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A Survey on Advancements in Deep Learning for Oral Lesion Detection and Categorization

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ABSTRACT:

This paper covers research on the Advancements in deep learning for Oral lesion detection and classification , with the objective to allow early detection of oral cancer, a global health concern but acutely so in lower and middle class-income countries. It has been quite established that the diagnosis of this particular life condition needs to be made early, given that late-stage diagnosis usually raises mortality rates abnormally.A mobile phone application called MeMoSA (Mobile Mouth Screening Anywhere) developed to document oral lesions and facilitate contact between priliminary healthcare practitioners and Oncologists. The study is one of the outputs of the MeMoSA initiative that looks towards building a large annotated database of images of oral lesions. The labels for the latter are collected in detail and clinically validated through a novel annotation tool from multiple experts to enhance the reliability of the collected dataset. The developed models are trained over the annotated data in detecting and classifying oral lesions.

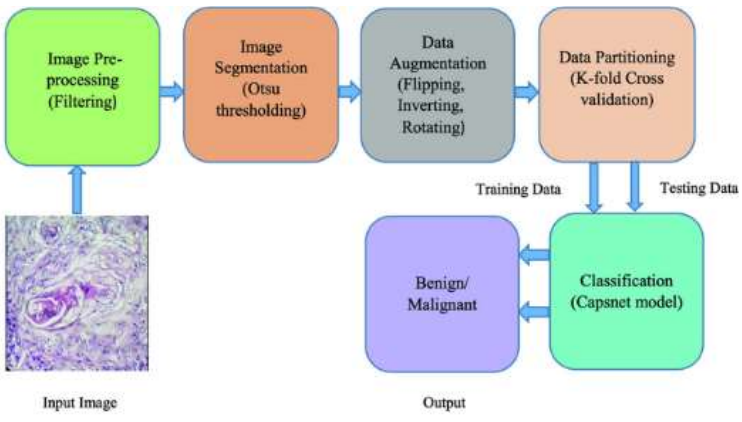
These findings show that deep learning demonstrates great potential in the automation of this detection process, as the outcomes have been promising both for image classification and lesion detection. This study represents an important milestone in telemedicine and AI-based diagnostic tools whose purpose is to help reduce the high mortality rates occasioned by delayed detection of oral cancers in resource-constrained settings.

KEYWORDS:- *Oral Cancer, Deep Learning, Early Detection, Oral lesions Automated Detection*

1. Introduction

Oral cancer presents a serious health challenge in the world today. It largely affects low- and middle-income countries with limited healthcare delivery resources. Of greater concern is the fact that most cases are diagnosed at late or advanced stages of the disease, significantly compromising survival rates and mortality rates. Detection of early oral cancers from identifiable lesions has critical importance in saving lives. Many remain inaccessible, creating an urgent demand for creative and affordable solutions because of the unavailability of traditional diagnostic methods requiring expertise and sophisticated medical equipment.

This recent deep learning and telemedicine research holds promise for replacing the traditional approach to diagnosis. In fact, such technologies appear to bridge the gap between resource and need for early diagnosis. The article explores the use of advanced deep learning techniques for the oral lesions categorization and detection. Building on pre-existing models such as ResNet-101 in the context of image classification and Faster R-CNN in the context of object detection, the findings here provide a foundation for developing scalable, efficient, and accessible diagnostic tools.



MeMoSA project, which tried to combine mobile technology with deep learning algorithms to screen the oral cavity for lesions. This project will create a robust, annotated database of images of oral lesions validated by multiple clinical experts. The annotated data set forms the training set for deep learning models that can accurately discriminate between benign, pre-cancerous, and malignant lesions. Furthermore, MeMoSA allows the remote areas' healthcare providers to document cases and consult specialists in real-time, further enhancing the reach and impact of early screening.

Besides, this research was aimed at developing model performance using advanced consolidation of annotation, data augmentation, and feature extraction techniques. Feature selection with optimization methods such as Fuzzy Particle Swarm Optimization (FPSO) and categorization using Convolutional Neural Networks (CNN) were effective for improving the accuracy while keeping it within the computational strength requirements. The utilization of fine-tuning and transfer learning on annotated data, together with an augmentation strategy, ensures that the models are robust to variability in lesion presentation and in imaging conditions.

It has broad implications because it not only demonstrates the potential of AI in the health sector but also establishes its feasibility for deployment in under-resourced settings with smartphone-based diagnostic tools. It addresses one of the serious barriers to access healthcare in a timely manner through integration into telemedicine, allowing for early detection and intervention.

As the study demonstrates, automated lesion detection and classification concerning cancer is the beacon of meaningful progress regarding the diagnosis of cancer. With further refinement and larger datasets, such systems can revolutionize oral cancer screening and almost certainly reduce worldwide mortality. This paper is an essential contribution to the burgeoning field of AI-assisted healthcare, paving the way for inventive solutions prioritizing accessibility, accuracy, and scalability.

2. Literature Survey

This study assesses the diagnostic use of Endogenous Fluorescence Lifetime Imaging (FLIM) endoscopy for the early detection of oral cancer and dysplasia. The pilot study conducted on 73 patients showed that FLIM could differentiate between mild dysplasia and early oral cancers and benign lesions with high sensitivity (>90%) and specificity (>85%). These results indicate that FLIM endoscopy does have the explore for initial detection and monitoring of oral cancer, especially in remote or underserved areas. Future research is presently looking to affirm these findings with more extensive clinical trials.[1]

This study focused on introducing a new hybrid optimization technique in the form of PSO and the BER algorithm which is supposed to be used to diagnose oral cancer. It is issued with an idea to increase the accuracy and functionality of the models that are applied for medical image analysis. On this basis, the hybrid algorithm makes it possible to better feature selection and classification than overcoming numerous challenges in diagnosis of oral cancer, given sensitivity and specificity. Their results suggest the possibility of making more reliable and precise predictions with this approach, therefore making big contributions to the development of advanced diagnostic tools for early-stage cancer detection.[2]

This study aimed on investigting the application of domain adversarial learning faced with the challenges of aligning small datasets for oral cancer automated diagnosis. In this paper,it has emphasized generalization performance across different data distributions; thereby, improving the efficiency of deep learning models for in vivo oral cancer detection. The research demonstrates the significance of robust methods for dataset alignment to decrease variability and increase diagnostics accuracy. This work gives significant contribution towards overcoming limitations with the dataset in automated health care applications, especially in resource - constrained environments.[3]

This study reviewed on treatments for oral cancer with a focus on chemotherapy and new therapies. Their paper evaluates how the old adjuvant cytotoxic agents perform as a combination with new targeted therapies, based on studies showing a more favorable outcome for treatment with an improvement in quality of life for the patient. Personalized medicine and the introduction of new drugs into classical protocols are also mentioned. Challenges posed by drug resistance and adverse effects are some of the key discussion points made in this work, which underscores the need for innovative strategies to enhance the efficacy and accessibility of oral cancer treatments, offering valuable insights into the evolving landscape of oncological care.[4]

This study proposed the method of early oral cancer diagnosis using Three-Dimensional Convolutional Neural Networks. The 3D CNN is used in this regard to analyze the spatial features from medical images so as to improve the differentiation between benign and malignant oral tumors. This research has developed considerable progress compared with traditional 2D CNN in its performance. The approach proposed here indeed focuses on extracting spatial as well as dynamic features, yielding much higher accuracy in classification. The work portrays the potential of 3D CNNs for improving early detection and thus presents a promising tool for better oral cancer management outcomes.[5]

This study introduced an ensemble deep learning model to detect OSCC from histopathological images. The proposed model integrates transfer learning and ensemble learning techniques with respect to the diagnosis accuracy of the model. It incorporates several pre-trained networks where in their strengths are used for improving precision, recall, and F1 scores. Challenges in connection with the imbalance of datasets are incorporated by using augmentation methods in the study. This ensemble-based strategy proved to be highly successful in diagnosing OSCC and provided a solid framework for early and accurate diagnosis. The study succeeds in highlighting how AI-driven approaches contribute to advancing the detection of oral cancer.[6]

The paper deals with applying deep learning techniques toward the automatic identification of oral cancer using images captured through smartphones. In this context, the proposed system, as put forward by the authors, is based on convolutional neural networks, aiming to enhance accessibility and efficiency in early diagnosis through classification of oral lesions. Approach This technique will address problems associated with high variability and the complexity involved in the quality of images through transfer learning. Such a study emphasizes the promising possibility of using smartphone technology and machine learning for cost-effective, non-invasive cancer detection, especially in resource-limited settings, and significantly contributes to early oral cancer diagnosis.[7]

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The paper presents a deep transfer learning model for the detection and categorization of oral cancer. The authors utilize pre-trained convolutional neural networks (CNNs) and fine-tune them for the task of identifying oral lesions from medical images. This approach helps in overcoming the challenges of limited labeled data by leveraging knowledge from larger datasets. The model demonstrates higher accuracy and performance in differentiating between benign and malignant lesions, offering a promising tool for early oral cancer detection. The study focuses on the effectiveness of transfer learning in enhancing the performance of deep learning models for medical image analysis.[9]

The paper suggests the utilization of a deep learning-based system for oral cancer detection. In this paper, the authors have used CNNs for the analysis of images of oral lesions and categorized these lesions as benign or malignant. Upon training the model by employing images associated with oral cancer, the prognosis serves to primarily aid in the initial diagnosis of oral cancers without causing invasive procedures. This thus demonstrated the deep learning techniques' potential in improving the accuracy and efficiency of oral cancer detection and the need for automation in images of medical analysis in clinical settings.[10]

This paper uses the multimodal pipeline for finding the oral cancer initially using a deep convolutional neural network (CNN). The work combines different sources of data, such as clinical images and patient information, to further achieve high accuracy and robustness in detecting oral cancer. Deep learning techniques have been applied in this study for uncovering useful features from various sources in the model that distinguish malignant lesions from benign ones. The study demonstrates the promising field of AI-assisted diagnostics, hereby paying attention to advantages of multimodal approaches in improving possibilities for initial detection of oral cancer and providing reliable non-invasive diagnostic support.[11]

This article proposes a hybrid approach based on AI for the diagnostic accuracy of oral squamous cell carcinoma or OSCC, based on Histological pathology images. This work aims to combine deep learning techniques with traditional machine learning models in order to better classify and analyze the tissue sample. Intended by the integration of several AI models, cancerous cells are to be produced with higher precision and at lower rates of errors in diagnostics. This will further the possibility of developing and training hybrid AI systems that can automate the very complex analysis of medical images, thus creating a reliable tool for early-stage pathologists to diagnose and treat OSCC.[12]

Discuss application of texture analysis techniques on color oral images for detection of lesions. A proposed method extracted and analyzed the texture features of interest from the oral image with a prediction regarding the likelihood of lesions. Advanced image pre-processing and machine learning algorithms will be applied to correctly classify and identify lesions. It was shown that texture-based approaches improve the reliability and precision in detecting dental and oral lesions, and hence, such methods are a promising tool in the early diagnosis and non-invasive screening of health issues in the oral cavity.[13]

The paper investigates oral microbiome as a potential biomarker for the fast detection of oral carcinomas. The authors reveal how changes in the mouth's microbial community relate to the development of oral cancer. A study based on the microbial profiles showed that there were certain bacterial signatures which could be used as markers for the beginning stages of oral carcinomas, thus providing a non-invasive method of early diagnosis. It has research that indicates the possibility of applying microbiome-based diagnostics in detecting cancer for early detection and prevention strategies in the case of oral cancer through microbiological analysis.[14]

This paper presents a hybrid model in the application of ABC optimization combined with PSO and Bayesian Linear Discriminant Analysis for oral cancer classification. By this, the authors have presented an application where ABC-PSO applies to optimize feature selection processes, whereas Bayesian LDA applies for classification. It presents an approach that enhances the accuracy and effectiveness of oral cancer identification with the hybrid selection of more relevant features through improving classification performance. The work demonstrates the feasibility of evolutionary algorithms in combination with statistical techniques to assure reliable and effective cancer classification.[15]

This paper introduces a portable, non-invasive oral cancer diagnosis system. The system is based on optical sensors coupled with advanced signal processing techniques in analyzing tissues and correlating them at an early stage with oral cancer. To put it bluntly, the authors focus on the portability of the system that perfectly fits various clinical and field locations without invasion. This has the potential to offer a quick, cost-effective, and reliable diagnostic tool for oral cancer, especially in resource-limited environments. This can lead to early detection and consequently improvement in patient outcomes.[16]

The proposed system is an oral cancer-detecting health alert designed with a combination of image processing and machine learning techniques. These images are captured for the oral lesions, analyzed for signs of cancer, and through application of algorithms for feature extraction and classification, the model determines the likelihood of malignancies. The authors emphasize their stance regarding such a system's ability to send alerts to healthcare professionals, thus triggering early medical intervention. This study thus demonstrates the possibility of introducing automated detection systems in the health sector as a tool of early oral cancer diagnosis as well as increased efficiency in monitoring and treating patients.[17]

A paper illustrates the approach to oral disease identification through a neural network. Deep learning models make use of analyses for recognizing several conditions through oral images, such as lesions and other abnormalities. Classification and detection of diseases are learned from this set of oral images with high accuracy after training on the same. This study has underpinned the ability of neural networks in medical image analysis tasks, thereby providing a sure and automatic method of oral disease detection. Such an approach would help healthcare providers in the early detection of conditions to improve patient outcomes through timely interventions.[18]

The paper conducts research about the use of data mining methods in the identification of oral cancer. Various algorithms were used by the authors in the analysis of clinical and medical data to identify pattern arising from oral cancer. Using the set of data mining tools, the study focused on classifying and predicting whether a patient had oral cancer or not. This research mentions that data-driven approaches can improve earlier detection and diagnosis of oral cancer through the effective management process by providing the most efficient automated device to support the process of decision-making and thus improve patient outcomes among healthcare professionals.[19]

This paper explores the possibility of cancer image measurements using very costly whole slide imaging (WSI) scanners and more available methods as well. Here, it compares conventional image quantification techniques with those results obtained with WSI scanners to identify the trade-offs between cost and accuracy. It assesses whether there is some potential for low-cost alternatives in cancer diagnosis without giving away the quality of image analysis based on the evaluation of several cancer images. Such outcome would show that cheap approaches could give accurate quantification results and thus available screening for cancer, with accuracy in diagnosis available in resource-limited settings.[20]

3. METHODOLOGY

For detection of oral cancer, methodologies often comprise data preprocessing, segmentation, feature extraction, and classification. Improvement in image quality through removal of noisy elements and adjustment of contrast is done during preprocessing. Segmentation isolates the critical region, such as lesions, which requires focused study. Feature extraction finds the patterns and characteristics critical for distinguishing the cancerous region. Classification uses a deep learning model or a machine learning to categorize the data.

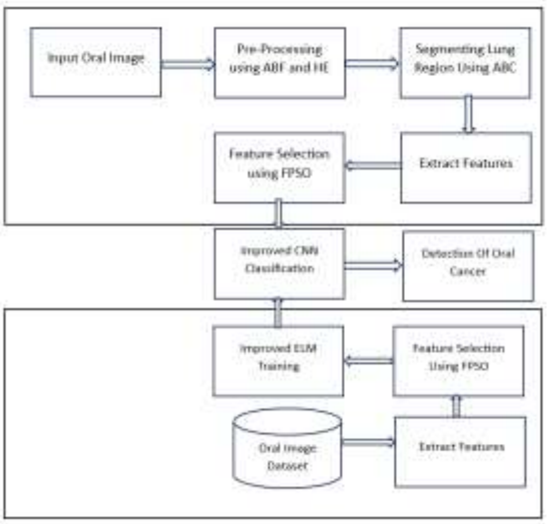
The methodologies referenced here cover a wide range of techniques, from advanced algorithms and deep models such as CNNs and ResNet, to hybrid methods combining old and modern techniques. All these methodologies report overcoming the challenges of variability in datasets, class imbalance, and inefficiency in computations to aid in early diagnoses, improved treatment planning, and better patient outcomes.

This systematic approach not only lends credence to the research but also brings about findings that are actionable and have an impact on the real world with medicine. The following sections detail specific methodologies commonly used in oral cancer detection, which unveils the diversity of methods and innovation in this very important field.

3.1 CNN

This approach follows a sophisticated procedure that uses deep learning techniques in oral cancer detection. Preprocessing involves removing noise through Adaptive Bilateral Filter and improving the contrast through Histogram Equalization so that the input images will be clear. Then comes segmentation where Artificial Bee Colony segregates the tumor areas from the non-tumor regions so that it emphasizes only tumor areas.

Feature extraction is performed using three approaches: wavelet transforms for texture detail acquisitions, Histogram of Oriented Gradients (HOG) for shape extraction, and Zernike moments for identification of structural features. Overall, these procedures collectively extract a range of image characteristics. To choose the best subset in the dataset, Fuzzy Particle Swarm Optimization (FPSO) which is applied to optimize the selection of the most essential features by reducing the computation load and enhancing the classification accuracy.

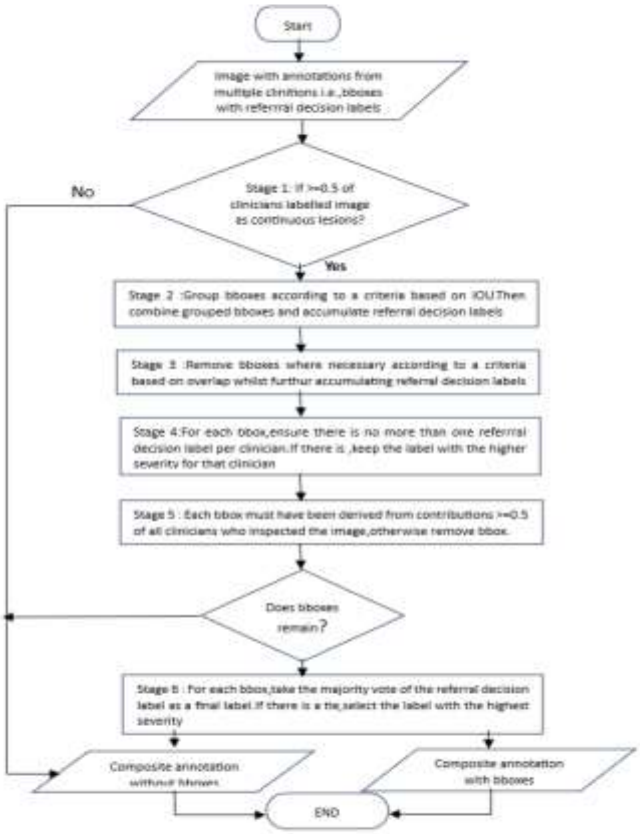


Then, using a Convolutional Neural Network (CNN), which was trained on 1,018 images of the oral cavity that were taken from the CT scan, provides a classification of the developed features, finally giving a robust tool for the detection of oral cancer.The three elements combining preprocessing, feature extraction, optimization, and classification will get accurate and efficient identification of oral cancer. Integration with deep learning and advanced algorithms makes it effective in application for medical diagnosis.

3.2 ResNet-101 & Faster-CNN

Clinicians annotate images with bounding boxes as well as further decision-making labels. A multi-stage process is employed to aggregate those annotations to a composite reference for training models. Annotations are binned on the basis of IoU criteria, and overlapping annotations are averaged. Any bounding box with contributions from fewer than 50% of clinicians is removed as those are not reliable annotations.

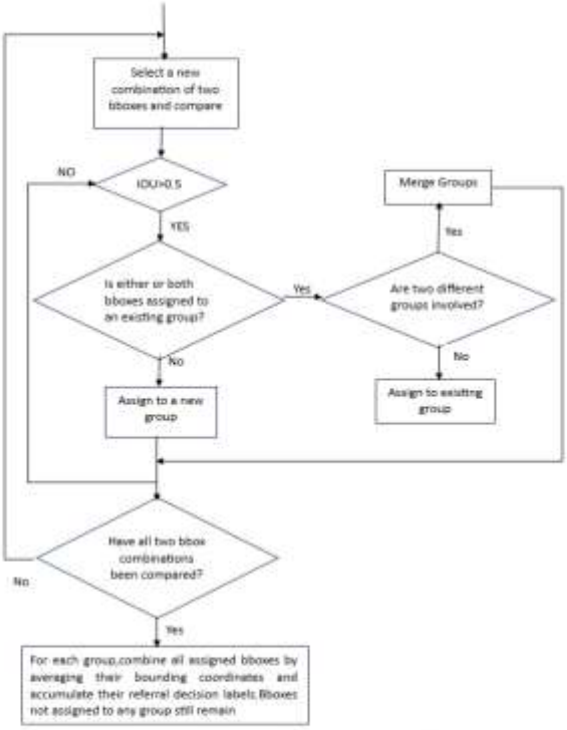
The dataset consists of images of oral structures from 1,085 patients, totaling 2,155 images. For 800 images, 3–7 clinicians performed annotation, while the remaining images were annotated by one clinician. Metadata such as demographics of patients, risk factors like tobacco use, and age are gathered but not used during this phase of the study. All images are again re modified to make them uniform, and further data changing techniques like flipping and rotation are applied on them to increase model robustness.



Strategy to combine annotations from multiple clinicians into a composite annotation.Bbox=Bounding box

There are two major deep learning methods. The first one is ResNet-101 that carries out the task of image classification with distinction between lesion images and non-lesion images, dividing them into referral categories. The second one is Faster R-CNN for object detection, used here to detect and classify specific lesions. Faster R-CNN performs in two consecutive stages: RPN stage (Region Proposal Network) producing a region of interest, and the detection network that refines the initial proposals based on label assignment and adjustment of bounding box coordinates.

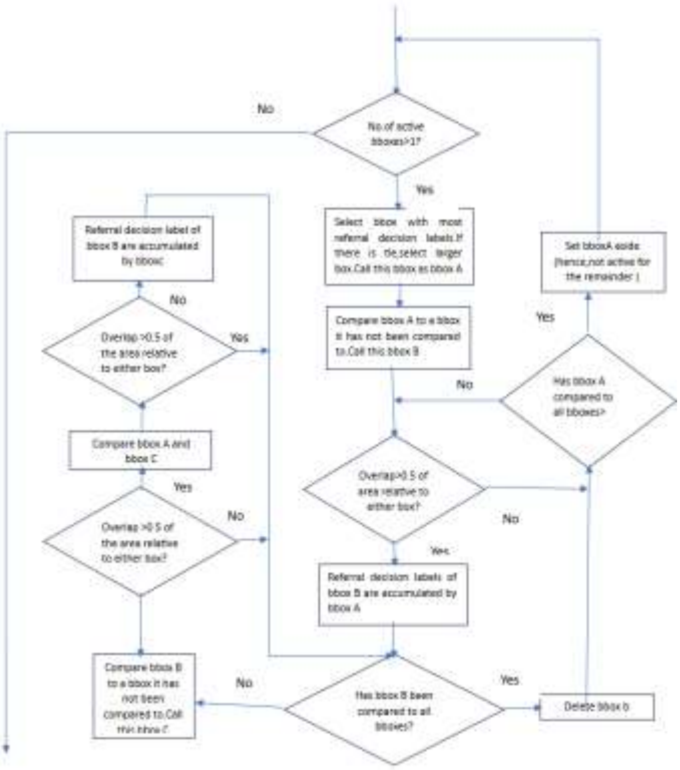
For annotations of the target, strict hierarchy is employed since each of the bounding boxes involves majority voting of clinicians. In cases where the votes tie, the most stringent label is favored. This yields annotations highly reliable and replicates consensus for the stage given. In further stages of refinement, all bounding boxes that do not align or overlap with clinicians are excluded.



Group bounding boxes according to a criteria based on IOU.Then combine grouped bounding boxes and accumulate referral decision labels.This is an expansion of above strategy. Bbox= Bounding box

It further incorporates precision, recall, and F1 scores for testing model performances of classification as well as detection performances. Considering object detection, a bounding box is reported to be correct if the IoU with ground truth is at least 0.5 and its lesion class matches. This methodology shows early oral lesion detection to be quite robust wherein clinical expertise converges with rich and advanced machine learning models in the quest for consistent and actionable outcomes.

3.3 Resnet, Gabor Filter, CatBoost

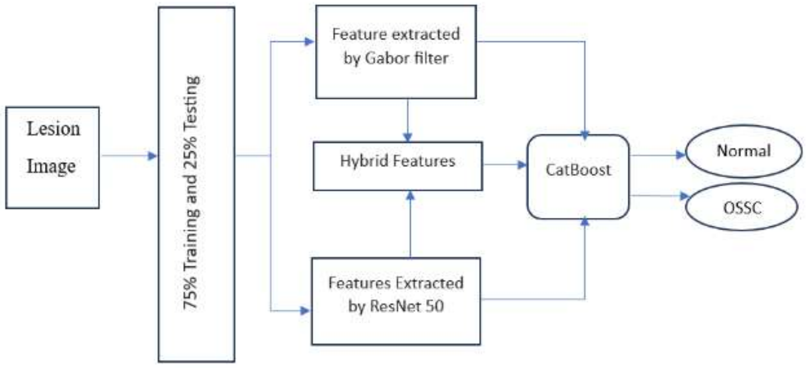


Remove bounding boxes where necessary according to a criteria based on overlap whilst further accumulating referral decision labels.This is an expansion of above strategy

This research utilized three methods of texture feature extraction and classification on histopathological images. For the first method, the texture feature was extracted by Gabor filtering and then classified with CatBoost. It is a simple technique, but very powerful, for a preliminary examination.

The second way employs ResNet50 as a deep learning - based feature extractor for image high-level patterns. These features are then reduced using PCA and classified with CatBoost, providing much more sophisticated insights into image characteristics.

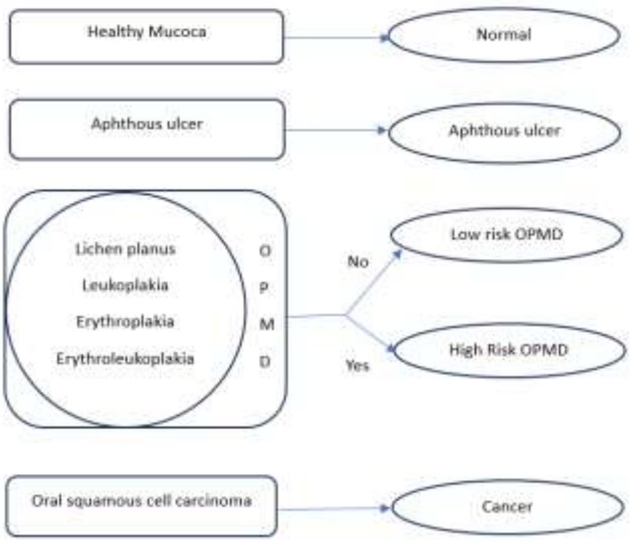
Thirdly, the most powerful method utilizes the strength of Gabor filter along with ResNet50. In this hybrid technique, the features of texture-based and deep learning-based data are incorporated into a single dataset, which enhances the classification accuracy. These combined features are classified using the superior performance of the CatBoost in the detection of OSCC.



The dataset has 5,192 histopathological images equally classified under normal and OSCC cases. Preprocessing of the images will standardize the input by resizing the images into pixels, 224×224. This approach gives an accuracy of 94.92%, hence the most reliable among the three approaches. Therefore, this method provides a cost-effective alternative for the very expensive imaging technologies used in the diagnosis of OSCC.

3.4 HRNet-W18

This methodology uses images captured through smartphone cameras for an early diagnosis of oral cancer. Images are taken under controlled conditions, paying attention to consistent position and focal distance. Preprocessing includes cropping of the lesion region and normalization of pixel intensity, followed by resizing to 512×512 pixels. This reduces background noise and enables some standardization of image quality for analysis.



There are 1,448 images in the dataset-these include 688 lesion and 760 casual images; the images were captured using the smartphones iPhone 11 and iPhone 12. Lesions are five classes including normal, low-risk OPMD ,aphthous ulcer, high-risk OPMD, and oral cancer. A resampling technique is employed to deal with class imbalances on photos that rotate and shift lesion center points; this ensures there is ample distribution within classes.

The HRNet-W18 classification model uses a very high-resolution technique to differentiate types of lesions. This model was initially pre-trained on ImageNet and afterwards fine-tuned on this dataset. High augmentation during the training process, such as flipping and brightness adjustments, is used to increase robustness and prevent overfitting.

The given high-risk enriched dataset was subjected to evaluation to establish sound validation. This smartphone-based approach could thus make it feasible to extend the opportunity of letting the masses identify oral cancers in an early stage at a low cost.

4. Case Study:

4.1 Case Study – 1:

Deep learning in the automation of Oral cancer detection

Overview : Oral cancer is a major concern especially in low-and middle-income countries owing to unavailability of specialists as well as the delayed diagnosis and resultant deaths. The current study addresses this challenge by use of deep learning integrated with mobile technology in making access and affordability of oral cancer early detection easier through the project called MeMoSA: Mobile Mouth Screening Anywhere. Using a smartphone, health professionals can capture images of a patient's oral cavity through the MeMoSA application that are then further processed by deep learning algorithms to detect any malignant or pre-malignant lesion present.

Solution : MeMoSA application comes with several innovative features that support foremost detection of oral cancer. The solution permits the capture images of patients' oral cavities and annotate possible lesions through bounding boxes. Then it classifies using deep learning models, such as ResNet-101 for classification and Faster R-CNN for object detection, the determined lesions on a scale of risk. This way, primary care providers will be able to categorize lesions as either benign or malignant and therefore make an informed decision, referring patients to further testing if necessary. The app further supports telemedicine, which allows primary care providers to consult with off-site specialists for confirmation.

Implementation : MeMoSA uses the strengths of deep learning algorithms in both image classification and object detection. The system relies on a vast annotated database of oral images annotated by different clinicians to validate the accuracy of the lesions detected. For both multi-class and binary-class classification, it makes use of the ResNet-101 model while the Faster R-CNN is set to work in detecting lesions and their locations within the images. Transfer learning is employed by using the pre-trained models from large datasets such as ImageNet and COCO and fine-tuning them on MeMoSA data to improve the precision of detection in oral lesions. The trained models are then inputted into the application in order to display the screening results in real time.

Conclusion : MeMoSA is a bridge between mobile technology and deep learning that solves an important health problem, with promising outcomes in the priliminary detection of oral cancer. The application has achieved an impressive 87.07% of the F1 score in the task of lesion classification. It has proved how efficiently it identifies early-stage oral cancers. As the dataset of MeMoSA is widened and its models develop, it promises to transform oral cancer screening-more than likely in regions with an underserved population-by making screenings faster, more accessible, and less costly.

4.2 Case Study -2

Early detection of Oral Lesions using Deep Learning

Overview : A significant challenge for better health outcomes in the present world is late diagnosis of oral cancer, especially in rural and resource-poor countries, which have little access to medical specialists. The paper posits a novel smartphone-based imaging mode for foremost detection of oral cancer by utilizing deep learning technology powered by the High-Resolution Network. Combining smartphone technology with AI results in a low cost screening tool that will assist healthcare providers and their patients in making proper treatment decisions.

Solution : This solution uses smartphone image acquisition with a deep learning model to classify oral lesions as malignant or potentially malignant. It starts by getting images clearly by focusing the lesion in an image to be rightly examined. To counter variability stemming from different phones used to take images, some forms of data augmentation are applied. A deep learning model of choice is HRNet for image processing with categorization into risk levels and an excellent classification F1 score of 83.6%.

Implementation : Application is through smartphone, such that the patient or the caregiver will take the images so that the lesion is centered for best quality, following center cropping to focus on the lesion and resampling to adjust for variation in camera angles. HRNet was trained initially on large datasets such as ImageNet and then fine-tuned using the collected dataset based on malignancy risk classification. The model was tested against other networks, namely VGG16, ResNet50, and DenseNet169. In all, HRNet performed best. All the system's code is built using Python and PyTorch and then accelerated using GPU for real-time analysis.

Conclusion : This study demonstrates the potential of smartphone-based deep learning technology for foremost oral cancer detection. The system's high sensitivity and specificity make it an attractive, almost costless, diagnostic tool, especially for low-resource environments. By extending accessibility, this technology reduces costs-a huge challenge in the quest for early detection and treatment of oral cancers, thus offering significant benefits for global health.

4.3 Case Study -3

Quantifying Cancer Images without costly whole slide imaging technology

Overview : Tissue samples in general are diagnosed by expensive facility-intensive whole-slide imaging WSI scanners. Such infrastructure may not easily be accessible in resource-poor healthcare settings which may only delay or provide a more imprecise diagnosis in such places. The purpose of this paper thus is to describe an approach on how to quantify images, independent of pricey WSI scanners. In an image-based alternative quantification method, this work is able to reduce the time of diagnosis and that associated cost. It may help to strengthen under-equipped health facilities of the world.

Solution : The alternative WSI-based image quantification system developed and presented here is avoiding the use of WSI scanners; and features of this procedure are:

Digital Image Acquisition: Use of ordinary standard digital cameras or even less expensive microscopes for high-quality acquisition of tissue samples.

Image Processing and Quantification algorithms employing advanced machine learning and processing techniques that evaluate images for features related to cancerous cells.

Accuracy Improvements: Normalization and calibration methods bring accuracy to a satisfactory range so that the system becomes reliable even with non-standardized equipment. It has opened a door for the real-time analysis of images without using expensive imaging apparatus, making cancer diagnosis relatively accessible.

Implementation : Implementation of this system would have the following components.

Data acquisition: Images of tissues are collected by high-resolution microscopes or cameras. Experienced pathologists annotate the cancerous as well as the non-cancerous regions in these images.

Image processing: Algorithms mark the regions where cancerous features are detected, such as aberrant cell morphology, nuclear-to-cytoplasmic ratio, and other morphological markers.

These techniques are used by Machine Learning Models wherein CNNs are applied to identify annotated images that classify the regions within samples. They train models that work with variability in images obtained from other sources that are non-WSI.

Calibration and Testing: The system underwent vigorous testing with validation data sets to ensure that it performs fairly across the type of equipment and lighting conditions. It should provide output that is direct and actionable to help clinicians make earlier diagnoses.

Conclusion: This study demonstrates the feasibility of obtaining high-quality quantification of cancer images with equipment other than very expensive WSI scanners, thereby making it an affordable means of diagnosis in resource-limited settings. Preliminary results show that it has promising prospects for the accurate identification of cancerous cells, which are as good as the older methods. With this accessible and adaptable solution, the approach can make a difference in the diagnosis of cancer across the globe, tearing down barriers associated with very expensive equipment that is usually needed for imagery, thus allowing early interventions and improved results among those populations relegated to the fringes.

5. Results and Discussion

The CNN model gained exceptionally high accuracy levels of 98.2% on the UCI dataset, indicating the strength of the model. At the MeMoSA dataset, ResNet-101 performed more efficiently than Faster R-CNN, with F1-score: 87.07%. The performance of Faster R-CNN was poor with metrics of F1-score 41.35%, which signifies the complexity of object detection in diverse imaging conditions. It can be noticed that HRNet-W18 performed with a very well-balanced accuracy of 91.0% and recall of 96.6%, where this model is mostly suitable for real-time, mobile-based applications.

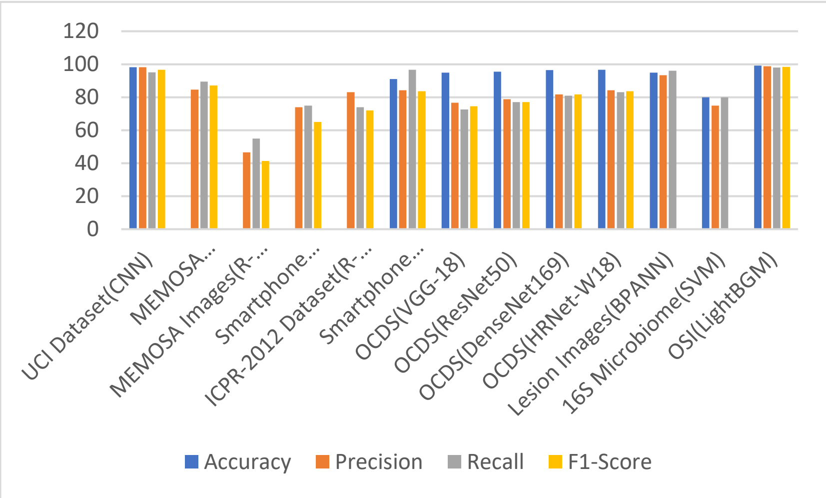
Deep learning approaches, especially transfer learning models - ResNet and DenseNet, yield better classification for complex datasets. For smartphone-based classification tasks, HRNet-W18 delivered far better performance with high sensitivity and specificity values through high values in all categories. Such performance clearly explains how adaptive AI can be in dealing with variability in imaging conditions, which is one major problem posed by resource-limited settings.

While DenseNet169 was confident on both accuracy of 96.5 % and fair metrics on oral cavity datasets, the HRNet-W18 was also powerful in delivering an F1-score of 83.6 %. The simpler methods like BPANN was found performing poorly in color lesion datasets, but showed potent architecture. Also, LightGBM showed a nearly perfect performance on online sources with an F1-score of 98.38%.

Availability of smartphone data authenticated the feasibility of real-time diagnostics. Models including HRNet-W18, with this domain specificity, processed the variability in image quality and camera angles through preprocessing techniques, resampling, and augmentation. This makes AI-driven mobile solutions a game changer for the early detection of oral cancer in resource-deprived regions, where accessibility would compromise the diagnostic accuracy achieved here.

DATASET	MODEL	ACCURACY	PRECISION	RECALL	F1-SCORE
UCI DATASET	**CNN**	**98.2**	**98.3**	**95.1**	**96.7**
MEMOSA Images	ResNet-101	-	84.7	89.51	87.07
	R-CNN	-	46.61	54.90	41.35

SMARTPHONE Dataset	R-CNN	-	74.0	75.0	0.65
ICPR-2012 Dataset	R-CNN	-	83.0	74.0	72.0
SMARTPHONE Images	HRNet-W18	91.0	84.3	96.6	83.6
Oral Cavity Dataset.	VGG16	95.0	76.7	72.5	74.5
	ResNet50	95.4	78.8	77.0	77.1
	DenseNet169	96.5	81.7	81.0	81.7
	HRNet-W18	96.6	84.3	83.0	83.6
Color Oral Lesion Images	BPANN	95.0	93.3	96.0	-
16S oral microbiome data	SVM	80	75	80	-
Online Source Images	LightBGM	99.25	98.86	97.92	98.38



6. Conclusion

The results of the conducted experiment proved that CNN is the powerful model for early oral cancer detection due to higher accuracies in lesion localization as well as classification. By using a two-stage structure, it ensured proper boundaries for accurate detailed diagnostic tasks to be performed. Hence feature selection through FPSO brought about an enhancement both regarding computation time and accuracy for such medical imaging tasks also optimization of feature extraction seems to play an essential role. Despite its strengths, Future work on CNN includes optimizing the computing requirements and relianc.e on image quality,model optimization on diverse datasets to enhance availability and robustness in practice.

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