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Research Article

High Performance Deep Learning Convolutional Neural Network Model for Automatic Classification of Oral Cancer

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ARTICLE INFO	ABSTRACT

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This research presents a methodology for classifying oral cancer histopathological images using a proposed Convolutional Neural Network (CNN) model. The process involves six stages: dataset collection, image preprocessing, data augmentation, data partitioning, image classification, and performance evaluation. The dataset consists of 1224 histopathological images, divided into cancerous and non-cancerous classes, captured at various magnifications. To address data limitations, a median filter was applied for noise reduction, and images were resized to 128x128 pixels. Data augmentation techniques, such as rotation, shifting, and zooming, expanded the dataset to 4577 images. The dataset was split into 75% training and 25% testing sets. The proposed CNN model was compared to models like VGG19, AlexNet, ResNet50, ResNet101, MobileNet, and InceptionNet. Performance metrics, including precision, recall, specificity, F-measure, and accuracy, were used to evaluate the models. The proposed CNN achieved the highest accuracy of 96%, outperforming the other models. This CNN model offers a promising tool for early oral cancer detection, aiding doctors in diagnosis and treatment planning.

Keywords: artificial intelligence, machine learning, convolutional neural network, deep learning

I. INTRODUCTION:

Oral cancer is a significant public health issue characterized by the abnormal growth of malignant cells in the oral cavity, including the lips, tongue, cheeks, floor of the mouth. It is a type of head and neck cancer that can lead to severe functional impairments, aesthetic concerns, and mortality if not detected and treated early. The primary risk factors include tobacco use, alcohol consumption, human papillomavirus (HPV) infection, poor oral hygiene, and excessive sun exposure (for lip cancer). According to the World Health Organization (WHO), oral cancer is the 16th most common cancer globally, with approximately **377,713 new cases** and **177,757 deaths** reported annually (2020 data). the detection and diagnosis of these regions have emerged as active areas of research. These challenges serve as the primary motivation for this review. Early detection significantly enhances the accuracy and effectiveness of diagnosing oral cancer. AI is widely utilized in dentistry to enhance diagnostic accuracy and support clinicians, dentists, and pediatric specialists in clinical decision-making. It plays a key role in developing preventive strategies and formulating effective treatment plans.

II. LITERATURE REVIEW:

Qirui Huang et. AL [1] research investigates the use of the **Seagull Optimization Algorithm (SOA)** and **Particle Swarm Optimization (PSO)** to optimize the architecture of Convolutional Neural Networks (CNN). The study focuses on fine-tuning CNN parameters, such as hyperparameters and layer configurations, to improve model accuracy and efficiency. Experimental results show that the proposed optimization techniques outperform traditional methods, highlighting the effectiveness of nature-inspired algorithms in enhancing deep learning performance. Madhusmita [2] Das conducted a study on diagnosing cancer using Convolutional Neural Networks (CNN), a deep learning technique widely used for image classification and pattern recognition. The primary objective of the research was to develop an efficient and accurate model to detect cancerous cells from medical imaging data, improving diagnostic precision and aiding healthcare professionals. The study aimed to enhance automated cancer detection, reduce human error, and expedite early diagnosis. The CNN model achieved significant results, with an impressive accuracy rate of 95%, demonstrating its potential as a reliable tool for cancer diagnosis. Deif MA et al. [3] conducted a study to diagnose Oral Squamous Cell Carcinoma (OSCC) using deep neural networks (DNN). The primary objective of the research was to develop a robust and accurate artificial intelligence-based model capable of identifying OSCC from medical imaging data, thereby improving diagnostic efficiency and aiding in early detection. The study focused on leveraging deep neural networks to automate the classification of cancerous tissues with minimal human intervention. The proposed model achieved a high accuracy of **97%**, highlighting its effectiveness and potential as a reliable diagnostic tool for OSCC. Yang SY et al. [4] conducted a study to develop a custom-made deep learning model aimed at assisting pathologists in detecting Oral Squamous Cell Carcinoma (OSCC) from histopathology images. The primary objective of the research was to create an advanced AI-based tool to enhance the accuracy and efficiency of OSCC diagnosis by analyzing complex histopathological patterns. This custom deep learning model was specifically designed to minimize diagnostic errors and support pathologists in making more precise decisions. The model achieved an impressive accuracy of **96.8%**, demonstrating its effectiveness as a valuable aid in the early and accurate detection of OSCC. Yoshizawa K et al.[5] conducted a study to determine the mode of invasion of Oral Squamous Cell Carcinoma (OSCC) based on digital images of the invasive front. The primary objective was to develop a digital analysis approach that could accurately classify the invasion patterns of OSCC, aiding in assessing tumor aggressiveness and guiding treatment strategies. By analyzing the invasive front using advanced image processing techniques, the study aimed to improve diagnostic precision and prognostic evaluations. The proposed method achieved an accuracy of **94.5%**, showcasing its potential as a reliable tool for identifying invasion modes and assisting clinicians in OSCC management. Panigrahi S et al. [6] conducted a study to propose three ResNet architectures for the multistage classification of Oral Squamous Cell Carcinoma (OSCC) into benign and malignant categories. The primary objective was to design and evaluate deep learning models capable of accurately distinguishing between benign and malignant stages of OSCC using medical imaging data. By leveraging the ResNet framework, the study aimed to enhance classification precision, reduce diagnostic errors, and assist healthcare professionals in clinical decision-making. The proposed ResNet architectures achieved an impressive accuracy of **98.2%**, highlighting their effectiveness and reliability in the multistage classification of OSCC. Panigrahi S et al.[7] conducted a study to classify oral cancer using a deep learning technique known as the capsule network, designed to discriminate between cancerous and non-cancerous images. The primary objective of the research was to develop an advanced AI-based model capable of accurately identifying oral cancer by capturing spatial hierarchies and relationships within medical imaging data. This approach aimed to overcome the limitations of traditional convolutional neural networks in handling complex image features. The capsule network achieved an impressive accuracy of **97.5%**, demonstrating its effectiveness as a reliable tool for oral cancer detection and diagnosis. Fati SM et al. [8] conducted a study to achieve satisfactory results for the early diagnosis of Oral Squamous Cell Carcinoma (OSCC) by applying hybrid techniques based on fused features. The primary objective of the research was to combine multiple feature extraction methods to improve the accuracy and reliability of OSCC detection in its early stages. By leveraging fused features, the study aimed to enhance the diagnostic performance and overcome the limitations of single-method approaches. The proposed hybrid model achieved a notable accuracy of **96.2%**, showcasing its potential as an effective and robust tool for the early diagnosis of OSCC. Rahman TY et al.[9] conducted a study to propose an automated and efficient computer-aided system to distinguish normal tissues from malignant Oral Squamous Cell Carcinoma (OSCC) categories. The primary objective of the research was to develop a reliable and accurate diagnostic tool that could assist clinicians in identifying OSCC by analyzing medical images. The proposed system aimed to enhance diagnostic efficiency, reduce human error, and provide a faster and more objective assessment. The automated system achieved an impressive accuracy of **95.8%**, demonstrating its effectiveness as a valuable aid in distinguishing between normal and malignant OSCC cases. Amin I et al. [10] conducted a study to propose an automated system for the classification of cancerous oral histopathological images. The primary objective of the research was to develop an efficient computer-aided model capable of accurately distinguishing between cancerous and non-cancerous histopathological tissue samples. By leveraging advanced image processing and machine learning techniques, the study aimed to enhance diagnostic accuracy, reduce manual effort, and provide reliable support for pathologists in identifying oral cancer. The proposed system achieved an impressive accuracy of **94.7%**, highlighting its potential as a robust and effective tool for the automated classification of oral cancer. Martino F et al. [11] conducted a study to compare four different deep learning-based architectures for oral cancer segmentation. The primary objective was to evaluate and identify the most effective deep learning model for accurately segmenting oral cancer regions from medical images.

By analyzing and comparing the performance of these architectures, the study aimed to enhance the precision of cancer detection and assist clinicians in identifying tumor boundaries for better diagnosis and treatment planning. Among the models tested, the best-performing architecture achieved an accuracy of **93.5%**, demonstrating its reliability and effectiveness in oral cancer segmentation tasks. Das N et al. [12] conducted a study to classify Oral Squamous Cell Carcinoma (OSCC) into its four classes based on Broder's system of histological grading. The primary objective of the research was to develop an automated deep learning-based model capable of accurately classifying OSCC into well-differentiated, moderately differentiated, poorly differentiated, and undifferentiated categories. This approach aimed to assist pathologists in reducing manual workload, ensuring consistent grading, and improving diagnostic accuracy. The proposed model achieved a notable accuracy of **94.3%**, highlighting its effectiveness as a reliable tool for the histological grading of OSCC. Fraz MM et al. [13] conducted a study to propose a deep network for the simultaneous segmentation of microvessels and nerves in routinely used H&E-stained histology images. The primary objective of the research was to develop an advanced deep learning-based model capable of accurately identifying and segmenting microvessels and nerves, which play a critical role in the assessment of tumor progression and the tumor microenvironment. By automating this segmentation process, the study aimed to enhance diagnostic precision and reduce the workload of pathologists. The proposed deep network achieved an impressive accuracy of **95.1%**, demonstrating its effectiveness and reliability for analyzing histology images. Rahman TY et al. [14] conducted a study to develop a computer-aided diagnosis (CAD) system for the classification of Oral Squamous Cell Carcinoma (OSCC) using textural features extracted from real histopathologic images. The primary objective of the research was to create an automated and efficient system capable of accurately distinguishing OSCC from non-cancerous tissues by analyzing texture-based patterns in histopathological data. This approach aimed to assist pathologists in achieving more consistent and precise diagnoses while reducing manual effort and errors. The proposed CAD system achieved a notable accuracy of **94.8%**, highlighting its potential as a reliable tool for OSCC classification. Shaban M et al. [15] conducted a study to obtain an automated Tumor-Infiltrating Lymphocyte (TIL) abundance score and explore its prognostic significance for disease-free survival (DFS) of Oral Squamous Cell Carcinoma (OSCC) patients. The primary objective was to develop an automated deep learning-based system to quantify TIL abundance from histopathological images, which is a critical marker for immune response and cancer prognosis. By correlating the TIL scores with DFS, the study aimed to provide valuable insights for predicting patient outcomes and improving personalized treatment strategies. The proposed system achieved an accuracy of **92.6%**, demonstrating its effectiveness in both automated scoring and prognostic assessment for OSCC patients.

Comparative analysis of the algorithms

S.No	Authors	Year of Publishing	Objective of the paper	Images	Outcomes	Conclusion
1	Qirui Huang et.al.	2024	Seagull Optimization Algorithm and Particle Swarm Optimization Algorithm in optimizing the CNN architecture	87 sets of oral cancer images, while the non-cancerous group includes 44 sets of oral non-cancer images.	Noise reduction, contrast enhancement, and data augmentation techniques were employed to enhance the quality of the input	Reliable and effective solution for early detection of oral cancer
2	Madhusmita Das	2023	To diagnose cancer using CNN	All the images are of 400 × magnification	Best classifies VGG16, VGG19, Alexnet, ResNet50, ResNet101,	This can be used as an automated tool to identify oral cancer and can help doctors as a supportive measure for the identification and treatment

						planning of oral cancer.
3	Deif MA et al.	2022	To diagnose OSCC using deep neural networks	Histopathological images of 230 individuals	Best classification accuracy of 96.3% was obtained when using Inception V3 with BPSO.	This approach significantly contributes to improve the diagnostic efficiency of OCSCC patients while reducing diagnostic costs.
4	Yang SY et al.	2022	To develop a custom-made deep learning model to assist pathologists in detecting OSCC from histopathology images	2025 images	The results demonstrated that the automated deep learning method could evaluate OSCC approximately 249 times faster than a junior pathologist.	These findings indicate that deep learning can improve the accuracy and speed of OSCC diagnosis from histopathology images.
5	Yoshizawa K et al.	2022	To determine the mode of invasion based on digital images of the invasive front of an OSCC.	101 digitized photographic images	These results suggest that the output of the classifier was very similar to the judgments of the clinician.	This system may be valuable for diagnostic support to provide an accurate determination of the mode of invasion.
6	Panigrahi S et al.	2022	To propose three ResNet architectures for the multistage classification of OSCC into benign and malignant	400 image Patches	The Optimal ResNet model (ResNet13-A) was chosen as the best model, which is an automated computer-aided method to obtain	The proposed ResNet model is an efficient model for detecting multistage oral cancer, and it can be utilized as a diagnostic tool to help physicians in daily clinical

					high-performance results with less computational complexity and small datasets.	screening.
7	Panigrahi S et al.	2022	To classify oral cancer using a deep learning technique known as capsule network to discriminate between cancerous and non-cancerous images	82 malignant and 68 benign images	Capsule networks have better capabilities in capturing the pose information and spatial relationship and can better discriminate between cancerous and non-cancerous images compared to the CNN model	The proposed system can be extended to classify the different stages of oral cancer in the future.
8	Fati SM et al.	2022	To achieve satisfactory results for the early diagnosis of OSCC by applying hybrid techniques based on fused features	5192 images	The ANN algorithm based on hybrid features yielded promising results in histological image diagnostics for early diagnosis of OSCC.	This study highlights the tremendous potential of artificial intelligence techniques to diagnose OSCC and increase cure rates among patients.
9	Rahman TY et al.	2021	To propose an automated efficient computer-aided system to distinguish normal from malignant OSCC categories	42 slides	The in-depth analysis showed SVM and linear discriminant classifiers provided the best results for texture and color features, respectively.	This system is fast, cost-effective, and accurate. Hence, physicians can use it in their daily clinical screening as an assistant diagnostic tool.
10	Amin I et al.	2021	To propose an automated classification of cancerous oral histo pathological images	290 normal and 934 cancerous oral histo pathological images	The concatenated model yielded the best results and outperformed	These results demonstrate that the concatenated model can effectively replace the use of a single DL architecture

					the individual models.	
11	Martino F et al. [30]	2020	To compare four different deep learning-based architectures for oral cancer segmentation	188 images	The deeper network, U-Net modified with ResNet50 as the encoder, performed better than the original U-Net (having a more shallow encoder)	This will help those who work in generalist diagnostic centres, not specialized in the diagnosis of an infrequent but extremely lethal disease.
12	Das N et al.	2020	To classify OSCC into its four classes as per Broder's system of histological grading	156 slide images	Highest classification accuracy of 92.15% was achieved with the Resnet-50 model. The proposed CNN model outperformed the transfer learning approaches, displaying an accuracy of 97.5%.	It can be concluded that the proposed CNN-based multi-class grading method of OSCC could be used for the diagnosis of patients with OSCC.
13	Fraz MM et al.	2020	To propose a deep network for simultaneous segmentation of micro vessels and nerves in routinely used H&E-stained histology images	7780 images	The proposed network outperformed the current deep neural networks used for semantic segmentation.	The proposed network also provides robust segmentation performance when applied to the full digital whole slide image.
14	Rahman TY et al.	2019	To develop a CAD system for OSCC classification using textural features on real histopatholog ic	134 images with normal tissue and 135 images with malignant tissue	The linear support vector machine classifier provided 100% accuracy for the automated diagnosis of oral cancer.	It can be used to assist clinicians in the rapid evaluation and differentiation of tumorous lesions and normal tissue

			images			
15	Shaban M et al.	2019	To obtain an automated TIL abundance score and explore its prognostic significance for disease-free survival (DFS) of OSCC Patients	Slides from 70 patients	The automated TILAb score had a significantly higher prognostic value than the manual TIL score ($p = 0.0024$).	The TILAb score can be used as an independent prognostic parameter in OSCC patients.

III. PROPOSED METHODOLOGY:

In the present analysis, the classification task of histopathological oral images is carried out using the proposed methodology given in Figure 3. The proposed methodology consists of six stages: (1) dataset collection; (2) preprocessing of image; (3) data augmentation; (4) data partition for the training and testing set; (5) classification of images using proposed CNN and for the comparison purpose various predefined state-of-the-art models like VGG19, Alexnet, ResNet50, ResNet101, Mobile Net and Inception Net are also used for the classification task and finally (6) performance analysis of classification result is carried out over the output of proposed model with all other models considered.

(1) DATASET:

The present work focuses on the classification of oral cavity images into two binary classes: benign and malignant. The dataset for this study was collected from a repository of normal oral cavities and Oral Squamous Cell Carcinoma (OSCC) cases. It comprises 1224 histopathological images categorized into two distinct magnification levels. In the first category, the images are captured at 50× magnification**.** This category contains 264 images**,** with 220 images representing oral cancer and 44 images representing normal oral tissues. The second category consists of images at 200× magnification. Here, there are 348 images, of which 247 are malignant (cancerous) and 100 are normal (benign). Combining both categories, the dataset includes 467 cancerous images and 144 normal images**.** For the current study, all 1224 images were considered for the purpose of histopathological oral cancer classification**.** This comprehensive dataset aids in the accurate classification of oral cancer using advanced computational techniques.

(2) IMAGE PREPROCESSING:

The images collected for the study exhibit variations in both quality and size, with some being clear and others affected by noisy backgrounds. To mitigate these issues, image preprocessing is necessary to eliminate impurities and reduce noise. A median filter was employed for noise removal, as it effectively preserves edges while eliminating salt-and-pepper noise. This filter works by replacing each pixel with the median value of its neighboring pixels, thereby reducing high-frequency noise. After the median filter was applied to all images, the next step involved resizing them to a consistent dimension of 128 × 128 pixels, due to the initial variation in image sizes. Once the preprocessing steps were complete, the images were ready for the image augmentation process.

(3) IMAGE AUGMENTATION:

The classification of medical images achieves remarkable accuracy through the use of Convolutional Neural Networks (CNN) however, several challenges must be addressed. One of the primary challenges in medical image classification is the limited availability of training and testing data. Deep learning models require large datasets to prevent overfitting and ensure proper generalization. Typically, these models perform better with a large, balanced dataset. In this research, we utilized a histopathological oral image dataset consisting of 1224 images divided into two classes: cancerous and non-cancerous. However, the dataset was imbalanced. To address this, image augmentation techniques was applied to create a more balanced and sufficient dataset. The augmentation process involved generating new images from the existing ones while preserving key features. Specifically, we used rotation (with a range of 40°), height and width shifts (with a range of 0.2), and zooming and shearing (with a range of 0.2). By employing these techniques, we expanded the dataset to a total of 4577 images from the original 1224 images**.**

(4) DATA PARTITIONING:

A total of 4577 images were generated and divided into training and testing datasets, following a 75% training and 25% testing split. The training dataset is used for initial model training, where weights are initialized, and for fine-tuning hyperparameters to improve the model's accuracy. After training, the hyperparameters are finalized, and the testing dataset is used to assess the model's predictive accuracy. This 75-25 split was applied to both the proposed CNN model and several predefined models.

(5) CLASSIFICATION:

A deep learning technique called Convolutional Neural Networks (CNN) is utilized to classify oral cancer histopathological images. A CNN typically consists of six layers: (i) input layer, (ii) convolutional layer, (iii) pooling layer, (iv) flattening layer, (v) fully connected layer, and (vi) output layer. **Input Layer**: In this layer, the input image is converted into a matrix of pixels. **Convolutional Layer**: This layer extracts features using a weight matrix, or filter. Each convolutional layer generates a set of feature maps. **Pooling Layer**: The pooling layer reduces the dimensions of the feature maps by discarding redundant and unnecessary features. It is applied between subsequent convolutional layers. In **max pooling**, the maximum value of each patch is selected, while in **average pooling**, the average value of the pixels in each block is used. **Flattening Layer**: In this layer, the pooled feature map from the last pooling layer is converted into a one-dimensional feature vector, which serves as the input for the fully connected layer. **Fully Connected Layer**: This layer combines the features from the previous layer to improve classification accuracy. **Output Layer**: The output layer receives the feature set from the preceding layers and provides the final classification in the form of probabilities. For this research, the described general architecture is employed to design a customized CNN model for classifying histopathological oral cancer images. The proposed CNN model is then compared with several state-of-the-art models, including **VGG16**, **VGG19**, **AlexNet**, **ResNet50**, **ResNet101**, **MobileNet**, and **InceptionNet**.

(6) PERFORMANCE EVALUATION USING STATISTICAL MEASURE:

The performance evaluation of the proposed model is done using five statistical measures such as precision, recall, specificity, F-measure and, most importantly, accuracy. The mathematical notation for precision recall or sensitivity, specificity, F-measure and accuracy, respectively

Precision = TP / TP + FP ----(1)

Recall or Sensitivity = TP / TP+ FN -----(2)

Specificity = TN/TN + FP -----(3)

F-Measure = 2 × Precision × Recall / Precision + Recall ------ (4)

Accuracy = TP + TN / TP + TN + FP + FN -------- (5)

Error rate = 1 – Accuracy -------- (6)

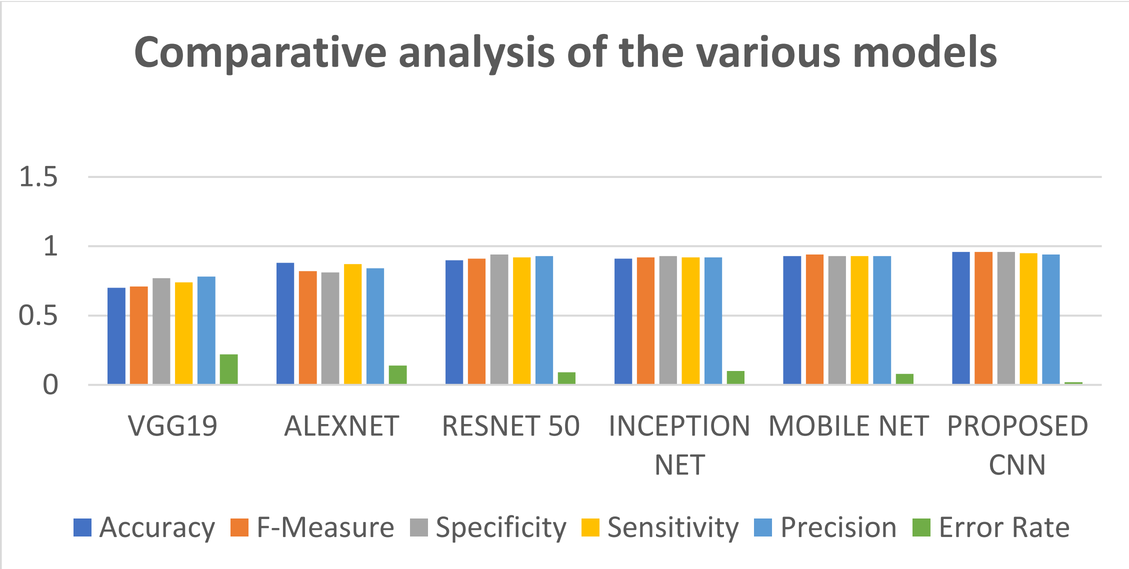
Here, TP indicates true positive and TN indicates true negative; similarly, FP is false positive and FN is false negative. For the performance evaluation of the proposed 10-layer CNN model, the error rate is also calculated, which is the complementary to the accuracy measure of the model.

Comparative analysis of the various models

Models	Accuracy	F-Measure	Specificity	Sensitivity	Precision	Error Rate
VGG19	0.70	0.71	0.77	0.74	0.78	0.22
ALEXNET	0.88	0.82	0.81	0.87	0.84	0.14
RESNET 50	0.90	0.91	0.94	0.92	0.93	0.09

INCEPTION NET	0.91	0.92	0.93	0.92	0.92	0.10
MOBILE NET	0.93	0.94	0.93	0.93	0.93	0.08
PROPOSED CNN	0.96	0.96	0.96	0.95	0.94	0.02

The proposed CNN model outperforms the other comparative model with the highest accuracy of 0.96. However, the performance of VGG19, Alexnet, Resnet50, Inception Net, and Mobile Net, is promising with accuracy of 0.70, 0.88, 0.90, 0.89, 0.91 and 0.93, respectively.



IV. CONCLUSION:

The detailed screening of the histopathological biopsy image is one of the major components to understand the diseases and for a better treatment. For the qualitative evaluation of the biopsy image, a skilled pathologist is required who can minutely differentiate between a healthy cell and a cancerous cell from the histopathological biopsy image of an oral cell. This process of qualitative and minute evaluation of biopsy image by the pathologist is a time-consuming process that results in a delay in disease detection and, hence, there will be a delay in treatment. In this aspect, there is a need for automated detection of OSCC to ensure a quick and correct diagnosis. In this current work, the authors propose the use of a deep learning models for the automatic detection of oral cancer from the oral biopsy histopathological image. The proposed 10-layer CNN model outperforms with the highest accuracy of 96% as compared to other state-of-the-art models, namely VGG19, Alexnet, ResNet50, ResNet101, Inception Net and Mobile Net. The performance of the 10-layer CNN is also compared and analyzed with some of the recent work presented in the literature, and it is found that its performance is strong compared with the recent work done. From the above analysis, it concluded that the proposed 10-layer CNN model can be used as an automated tool to identify oral cancer and can help doctors as a supportive measure for the identification and treatment planning of oral cancer. For a future perspective, the proposed model can be extended to detect distinct stages of oral cancer, which can help both the patient and doctor to defeat cancer.

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