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OCNet-23: a fine-tuned transfer learning approach for oral cancer detection from histopathological images

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ABSTRACT

Oral squamous cell carcinoma (OSCC) is emerging as a significant global health concern, underscoring the need for prompt detection and treatment. Our study introduces an innovative diagnostic method for OSCC, leveraging the capabilities of artificial intelligence (AI) and histopathological images (HIs). Our primary objective is to expedite the identification process for medical professionals. To achieve this, we employ transfer learning and incorporate renowned models such as VGG16, VGG19, MobileNet_v1, MobileNet_v2, DenseNet, and InceptionV3. A key feature of our approach is the meticulous optimization of the VGG19 architecture, paired with advanced image preprocessing techniques such as contrast limited adaptive histogram equalization (CLAHE) and median blur. We conducted an ablation study with optimized hyperparameters, culminating in an impressive 95.32% accuracy. This groundbreaking research ensures accurate and timely diagnoses, leading to improved patient outcomes, and represents a significant advancement in the application of AI for oral cancer diagnostics. Utilizing a substantial dataset of 5,192 meticulously categorized images into OSCC and normal categories, our work pioneers the field of OSCC detection. By providing medical professionals with a robust tool to enhance their diagnostic capabilities, our method has the potential to revolutionize the sector and usher in a new era of more effective and efficient oral cancer treatment.

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1. INTRODUCTION

Oral cancer is a prevalent form of cancer with a widespread presence throughout the world. In recent decades, both the incidence and fatality rates have seen concerning increases [1]. Oral cancer remains a grim prognosis, with low survival rates despite advancements in surgical and radiotherapeutic techniques [2]. In most cases, the disease starts with dysplasia, which is followed by carcinoma in situ, where cells proliferate uncontrollably but remain localized, offering a chance of recovery [3]. In the final stage, cancer is invasive and may spread to other organs. There is a crucial need for early detection of abnormal oral tissue growth, as this facilitates more efficient treatment planning and increases the likelihood of a successful outcome [4]. With 354,864 new cases and 177,384 deaths in 2018, oral cancer posed a significant global health challenge [5]. It is estimated that 90% of all cases of oral cavity cancer are squamous cell carcinomas

(SCCs) [6]. A rapid, non-invasive, efficient, and user-friendly deep learning system is developed here for the identification of oral squamous cell carcinomas (OSCCs) using histopathological images.

Betel quid consumption contributes to the late detection of oral lesions, with over two-thirds detected in advanced stages, resulting in lower survival rates. The cost of managing lesions, especially those in advanced stages, is substantial [6]. Premalignant oral lesions such as leukoplakia, erythroplakia, lichen planus, and submucous fibrosis are common in high-risk groups. A clear distinction between these lesions and their malignant counterparts is critical [7].

A subset of machine learning entitled deep learning has become the dominant force in the data analytics and artificial intelligence domains. This sophisticated method, which is similar to neural networks found in the human brain, has the amazing capacity to learn and extract complex patterns and representations from large datasets on its own. At the leading edge of modern technological progress, deep learning is especially proficient at image identification, natural language processing, and self-directed decision-making. Its transformational potential extends across a wide range of industries, including robotics, healthcare, banking, and autonomous driving [8].

In this research, AI-based technology is being used to revolutionize early diagnosis of OSCC. The focus is specifically on utilizing histopathological images (HIs) to provide healthcare practitioners with a rapid and dependable diagnostic tool. By employing transfer learning models like VGG16, VGG19, MobileNet_v1, MobileNet_v2, DenseNet, and InceptionV3 [9]–[18], [19], alongside a fine-tuned model OCNet-23, our research aims to enhance the accuracy of OSCC identification from histopathological images. By leveraging AI-driven image analysis, we can not only expedite diagnosis but also provide early intervention, improving patient outcomes significantly. In addition, we explore advanced image preprocessing techniques, such as speckle noise removal, morphological operation, and contrast limited adaptive histogram equalization (CLAHE), to enhance image quality, which is a crucial component of reliable analysis.

Our ultimate goals are to improve healthcare standards and prevent deaths. We anticipate that this research will bridge the gap between technological innovation and healthcare delivery, significantly advancing the field of oral cancer diagnostics. The key contributions of this study are summarized below:
- The quality of oral cancer histopathological images is systematically improved by using a variety of image preparation methods, such as median filter, CLAHE, and image resizing.
- A rigorous evaluation procedure is used to determine the best transfer learning model among several different methods of transfer learning that have been applied to the dataset. To improve the model's performance and resilience, additional development processes are applied.
- To improve resilience, a carefully designed Fine-tuned transfer learning model named OCNet-23 is built through a hyperparameter ablation study.
- After development of OCNet-23, it is put through a rigorous testing process with key performance metrics. In these tests, the accuracy and reliability of the model have been determined.

2. METHOD

The advancement of deep learning techniques has garnered substantial attention due to their potential to enhance the precision and efficacy of medical image analysis. Among these applications, the classification of oral cancer for diagnostic purposes stands out as particularly crucial, with the promise of significantly improving the accuracy of oral health assessments. This paper introduces a state-of-the-art deep learning method for categorizing histopathological images of oral cancer [20]–[24], utilizing the OCNet-23 model. The project aims not only to improve diagnostic accuracy for oral cancer but also to alleviate the workload on healthcare professionals. In the realm of oral oncology, this innovative approach has the potential to revolutionize diagnostic processes and ultimately elevate patient care. Figure 1 depicts our comprehensive study workflow, encompassing data preprocessing, the development of the OCNet-23 model, and subsequent statistical analysis.

The complete study procedure is summarized as follows:
- Dataset: The study utilizes 5,192 histopathological images of oral cancer, classified into two categories: “normal” and “OSCC” (oral squamous cell carcinoma).
- Image enhancement: various preprocessing techniques, including median filtering, contrast limited adaptive histogram equalization, and image resizing, are applied to improve the quality of the histopathological images.
- Assessment of transfer learning models: several transfer learning models are initially tested on the dataset. An evaluation process identifies the optimal model, which is then further developed to enhance its performance and robustness.

- Customized OCNet-23 Model: A variety transfer learning model, OCNet-23, is meticulously designed based on traditional transfer learning architecture. This model's performance exceeds that of the base model and other comparable models, as evidenced by a comprehensive ablation study.
- Evaluation: The refined OCNet-23 model is extensively tested using various evaluation metrics, including mean square error (MSE), peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and root mean square error (RMSE). The results confirm the model's robustness and precision in classifying oral cancer cases.

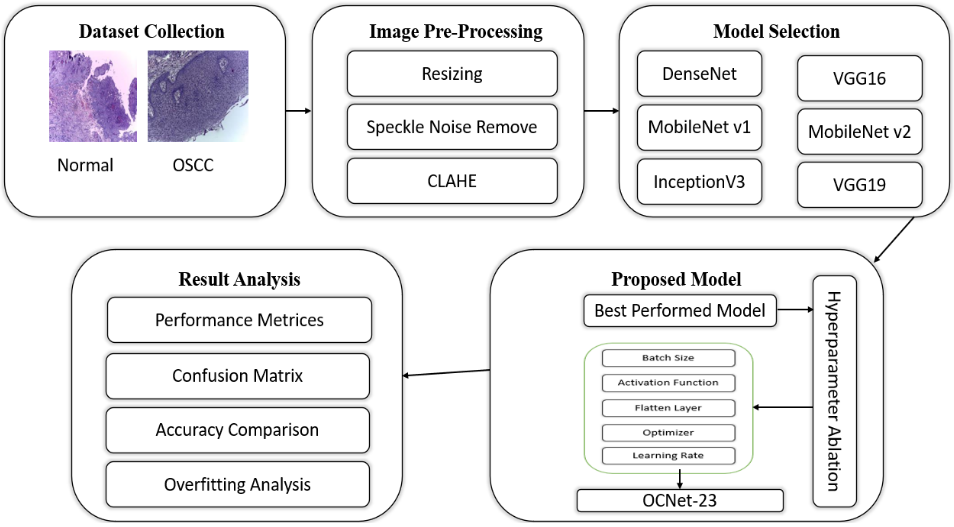

Figure 1. Workflow of the entire classification

2.1. Dataset description

A total of 5, 192 histopathological images has been carefully collected from Kaggle, a credible source of data. Two categories have been meticulously distinguished “OSCC” which stands for cases of oral squamous cell carcinoma and “normal” which refers to non-cancerous conditions. The class of OSCC contains 2494 images and normal contains 2698 images.

2.2. Image preprocessing techniques

In this section, several image processing techniques, such as median filtering, morphological opening, CLAHE, and image resizing, were utilized. These methods aimed to enhance image quality by removing noise, increasing contrast, and refining details. The improved clarity of histopathological images facilitated precise feature extraction, which is essential for accurate and efficient image analysis [25].

2.2.1. Image resizing

The preprocessing stage starts with image resizing [26], a fundamental step in image processing that adjusts image dimensions while maintaining the aspect ratio. In this study, oral cancer histopathological images were resized to 224×224 pixels to match the input specifications of the analysis pipeline. This step ensures uniformity in data preparation, which is essential for achieving reliable and consistent results in subsequent analyses.

2.2.2. Median filter

This technique efficiently removed noise while preserving crucial image details, leading to enhanced clarity. The preservation of these details ensured that critical features remained intact for further processing. By applying this method, we enhanced the accuracy and reliability of our diagnostic analysis [27].

$$g\,(p,q) = f\,(p,q) * u\,(p,q) + \eta\,(p,q)$$

2.2.3. CLAHE

In histopathological image processing, CLAHE is a potent image enhancement method. It works by first dividing the image into smaller sections, then separately equalizing each region's histogram [28]. In doing so, CLAHE successfully improves the image's visibility of important elements, leading to more precise medical diagnosis. The CLAHE formula is:

$$I_C(p,q) = D\ (I\ (p,q)) = \frac{(L-1)}{PQ}\sum_{j}^{k} nj$$

The overall preprocessing approach is demonstrated in Figure 2.

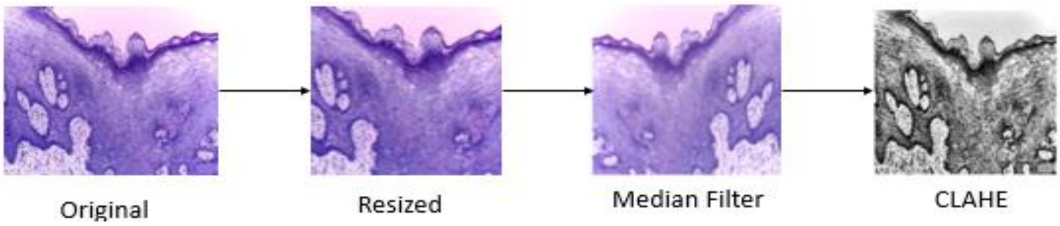

Figure 2. Image pre-processing techniques

2.3. Proposed OCNet-23

OCNet-23 was painstakingly constructed using hyper-parameter ablation research, with the VGG19 model serving as its core architecture. The selection of VGG19 highlights a dedication to accuracy because it has been shown to be more accurate than other transfer learning models. After that, thorough ablation research was carried out to further enhance the model's resilience using fine-tuning approaches, guaranteeing the best performance in tasks involving the categorization of oral cancer [29]–[32].

3. RESULTS AND DISCUSSION

3.1. Results of transfer learning models

Table 1 presents the results of six different transfer learning models for a given task. Six metrics—test accuracy, validation accuracy, train accuracy, train loss, test loss, and validation loss—are shown in the table for each model. The table displays six models of transfer learning [33]–[39]: InceptionV3, MobileNetV1, MobileNetV2, VGG16, VGG19, DenseNet201, and MobileNetV2. The table shows that, out of the six models, VGG-19 performs the best, with the highest train accuracy (96.84%), test accuracy (90.75%), and Val accuracy (92.24%). However, VGG-16 performs the worst out of the six models, as evidenced by its lowest train accuracy of 95.84%, test accuracy of 84.75%, and Val accuracy of 82.24%.

Table 1. Results of six transfer learning model

Model	Train accuracy	Test accuracy	Val accuracy	Train loss	Test loss	Val loss
MobileNetV1	97.80	88.22	81.85	0.17	0.28	0.18
MobileNetV2	97.00	85.71	83.78	0.31	0.32	0.32
VGG16	95.84	84.75	82.24	0.21	0.16	0.29
VGG19	96.84	90.75	92.24	0.21	0.14	0.20
DenseNet201	96.59	88.42	85.71	0.31	0.32	0.32
InceptionV3	95.32	86.49	84.17	0.32	0.36	0.37

3.2. Result of ablation study

This crucial section involves a careful examination of the results obtained from our extensive ablation research, which finely tunes the stable and optimal OCNet-23 model based on the renowned VGG19 architecture. Critical hyperparameters such as batch size, flatten layer, optimizer, learning rate, and activation function were examined and fine-tuned. These parameters collectively accounted for a large portion of the model's remarkable performance and durability.

3.2.1. Case study 1: changing batch size

The findings of a case study on how batch size affects a machine learning model's test accuracy are displayed in Table 2. Three setups with varying batch sizes, epochs, training times, and test accuracies are shown in the table. Configuration number two, where the batch size is 32 and the model is trained for

43 epochs with a training duration of 4 seconds, yields the highest accuracy of 92.74%. According to the table, selecting the ideal batch size is essential to getting the best accuracy.

Table 2. Changing batch size

Configuration no	Batch size	Epochs × training time	Test accuracy	Finding
1	64	82×5 s	91.73%	Accuracy decreased
2	32	43×4 s	92.74%	Highest accuracy
3	16	97×5 s	90.75%	Accuracy increase

3.2.2. Case study 2: changing flatten layer

Table 3 shows that the best accuracy is obtained when the flattened layer is used. Moreover, pooling techniques such as global max pooling do not provide higher performance. Consequently, the layer can be flattened to produce 96.13% accuracy.

Table 3. Changing flatten layer

Configuration no	Flatten layer types	Epochs × training time	Test accuracy	Finding
1	Flatten	97×5 s	92.79%	Highest accuracy
2	Global Max Pooling	60×4 s	90.65%	Accuracy decreased

3.2.3. Case study 3: changing optimizer

The effects of using various optimizers on the VGG-16 model's test accuracy are shown in Table 4. In configuration no. 1, when the model is trained for 97 epochs with a training time of 5 seconds, the Adam optimizer hit the highest accuracy of 92.82%. Here, accuracy drops were the outcome of the Adam optimizer's superior performance over the other optimizers, including Nadam.

Table 4. Changing optimizer

Configuration no	Optimizers	Epochs × training time	Test accuracy	Finding
1	Adam	97×5 s	92.82%	Highest accuracy
2	Nadam	44×5 s	90.99%	Previous accuracy

3.2.4. Case study 4: changing learning rate

Table 5 presents the outcomes of varying learning rates in terms of improving the accuracy of the model. setup no. 1 yields the maximum accuracy of 94.88%. In this setup, the model is trained for 55 seconds across 97 epochs at a learning rate of 0.001. The best accuracy in this instance was obtained with a learning rate of 0.001, but lower or higher learning rates led to decreases in accuracy.

Table 5. Changing learning rate

Configuration no	Learning rate	Epochs × training time	Test accuracy	Finding
1	0.001	94×55 s	94.88%	Highest accuracy
2	0.008	97×5 s	91.88%	Accuracy decreased
3	0.0001	68×57 s	92.28%	Accuracy decreased

3.2.5. Case study 5: changing activation function

The effects of using various optimizers on the VGG-16 model's test accuracy are shown in Table 6. In configuration no. 2, when the model is trained for 97 epochs with a training time of 5 s, the SoftMax activation function attained the maximum accuracy of 95.32%. Here, accuracy losses were the outcome of the SoftMax's superior performance over the other activation function, which included PReLU and Leaky ReLU.

Table 6. Changing activation function

Configuration no	Activation function	Epochs × training time	Test accuracy	Finding
1	PReLU	9×5s	99.88%	Previous accuracy
2	SoftMax	97×5s	95.32%	Highest accuracy
3	Leaky ReLU	88×5s	90.65%	Accuracy decreased

3.3. Performance comparison between transfer learning models with proposed model

This section presents a thorough comparison study that compares the proposed model to the most advanced transfer learning models. The results show how well the suggested model performed—better than any other model taken into consideration in the study—in classifying B-All into discrete categories. This strong proof of concept places the proposed model at the top of the list for precise and effective classification tasks, underscoring its effectiveness in the field of transfer learning.

The detailed findings shown in Table 7 clearly demonstrate the superiority of the proposed model. These results, which surpass the performance of all other models considered, highlight the extraordinary effectiveness and expertise ingrained in the design of the recommended model. Our model's strong performance demonstrates its sophisticated nature and makes it a unique option for applications that need more precision and efficiency than those of its competitors.

Table 7. A through comparison of the performance of the suggested model with transfer learning models

Model	Train accuracy	Test accuracy	Val accuracy	Train loss	Test loss	Val loss
MobileNetV1	97.80	88.22	81.85	0.17	0.28	0.18
MobileNetV2	97.00	85.71	83.78	0.31	0.32	0.32
VGG16	95.84	84.75	82.24	0.21	0.16	0.29
VGG19	96.84	90.75	92.24	0.21	0.14	0.20
DenseNet201	96.59	88.42	85.71	0.31	0.32	0.32
InceptionV3	95.32	86.49	84.17	0.32	0.36	0.37
OCNet-23	98.84	95.32	95.23	0.15	0.16	0.03

4. CONCLUSION

The study presents OCNet-23, a cutting-edge CAD system based on VGG19, aimed at accurately identifying and classifying microscopic images of oral cancer. Extensive evaluations and rigorous testing demonstrate its reliability and optimal performance. Future validation with larger datasets and real-time data is planned. OCNet-23 shows promise as a tool for early detection and diagnosis, potentially improving patient care by reducing unnecessary treatments and enhancing classification accuracy.

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