption, making it particularly suitable for large datasets where computational resources may be limited [17]. This makes it a practical choice in clinical or research settings with constrained hardware.

However, a potential drawback of Adadelta is its longer convergence time compared to other optimization algorithms. As such, the choice to use Adadelta should depend on the specific characteristics and computational constraints of the dataset and task.

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As with all machine learning applications in healthcare, the use of Adadelta for feature extraction should be complemented by expert clinical judgment and used alongside other diagnostic tools to ensure reliable outcomes.

The figure 3 shows the images of data after applying optimization in process of training the model. After applying feature extraction using optimization techniques, we need to select the optimal set of features that can best discriminate between differentclasses ofimages.

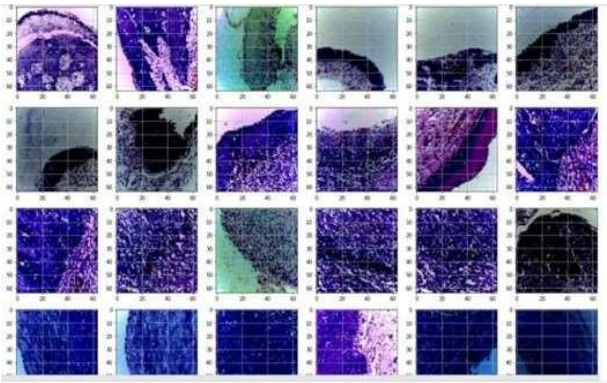

Fig.3 .Images from Data set after Optimization

C. Classification Phase

In this study, the primary classification algorithm employed is the Convolutional Neural Network (CNN). CNNs are particularly effective for image-based tasks due to their ability to automatically learn hierarchical features, making them highly suitable for oral cancer histopathological image classification.

To enhance performance and achieve greater precision, modifications were made to the conventional CNN architecture. CNN was chosen over other binary classification algorithms due to its superior accuracy in image processing tasks. Additionally, fine-tuning its architecture—such as adjusting layers and parameters—can significantly improve the model's performance.

A typical CNN architecture consists of the following layers:

• Convolutional Layers: These layers extract spatial features from the input images by applying filters. They detect local patterns such as edges, textures, and shapes, which are crucial for identifying cancerous cells.

• Pooling Layers: Pooling reduces the dimensionality of feature maps, making the network computationally efficient while retaining essential features. Two common pooling techniques include:

o Max Pooling: Selects the maximum value from each region of the feature map.

o Average Pooling: Computes the average value from each region of the feature map [18].

Activation Layers: These layers introduce non-linearity into the model, enabling it to capture complex patterns. In this study, the Rectified Linear Unit (ReLU) activation function is used due to its simplicity and effectiveness. Other activation functions such as Softmax may also be used, especially in the final output layer for classification.

Fully Connected Layers: These layers perform the actual classification. They take the high-level features learned by the convolutional layers and output a prediction—either cancer-affected or normal.

During the training phase, the CNN learns to identify relevant features by adjusting weights through backpropagation and minimizing the loss function. Once training is complete, the model is evaluated using a validation set or a test set to measure its effectiveness in real-world scenarios [19].

Model performance is assessed using standard evaluation metrics, including accuracy, precision, recall, and loss values, which are discussed in the next section.

IV. RESULTS AND ANALYSIS

This section presents the outcomes of the implemented models and analyzes their performance. The models are evaluated using a range of metrics, including:

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- Training Accuracy
- Training Loss
- Validation Accuracy
- Validation Loss
- Precision
- Recall

TABLEI. PERFORMANCE METRICS

MODELST RAINED	METRICS					
	TACCURACY	*TLOSS*	*VACCURACY*	*VLOSS*	*Precision*	*Recall*
CNN	0.5073	0.6934	0.246	0.6962	0.754	1.0
DWT+CNN	0.5077	0.6931	0.754	0.6858	0.753	1.0
Fourier Transform+CNN	0.5077	0.6931	0.754	0.685	0.75	1.0
Adam+CNN	0.8142	0.4276	0.858	0.37	0.8737	0.8411
SGD+CNN	0.6933	0.3077	0.787	0.47	0.8737	0.884
Gradient Descent+CNN	0.6759	0.6173	0.7778	0.512	0.75	0.91
Adadelta+CNN	0.8229	0.3856	0.7857	0.4038	0.89	0.82
RMSprop+ CNN	0.4932	0.502	0.754	0.4851	0.75	0.91

Fig.4.Performance Metrics of the model.

This section presents the comparative performance of various models applied to the oral cancer histopathological image dataset. Each model was evaluated based on key metrics, including training accuracy, training loss, validation accuracy, validation loss, precision, and recall.

The baseline CNN model showed limited performance, with a training accuracy of 50.73%, a high loss of 0.6934, and a poor validation accuracy of 24.6%. The validation loss was similarly high at 0.6962, indicating significant overfitting and limited generalization capability.

The CNN model enhanced with Discrete Wavelet Transform (DWT) exhibited the same training metrics as the baseline, but its validation accuracy improved significantly to 75.4%, although its validation loss remained relatively high at 0.6858. No notable improvements were observed in precision and recall compared to the base model.

The best-performing model among all tested configurations was the CNN model optimized using the Adam algorithm. This model achieved the highest training accuracy of 81.42% and the lowest training loss of 0.4276. Furthermore, it recorded a validation accuracy of 85.8% and a validation loss of 0.37, demonstrating strong generalization. The precision and recall scores for this model were 0.8737 and 0.8411, respectively.

The Stochastic Gradient Descent (SGD)-based model yielded slightly lower results than the Adam optimizer in most metrics, though its precision was competitive.

In contrast, the Gradient Descent (GD)-based model had a relatively lower training accuracy of 67.59%, a higher loss of 0.6173, and a validation accuracy of 77.78%. Its validation loss was 0.512, and it achieved moderate precision and recall scores of 0.75 and 0.91, respectively.

The Adadelta-optimized CNN model showed strong performance with a training accuracy of 82.29%, a low training loss of 0.3856, and a validation accuracy of 78.57%. It also had a reduced validation loss of 0.4038 and achieved solid precision and recall values of 0.89 and 0.82, respectively.

Finally, the RMSprop-based model demonstrated the lowest training accuracy and the highest training loss compared to other models, indicating it was the least effective among the evaluated techniques.

V. CONCLUSION

The results from this study demonstrate that deep learning- based approaches, particularly CNNs combined with optimization techniques, are effective in the classification of oral cancer using histopathological images. While earlier works reported classification accuracies of less than 76%, this study successfully improves upon that benchmark.

Among all models tested, the CNN model trained with the Adam optimization algorithm delivered the most balanced and reliable performance, achieving high training and validation accuracy, low loss values, and strong precision and recall. Although the Adadelta-based model achieved slightly higher training accuracy, its lower validation accuracy and higher validation loss indicate overfitting and weaker generalization.

Therefore, the most effective model for oral cancer detection in this work is the CNN with Adam optimizer, as it provides the best balance between training accuracy, generalization ability, and classification metrics.

This study suggests that deep learning, when enhanced with appropriate optimization techniques, can play a significant role in early and accurate detection of oral cancer, thereby aiding medical professionals in timely diagnosis and treatment planning.

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