A Hybrid Deep Learning Framework for Oral Cancer Diagnosis

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ABSTRACT

Introduction

Oral Cancer has been one of the deadliest diseases which has claimed many lives. The diagnosis of oral cancer has been a challenging task for the pathologists. Early detection of cancer can help in increase of mortality rate. Advanced technologies like Machine Learning, Deep learning etc has been beneficial for the early identification and segmentation of oral cancer. But every deep learning models have their own boon and bane.

Methods

In this study we have combined two advanced deep learning models into a single model by taking the advantages of both models, a novel and hybrid method is used for early identification and segmentation of cancer. In this two advanced deep learning models DINOv2 and YOLOv8 are used together for the classification and segmentation of cancer cells. We have trained the models with the available sample data set from Kaggle and then evaluated the performance of the hybrid model in real-time test dataset. In this study we have trained the hybrid model with comprehensive oral dataset which contains both clinical and Histopathological images.

Results

In the suggested method's the results of the evaluation showed that DINOv2 has achieved 97.9% accuracy in Histopathological images and 89% Accuracy in Clinical images. DINO-V2 performed the best classification in histological images. When it came to identifying oral cancer in Clinical images with 98% accuracy, YOLOv8 fared the best. In histopathological images, YoloV8 has performed similar results as DINOV2 with 96% accuracy. Through this work, we propose a hybrid deep learning model that utilises both the models YOLOv8 and DINOv2 to diagnose oral cancer.

Keywords: Histological, Dinov2, Yolov8, Oscc, Opmd.

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INTRODUCTION:

WHO forecasts for 2020 show that there would be around 380,000 new cases and 180000 deaths globally from lip and oral cavity cancer. Males are more likely than women to have oral cancer, and the disease has affected more males than women. Socioeconomic position also has a big impact on oral cancer incidence. With a high mortality rate, oral cancer is a serious health problem. Improved patient outcomes and 75–90% survival rates are dependent on early identification of oral cancer. More than 90% of instances of oral cancer are caused by oral squamous cell carcinoma (OSCC), which was preceded by oral potentially malignant diseases (OPMD) such as erythroplakia and leukoplakia. The primary goal of screening programs has been to identify OPMD, which could develop into cancer[1]. To reduce morbidity and death from oral cancer, early detection is essential. However, as primary care physicians are usually inexperienced or unskilled in identifying these lesions, it has been shown that implementing these systems—which rely on visual inspection—can be difficult in practical settings. Small, benign lesions can manifest as OPMD and early-stage OSCC lesions, which frequently don't produce any symptoms. This might cause patients to present later than necessary, which can further delay diagnosis. Advances in computer vision and deep learning have allowed for the development of effective tools for the creation of auxiliary technologies that can automatically scan the oral cavity and provide feedback to doctors and patients for patient examinations and self-examinations. It can be time- and money-consuming to enable vision-based automation systems for the identification and early detection of cancer and potentially malignant lesions.

The detection of OPMD has a vital role in improving the early diagnosis of oral cancer and influences the establishment of screening protocols for the illness. Cancer detection has been possible with Deep learning technologies[1]. In this paper we have applied a novel method to detect oral cancer using either histopathological or clinical images of the patient by applying the DINOv2, vision transformer of MetaAI [2] and YOLOv8[3] segmentation model. In this work, we have trained our deep learning models using the sample dataset of 2105 images from Kaggle and tested our model with real-time dataset of 152 patients data collected from a Private hospital. In this, we have trained our model for both Histopathological images and clinical images. YOLOv8 demonstrated 98% accuracy in identifying and segmenting cancer tissue on the Clinical test dataset. In the histopathology test dataset, DINOv2 showed impressive accuracy (96%) in differentiating between photographs that were malignant and those that weren't. The manuscript for this article is written in the manner described below. Section 2 looks at the variety of relevant recent content. In section 3, the suggested remedy is fully discussed using examples. Section 4 presents a broad comparison and the experimental results. There is a conclusion in Section 5.

RELATED WORK:

The detection and diagnosis of oral cancer have benefited greatly from the use of computer-assisted tools and technologies in recent years. Using deep learning approaches, R. A. Welikala and P. Remagnino [4,5] applied automated oral lesion detection. Their methods included using ResNet-101 for image classification and Faster R-CNN for object detection. Another technique, that uses CNN and transfer learning, is the automated detection of oral cancer, as reported by Aubreville et al.[5]. Baliarsingh et al. (2024)[1] were at the forefront of this revolution, having pioneered a groundbreaking smartphone-based DL framework tailored specifically for early oral cancer detection. Their approach, which achieved an impressive accuracy rate of 87.89%, highlights the potential of DL in facilitating prompt diagnosis—a crucial factor in mitigating the mortality rates associated with oral cancer [1][6]. In a different approach by S.K Baliarsingh et al,[1] a cost-effective method is used to detect oral cancer using smartphone. They have identified oral lesions and detected cancer cells using this method, although they have only employed one version of YOLOv8. Building upon this pioneering work, Esteva et al. (2017)[7] and Litjens et al. (2017)[8] showcased DL's versatility and efficacy in medical imaging tasks, demonstrating its capabilities in classifying skin cancer and its broad applications across various medical imaging modalities[9]. These studies underscore the adaptability of DL algorithms to different diagnostic scenarios, further cementing their role in revolutionizing medical diagnostics. The foundational principles laid down by LeCun et al. (2015)[10] and the specific applications elucidated by Rajpurkar et al. (2017)[11] and Xu et al. (2019) [12] provide crucial insights into the depth and breadth of DL's impact on medical diagnostics. From fundamental concepts to practical implementations, these studies highlight the transformative potential of DL in enhancing diagnostic accuracy and efficiency.

Furthermore, Peng et al. (2020)[13] emphasized the critical role of DL in medical image segmentation, a fundamental component of precise diagnostic tasks[14]. DL models greatly improve the accuracy of diagnosis and treatment planning, especially in complicated medical illnesses like cancer, by strengthening the capacity to precisely outline and evaluate medical pictures[11]. Talib et al. (2024)[3] pushed the boundaries of DL by enhancing object detection algorithms, achieving remarkable precision in identifying small objects. This advancement not only improves the accuracy of DL models but also enhances their applicability in various real-world scenarios, including medical diagnostics. Moahaimen Talib et al.[2] used content attention block (CAB) in conjunction with YOLOv8 to find and identify tiny things in the photos. Their technique is used to detect things in real-time, such as computers, mice, pens, cats, and other items. It predicts the object by drawing a block around it using the detection and identification algorithm.

Systematic reviews conducted by Kavyashree et al. (2024)[15] and Warin and Suebnukarn (2024)[16] underscore the impressive performance metrics achieved by DL models in oral cancer diagnosis and prognostic prediction. These reviews highlight DL's potential to enhance informed clinical decision-making and improve patient outcomes, while also identifying areas for future research and development. Comprehensive reviews by Alabi et al. (2021, 2022) [17] develop into the specific application of DL in oral squamous cell carcinoma (OSCC)[5] prognosis and detection. They provide detailed insights into DL's role in improving patient outcomes through precise diagnostics and treatment planning, advocating for standardization and integration of DL models into clinical practice. Kavyashree C et al,[3] have mentioned different methods of oral cancer prediction and detection, it has not taken into consideration new methods like vision transformer and the performance analysis is not mentioned.

Mira et al. (2024) introduced a novel approach leveraging smartphone-based DL algorithms for early oral cancer diagnosis[8]. By harnessing the ubiquity of smartphones and combining it with cutting-edge DL techniques, this study exemplifies the potential of AI-driven solutions to democratize access to healthcare and enable early disease detection, even in resource-constrained settings. Jha (2024) presented an overview of recent research efforts concentrated on oral squamous cell carcinoma (OSCC) prevention and early detection, stressing the need for collaborative methods to enhance patient outcomes[9].

SYSTEM ARCHITECTURE

Figure 1 shows the overall development of this project. On the top side, the training process of the deep learning model is shown. The oral cancer images of clinical and histopathological are included in the database. In the preprocessing block, the images are processed and filtered to be able to extract information in the next blocks. In the next section, Data Augmentation is done to increase the number of images in the dataset and to effectively train the model. In the next section, we extract the features from the images given. A classifier model was trained using these features and then utilized. In this project, we are applying transfer learning by which we train the model with the dataset available on the internet. The trained deep learning model is then applied to real-time applications by gathering the data from dental hospitals. Thus, we analyze the efficiency of our project with real-time test data. We suggest using the cutting-edge vision transformer model DINOv2[3] to categorize photos with histopathology. Transfer learning will be utilized by pre-training DINOv2 on a large-scale image dataset and then fine-tuning it on the histopathological dataset for oral cancer classification. YOLOv8, a fast and efficient object detection model, will be used for classifying oral cancer based on clinical images. this approach aims to identify the presence or absence of cancerous lesions within the clinical images[3]. YOLOv8 will be employed for segmentation on the clinical dataset. this task aims to segment and delineate potential cancerous lesions within the clinical images, providing a more precise localization of suspicious areas. Each model's performance will be assessed using pre-established criteria relevant to its particular job (segmentation vs. classification). Metrics including recall, accuracy, precision, and F1-score will be employed for categorization. Metrics such as mean Average Precision (mAP) and Intersection over Union (IOU) will be used for segmentation.

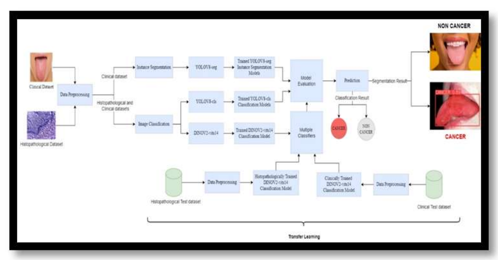


Figure 1: Proposed System Model

EXPERIMENT

Using Architecture Vit-S/14, the histological and clinical datasets pertaining to oral cancer are gathered and classified using Dino-V2[18], a meta-AI model. The following procedures were followed for the image classification challenge, and using Dino-V2 Embeddings was crucial. Data augmentation for the Histopathology oral cancer dataset involves combining the first and second sets of data and using ImageDataGenerator from the Tensorflow Keras processing image package. This includes setting rotation range=20, assigning width_shift_range, height_shift_range, shear_range, and zoom_range values to 0.1, setting horizontal_flip and vertical_flip as True, and fill_mode to the nearest. Similarly, for the Clinical oral cancer image dataset, the clinical oral cancer dataset has 7469 images, while the histopathological dataset has 8570 images after

TABLE I: V8 Versions Trained Parameters And Layers In Classification

MODEL NAME	YOLOv8n-cls	YOLOv8s-cls	YOLOv8m-cls	YOLOv8l-cls	YOLOv8x-cls
PARAMETERS	1.438723M	5.077762M	15.765218M	36.187138M	56.1257621M
LAYERS	73	73	103	133	133

applying augmentation. Additionally, loading the dinov2_vits14 Model, composing the image, and normalizing it to ([0.5], [0.5]) using the Torchvision package are all included in this process. Finally, computing Embeddings using the dinov2_vits14 Model yields low- dimensional representations that are used as input for a classification. Model, we created lists of every embedding and the labels that go with it, which a classifier may use to determine an image's class. Using several classifiers, such as SVM[19], Random Forest[20], AdaBoost[21], KNN[22], Gaussian Naive Bayes[23], Decision Tree, Logistic Regression[24], and Multi-layer Perceptrons, can increase the accuracy of the image classification task. Figure 1 illustrates this. Test datasets from other datasets are used for model evaluation in order to carry out transfer learning. so based on the Highest Accuracy observed under the Model Evaluation, Final predictions are Made. Utilizing YOLOV8 Models from Ultralytics, clinical dataset classification is carried out by custom labelling the dataset from Roboflow's cancer and non-cancer classes. The training set contains 648 photos, the testing set contains 92 images, and the validation set has 184 images in two classes. All of the images in the dataset are stretched to 640x640. The five models are trained using 100 epochs, a batch size of 16, and an image size of 128 × 128 pixels in Table I. An example of one of the trained batches is seen in Figure 2, where 0 denotes cancer and 1 denotes non-cancer. There were sixteen cutout photos in the training set.

FIGURE 2: One of the Trained Batches in Classification

SEGMENTATION:

To facilitate segmentation, Roboflow can be used to annotate[25][26] the current clinical dataset and create three splits. 735 photos make up the training set, and 91 images, which have been resized to 640x640 pixels and trained using YOLOV8 segmentation models, make up the validation and testing set. Table II shows that the models are trained using 50 and 100 epochs of 640x640 pixel images, a batch size of 16, a learning rate of 0.001111, a momentum of 0.9, and a weight decay of 0.0005.

TABLE II: V8 Versions Trained Parameters And Layers In Segmentation

MODEL NAME	YOLOv8n-seg	YOLOv8s-seg	YOLOv8m-seg	YOLOv8l-seg	YOLOv8x-seg
PARAMETERS	3.25845M	11.78037M	27.223542M	45.91343M	71.722582M
LAYERS	195	195	245	295	295

See Figure 3 for an illustration. One of the segmentation's trained batches has two classes: 0 denotes cancer and 1 denotes non-cancer.

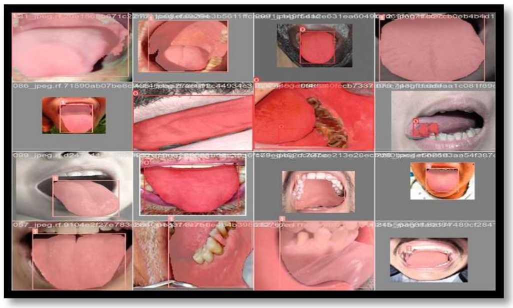


FIGURE 3: One of the Trained Batches in Segmentation

RESULTS AND DISCUSSION

Regarding classification Utilizing dinov2, the Multi-layer Perceptron achieved the greatest accuracies of 97.9% and 89% on the Histopathology and Clinical datasets, respectively, and consistently outperformed other models on both datasets. Both SVM and KNN displayed comparatively high accuracy levels in the two datasets. There appears to be a discrepancy between the model assumptions and the data characteristics of the Gaussian Naïve Bayes model, as evidenced by the notable decline in accuracy for the model on the Clinical Dataset when compared to the Histopathology Dataset. Both datasets displayed consistent performance from AdaBoost and Random Forest, demonstrating their potency in capturing intricate correlations in the data. The classification report for the Histopathology and Clinical datasets is displayed in Table III and Table IV. Sample predictions made using histopathological test data with dinov2+MLP are shown in Figure 4.

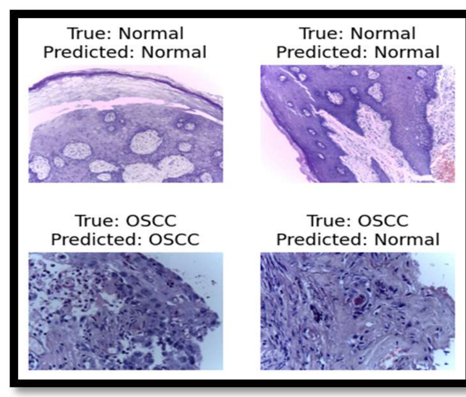
TABLE III: Classification Report Of Histopathology Dataset Using Dinov2+Mlp

CELLS	PRECISION	RECALL	F1-SCORE	SUPPORT	ACCURACY
NORMAL	0.93	0.90	0.92	31	0.96
OSCC	0.97	0.98	0.97	95	

TABLE IV: Classification Report Of The Clinical Dataset Using Dinov2+Mlp

CELLS	PRECISION	RECALL	F1-SCORE	SUPPORT	ACCURACY
CANCER	0.89	0.94	0.92	87	0.89
NON-CANCER	0.87	0.77	0.82	44	

In Figure 5 First Confusion Matrix shows that, for the Normal class, the model successfully classified 80 out of 90 normal examples (90.3%), based on two confusion matrices from the figure. Ten false positives (9.7%) were identified as OSCC. Comparably, 60 out of 62 OSCC cases (97.9%) were properly classified by the model for the OSCC class. Two false negatives (2.1%) were identified as normal. With a high accuracy rate for both classes, the model seems to have done well overall on this job. False positives and false negatives, however, were rare. As can be seen in Figure 9, the second confusion matrix, the model properly identified 94.3% of the cases in the cancer class. Incorrectly labeled as non-cancerous, 5.7% of false negative results were found. In the category of non-cancerous patients, the model accurately identified 77.3% of the instances. false positives that were misclassified as malignant in 22.7% of cases.



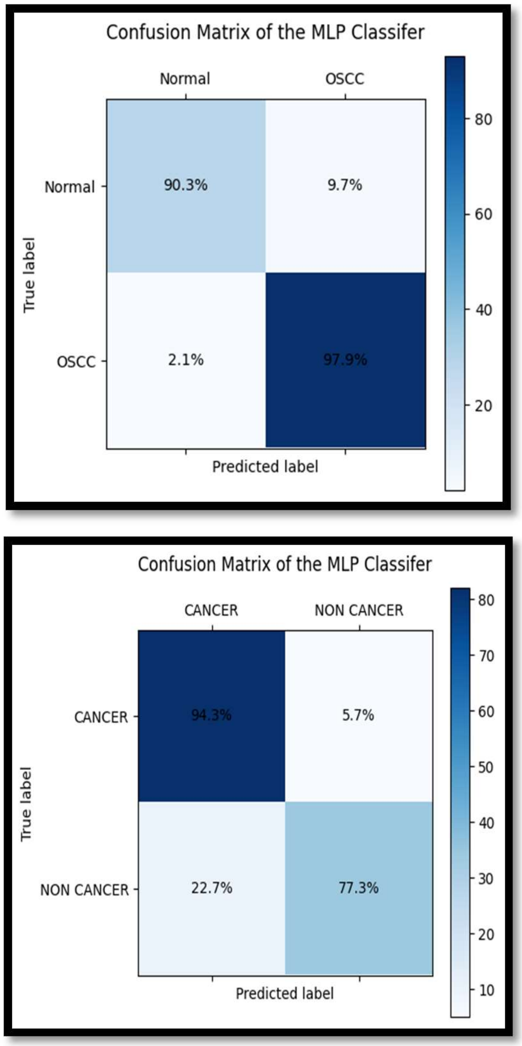


FIGURE 5: Confusion Matrices Of Histopathology And Clinical Datasets Using Dinov2.

Comparing the results the YOLOv8 models, in particular YOLOv8s-cls, YOLOv8l-cls, and YOLOv8x-cls, clearly beat the dinov2+MLP model in terms of classification accuracy of the above 98% when these findings are compared with the above dinov2+MLP model accuracy of 89%. Figure 10 illustrates how training loss and validation loss reduce with an increase in epochs. This demonstrates how all models are always learning and becoming more effective. It seems that YOLOV8n-cls has the lowest validation loss as well as training loss. For every version, the accuracy seems to be more than 0.95 by 100 epochs.

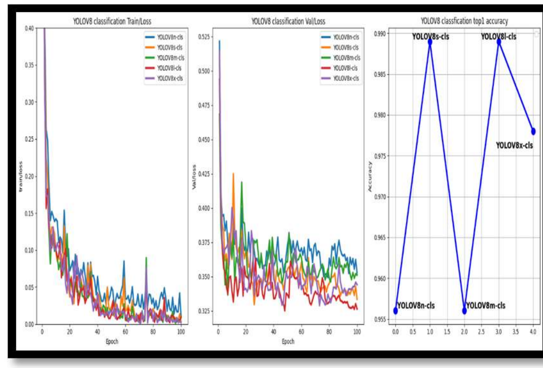


FIGURE 6: YOLOV8 (NANO, SMALL, MEDIUM, LARGE, EXTRA-LARGE) CLASSIFICATION RESULTS

When segmenting using the Clinical dataset, YOLOV8 segmentation models trained over 50 epochs yielded moderate box detection performance overall. Yolov8n-seg has the greatest mAP50 (Box) of any model, at 0.62344, but a very low recall (0.53608). This shows that the precision is strong (fewer false positives), but that a sizable number of actual items may be missed. According to mAP50-95 (Box) data, at higher IOU thresholds, all models have difficulty accurately localizing boxes. This suggests that bounding box placement accuracy has improved. When it comes to mask precision, the models typically outperform recall. This implies that while masks may under-segment or miss certain object pixels, they tend to catch some object areas. With a mAP50 (Mask of 0.67822, yolov8s-seg has the highest segmentation accuracy overall. Table IV follows 100 epochs of training. Notable improvements are seen in Mask Segmentation, Yolov8x-seg, and Box Detection.

TABLE V: Yolov8 Segmentation Trained With 100 Epochs

ABLE VI: Prediction Of Real-Time Images Using The Yolov8x Model.

S.NO	Image	Prediction using YOLOV8x

Models	**Precision(B)**	**Recall(B)**	**mAP50(B)**	**mAP50-95(B)**	**Precision(M)**	**Recall(M)**	**mAP50(M)**	**mAP50-95(M)**
Yolov8n-seg	0.62457	0.59794	0.60829	0.36967	0.57899	0.55670	0.54818	0.32016
Yolov8s-seg	0.66588	0.64948	0.67314	0.40260	0.61163	0.59794	0.59911	0.33457
Yolov8m-seg	0.59804	0.64948	0.63363	0.37212	0.57831	062887	0.6059	0.32752
Yolov8l-seg	0.61361	0.63918	0.59575	0.40242	0.55909	0.57520	0.53382	0.33702
Yolov8x-seg	0.69923	0.59794	0.64486	0.41453	0.65443	0.55670	0.58284	0.36592

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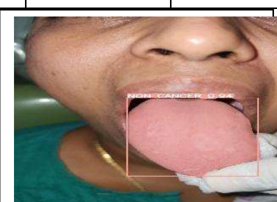
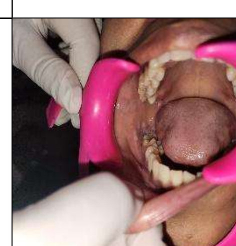
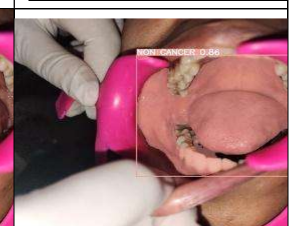
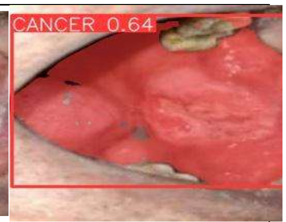
2		
3		

4		
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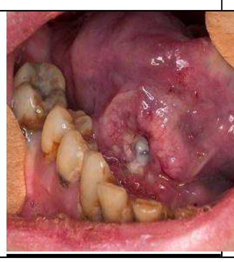
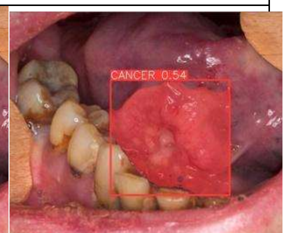
7		

CONCLUSION

This study used clinical and histological datasets to examine the use of deep learning models for oral cancer identification. On the clinical dataset used for this study's segmentation, the YOLOv8 segmentation models produced encouraging results. This implies that they are able to recognize possibly malignant lesions when doing ocular examinations. To increase the precision of mask segmentation and bounding box localization, more work must be done. In order to classify the Histopathological Dataset, DINOv2 was used for classification since an appropriate histopathology dataset for cell detection was not available. The model demonstrated remarkable accuracy (97.9%) in distinguishing between malignant and non-cancerous pictures in the histopathology dataset. YOLOv8 classification demonstrated its strength in classifying oral cancer based on clinical photos, yielding outstanding performance (98% accuracy) on the clinical dataset. The study's overall importance is that it shows how deep learning may be used to detect oral cancer utilizing histopathological and clinical data. Future research can provide more precise and trustworthy instruments for early cancer diagnosis, improving patient outcomes, by addressing data restrictions and investigating model combinations.

- Competing Interests: Not Applicable
- Funding Information: Not Applicable
- Data Availability Statement
  - Trained Datasets from Kaggle
  - https://www.kaggle.com/datasets/shivam17299/oral-cancer-lips-and-tongue-images
  - https://www.kaggle.com/datasets/ashenafifasilkebede/dataset
  - https://www.kaggle.com/datasets/zaidpy/oral-cancer-dataset
  - The above datasets are used to train the deep learning models and the model is applied on Practical application created by 152 patients data built by Sibar Institute of Dental Sciences.
- Research involving Human and / or Animals
  - This research involves the photographic images clinical and Histopathological images of oral (mouth, lips and Tongue) of the patients of Cancer and Non-Cancer.
- Informed Consent: Not Applicable

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