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Analysis Brain Tumor Segmentation Using a custom 3D UNet Model on Limited Dataset

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ABSTRACT
Semantic segmentation plays a pivotal role within the theoretical domain, facilitating a meticulous and precise comprehension of medical scans at the pixel level.In this scholarly contribution, I shall elucidate the results of my research endeavours subsequent to the implementation of a custom 3D Net model. The essence of this work lies in the comprehensive evaluation and analysis of these models using the BraTS 2020 dataset. This endeavour aims to urnish medical professionals with essential insights for enhancing their understanding and enabling informed decision-making when faced with diverse medical challenges, especially when the data.
Keywords—BrainTumor,3DUnet,DiceLoss,FocalLoss, MedSem, UniverSeg, Segmentation, MRI Scans,FCT, electron microscopy images, enhancing tumour,peritumoral edema, necrotic and non-en-enhancingtumour

I. INTRODUCTION

Thisresearchpaperintroducesanimplementationfocusedonthecriticaltaskofsemanticsegmentationwithintherealm ofcomputervision. Semantic segmentation involves the precise assignment of labels to each individual pixel within an image, and its applications span a wide range of fields, including autonomous driving,image and video analysis, medical imaging,andsceneunderstanding.Notably, deep learning techniques have consistently demonstrated significant advancements and effectiveness in the domain of semantic segmentation.
The primary emphasis of this paper centres on the segmentation of brain tumours. We conduct a comprehensive comparative analysis of variable segmentation models while employing the BraTS 2021 dataset. The principal objective of this project is to provide valuable insights and comparisons intended for researchers and medical practitioners with a vested interest in brain tumour diagnosis through semantic segmentation.
Our exploration delves into the practical implementation of TensorFlow models, with a specific focus on the examination of the Unet [9] architecture. These neural networks have garnered attention as recent positions for semantic segmentation tasks.
Thecoreaimofourinvestigationistogainacomprehensiveunderstandingofthearchitecturalintricaciesoftheseindividualmodelsandtoelucidatetheiroperationalmechanisms.
To enhance the accessibility and utility of our work, we have undertaken meticulous documentation of the codebase.Thisdocumentationincludesexplicitandcomprehensiveinstructionsthatfacilitateeaseofuse. Moreover,

our documentation encompasses in-depth explanations of the training procedures applied in the context of our research. In the pursuit of efficiency, we have also harnessed pre-trained weights, which expedite the fine-tuning of the model on our specific datasets,streamliningtheresearchprocess.

II. LITERATURESURVEY

The Brain Tumor Segmentation (BraTS)dataset undergoes updates and improvements fromyeartoyear.BraTS 2019includesasubstantialnumber of patient cases with high-resolution brainMRIscans.Thedatasetincludesmulti-modalimages,includingT1-weighted,T2-weighted,FLAIR, and post-contrast T1-weighted images Thetumor annotations inBraTS 2019 were carefullydelineatedbyexpertradiologists.Thedatasetprovidesgroundtruthsegmentationsforglioblastoma, astrocytoma, and oligodendrogliomatumors.BraTS2019wasusedasabenchmarkfor evaluatingbraintumorsegmentationalgorithms,withparticipantsintheBraTSChallengesubmittingtheirsegmentati onresultsforevaluationBraTS2020,likeitspredecessor,isknownforitslargeandhigh-quality dataset,providing awide variety ofmulti-modalMRIimagesandexpertannotationsforbraintumorsegmentation.

BraTS 2020 introduced new sub-tasks inthe BraTS Challenge, including the segmentation ofthree tumorsub-compartments: enhancing tumor,peritumoral edema, and non-enhancing tumor. Thisadditionaimedtofurtheradvancethefieldbyencouraging the development of more fine-grainedsegmentationmethods.BraTS2020alsoemphasizedtheimportanceofmodelingtumorheterogeneitybyprovid ingmoreextensiveannotations and adding more tumor types, makingthedatasetmorerepresentativeofreal-worldclinicalscenarios. The 2020 dataset continues to be highlyrelevant to clinical practice, as accurate brain tumorsegmentationiscrucialfordiagnosis,treatmentplanning, andpatientmonitoring.

UNetisaconvolutionalneuralnetwork(CNN)architecturethatwasdevelopedforsemanticsegmentationtasksinmedic alimageanalysis.Itwasintroduced by Olaf Ranneberger, Philipp Fischer,andThomas Broxin2015.UNethas becomeafoundationalarchitectureforvariousimagesegmentationtasks,particularlyinthemedicalfield,due to its effectiveness incapturingfine-graineddetails and preserving spatial context. Here's a briefoverviewofUNetfollowsanencoder-decoderarchitecture.Theencoderconsistsofseveralconvolutionalandmax-poolinglayersthatprogressivelyreducethespatialdimensionsandincreasethedepthoffeaturemaps.

The decoder, on the other hand, comprisesup-samplingandconcatenationoperationstorecoverspatialinformationandgeneratehigh-resolutionfeature maps.AdistinctivefeatureofUNet is the inclusion of skip connections. Theseconnectionslinkcorrespondingencoderanddecoderlayers,enablingthemodeltoretainandreusefeatureinform ation at different scales. This helps preservefinedetailsduringtheup-samplingprocessandcontributes tomoreaccuratesegmentation.

In the middle of the network, there is abottlenecklayer,whichtypically hasthe highestfeaturedimensionality.Thislayeractsasabottleneckintheinformationflow,forcingthenetworktolearncompa ctandinformativerepresentations.

Dependingonthespecificsegmentationtask,UNetcan have a SoftMax or sigmoid activation functionin its final layer. For binary segmentation tasks, asigmoidfunctionisoftenused,whileformulti-class segmentation,SoftMaxisemployed.UNetwasinitiallydesignedforbiomedicalimagesegmentation, specifically for the segmentation ofneuronal structures in electron microscopy images.However, it hasbeenwidely adoptedinvariousimage segmentation tasks, including medical imagesegmentation(e.g.,braintumorandorgansegmentation),industrialinspection,andsatelliteimageanalysis Researchers often customize UNet to suittheirspecificsegmentationtasks.Thiscustomizationcaninvolvemodifyingthearchitecture, incorporating attention mechanisms, oradjustingthelossfunctionstooptimizeperformancefor particular applications. UNet is known for itssimplicity,effectiveness,andefficiency.Itiscapableofproducinghigh-qualitysegmentationresultswithrelatively smallamountsoftrainingdata. The skip connections allow it to capture bothlocalandglobalcontext,makingitsuitablefortaskswithvaryingscalesandcomplexobjectshapes.While UNet is powerful, it may still face challengeswith imbalanced datasets, handling class imbalanceinsegmentationtasks,andtheprecisedelineationofobjectboundaries,whichcanbeparticularlyimportantin medicalimageanalysis.

Overall, UNet remains a popular choice for imagesegmentation tasks due to its architectural designandadaptabilityforvariousapplications.Researchers and practitioners continue to build onitsfoundationby extending andcustomizingthearchitecturetoaddressspecificchallengesinsegmentation.

Our study involved the studying and understandingof experiments across several datasets to illustratetherobustnessofthe3D-UCapsframework,encompassing iSeg-2017, LUNA16, Hippocampus,andCardiacdatasets.Inourresearch,wehavedemonstratedthatourmethodconsistentlysurpassesprevious Capsule networks and 3D-Unets. The keyinnovation,DilatedDenseAttentionUnet[8](DDAUnet), capitalizes on the inclusion of spatialandchannelattentiongateswithineachdenseblock.Thesegatesenableselectivefocusonpivotalfeaturemapsand regions.Furthermore,dilatedconvolutionallayershavebeenemployedtomanageGPU memory efficiently and expand the network'sreceptivefield.

Our investigation also entailed the implementationof various Unet Models for Image Segmentation,includingUnet,RCNN-Unet,AttentionUnet,RCNN-AttentionUnet, andNestedUnet[9].Theintroduction of Attention gates (AG)[10] has been asignificantdevelopmentinthe realmofmedicalimaging,asitautonomouslylearnstoconcentrateontargetstructuresofvaryingshapesandsizes.Models trained with AGs implicitly acquire the ability tosuppress irrelevant regions in input images whileaccentuatingsalientfeaturesrelevanttospecifictasks. Consequently, there is no longer a need forexternaltissue/organlocalizationmodulesincascaded convolutionalneuralnetworks (CNNs).

Toaddressthedemandforefficientskinlesionsegmentation[11], we have designed a lightweightmodel that delivers competitive performance withminimal parameters and computational complexity.OurRecurrentConvolutionalNeuralNetwork(RCNN)andRecurrentResidualConvolutionalNeural Network (RRCNN) models, named RU-Netand R2U-Net[12], draw on the strengths of U-Net,ResidualNetworks,andRCNN.Thesearchitecturesofferseveraladvantagesforsegmentationtasks,including improved feature representation, makingthemwell-suitedformedicalimagesegmentationonbenchmark datasets like blood vessel segmentationinretinaimages,skincancersegmentation,andlunglesionsegmentation.

The UNet 3+ model[13], which integrates full-scaleskip connections and deep supervisions, has beendevelopedtoenhancesegmentationaccuracy.Theseskip connections merge low-level details with high-levelsemanticsfromfeaturemapsofvariousscales.Deepsupervisionfosterstheacquisitionofhierarchical representations from the amalgamatedfull-scalefeaturemaps.UNet3+isparticularlyadvantageousfororgansthatappearatvaryingscales. In addition to boosting accuracy, this modelreducesnetworkparameterstoenhancecomputational efficiency. We have also introduceda hybrid loss function and a classification-guidedmoduletorefineorganboundariesandmitigateover-segmentationinnon-organimages,therebyyieldingmoreprecisesegmentationresults.

Lastly,weintroduceSwin-Unet[14],apureTransformer-basedapproachformedicalimagesegmentation. This model utilizes tokenized imagepatchesandemploysaTransformer-basedU-shapedEncoder-Decoderarchitecturewithskip-connectionsforlocal-globalsemanticfeaturelearning. The encoder leverages hierarchical SwinTransformerswithshiftedwindowstoextractcontextfeatures,whilethedecoder,basedonsymmetricSwinTransformers,performsup-sampling to restore spatial feature map resolution.Experimentsonmulti-organandcardiacsegmentationtaskshaveshownthatthispureTransformer-based approach outperforms methodsrelyingonfull-convolutionorcombinationsoftransformersandconvolutions.

FromthisitisevidentthattheUNetmodelsareusedextensivelyinmedicalsegmentationFeilds

III.METHODOLOGY

TheBrainTumourSegmentation(BraTS)dataset is widely used in the field of medical imageanalysis,particularlyforbraintumoursegmentation,duetoseveralcompellingreasons.TheBraTSdatasetencompassesvarioustypesofbraintumours,includingglioblastoma,astrocytoma,andoligodendroglioma,amongothers.Itincludesmultiple MRI modalities, such as T1-weighted, T2-weighted,FLAIR,and post-contrastT1-weightedimages. This diversity in tumour types and imagingmodalities allows researchers to test the robustnessand adaptability of segmentation algorithms acrossdifferentclinicalscenariosThe BraTS datasetissubstantialinsize,with asubstantial numberofpatient cases, and it is meticulously annotated byexperts.

The dataset includes both training and testingsubsets, facilitating the development and evaluationof segmentation algorithms. The large, high-qualitydatasetminimizestheriskofoverfittingandenhances the generalization of models to real-worldclinicaldata.Braintumoursegmentationisachallengingtaskdueto thecomplexshapesandinfiltrative nature of tumours. The BraTS datasetincludesgroundtruthsegmentationsthatarecarefullydelineatedbyradiologists,providingavaluablebenchmarkforalgorithmevaluation.Researchers can compare the performance of theirmethods against these expert annotations to assessthe accuracy and reliability of their segmentationmodels.

TheBraTSChallenge,associatedwiththedataset, has been held annually and has become abenchmarkfortheevaluationofbraintumoursegmentation algorithms. Researchers from aroundthe world participate in this challenge, contributingto a collaborative and competitive environment thatdrivesinnovationinthefield.Itallowsforfaircomparisonsbetweendifferentapproachesandencouragesthedevelopmentofstate-of-the-artmethods. Brain tumour segmentation is of criticalimportanceinclinicalpractice.

Accurate tumour segmentation plays a crucialroleinthediagnosis,treatmentplanning,andmonitoringofbraintumourpatients.Algorithmsdeveloped and validated on the BraTS dataset canpotentially beintegratedintoclinicalworkflows,aiding radiologists and healthcare professionals inmaking informed decisions. The BraTS dataset ispubliclyavailable,makingitaccessibletoresearchers, enabling them to conduct experimentsand develop segmentation models without the needfor extensive data collection and annotation, whichcanbecostlyandtime-consumingTheBraTSdataset has evolved overthe years, incorporatingnewchallenges,sub-datasets,andupdatedannotations. This continuous development ensuresthatitremainsarelevantandup-todateresourceforthe researchcommunity. The BraTS dataset is avaluableresourceforbrain tumour segmentation researchduetoitsdiversity,size,expertannotations,benchmarkstatus,clinicalrelevance,andaccessibility.Itservesasafoundationforthedevelopmentandevaluationofstate-of-the-artsegmentation algorithms, ultimately contributing toimproved medical diagnosis and treatment for braintumourpatients.

A. Dataset

The BraTS 2020 [4][5][6][7] dataset is a widelyrecognized and extensively employed dataset in thedomainofmedicalimageanalysis,primarilyfocusingonthesegmentationofbraintumours.Thisdatasetencompassesmultimodal Magnetic Resonance Imaging(MRI)scansstoredintheNIfTIfile format. These scans encompass fourdistinctMRIsequences,eachservingaspecificpurpose:

a) Native(T1):ComprisingT1-weightedMRIscans.
b) Post-contrastT1(T1CE):EncompassingPost-contrastT1-weightedMRIscans.
c) T2-weighted(T2):IncorporatingT2-weightedMRIscans.
d) T2 Fluid Attenuated Inversion Recovery (T2-FLAIR):EncompassingT2-FLAIRMRIscans.

It is noteworthy that these MRI scans have beenacquiredfromvariousclinicalprotocolsandscannersspanningmultipleinstitutions.Notably,datacontributorstothisdatasethaveemanatedfroma total of 19 different institutions, attesting to itsbroadrepresentation.

Anintrinsicfacetofthisdatasetisthemeticulousmanualsegmentationundertakenbyonetofourraters.Thissegmentationprocessadherestoarigorously standardized annotation protocol. Theseinitialannotationsaresubsequentlysubjectedtocomprehensivereviewandvalidationbyexperiencedneuro-radiologists.Theannotationsencapsulatediversetumourregions,classifyingthemasfollows:

1. GD-enhancingtumour(ET),identifiedandlabelledas4.
2. Peritumoraledema(ED),designatedwiththelabel2.
3. Necroticandnon-enhancingtumourcore(NCR/NET), demarcated and marked with the label1.

Toensureuniformityandcompatibilityforresearch and analytical purposes in the domain ofbraintumoursegmentation,thedatasethasundergone crucial pre-processing steps. These stepsencompass co-registration to a common anatomicaltemplate, interpolation to a uniform resolution of 1mm^3,andskull-stripping.Suchpre-processingmeasureshavebeendiligentlyexecutedtoguaranteethe consistent formatting of the data, thus renderingitamenabletoresearchandanalysiswithintherealmofbraintumoursegmentation.

B. Procedure

Theprimaryobjectiveofthisendeavoristostreamline the process of model development whilemaximizing efficiency. In pursuit of this goal, wewill embark on a series of data preprocessing stepsaimedatpreservingpertinentinformationwhileupholdingmodelaccuracy.Anotablechallengeencountered in this regard pertains to discrepanciesin the number of scans and available masks due toerroneouslabellingwithinsegmentationmasks.Consequently,wehavebeencompelledtoexcludeaspecific scan from the dataset. The initial phase ofour data preprocessing entails the removal of T1Gdimages,astheirexpectedcontributiontothemodel'sperformanceisdeemednegligible.

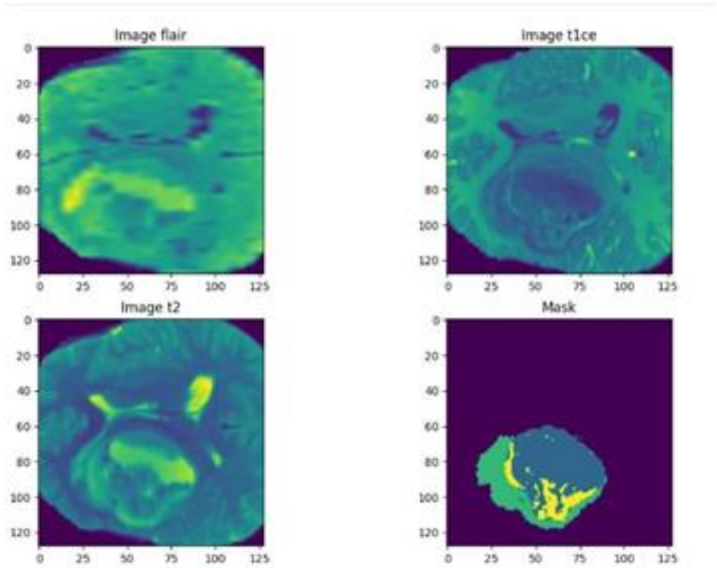

Fig1PlottingPost-contrastT1,T2-weightedT2,FluidAttenuatedInversionRecoveryandgivensegmentations

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Subsequenttotheexclusionoftheseimages,wewillundertake cropping of the scans to retain only therelevant pixels, eliminating redundant empty space.Furthermore,scanscharacterizedbyanemptyspaceof less than 8% will be selectively removed fromconsideration.Ournextstepinvolvestheconversion oftheNIfTIimagesintothe.ndyformat, essentiallysaving them as NumPy arrays. This process will beaccompanied by resizing and scaling to align withthemodel'srequirements.Additionally,wewillconsolidatethethreeinputarraysintoasinglecombinedarray.

GiventhatTensorFlowlacksabuilt-indatagenerator tailored to NumPy arrays, we will developa straightforward custom data generator to facilitatedatahandling.Thiscustomdatageneratorwillconsist of two core functions: the first function willberesponsibleforloadingtheNumPyarrayfromthespecifiedpath,whilethesecondfunctionwill

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$$\mathbf{L}_{dice} = \frac{2 * \sum p_{true} * p_{pred}}{\sum p_{true}^2 + \sum p_{pred}^2 + \epsilon}$$

Fig2DiceLoss

Subsequenttothemeticulousdatapreparationprocess,theprocesseddatawillbechannelledintoacustom 3D Unet model. Notably, our selection oflossfunctionswillencompassboth thedicelossandfocal loss. This choice also offers us the flexibilitytoincorporatecustomweightsintothelossfunctionsinthefuture, as circumstancesmayrequire.

$$FocalLoss = -\sum_{i=1}^{i=n} (i - p_i)^{\gamma} log_b(p_i)$$

Fig 3FocalLoss

Thisstructuredandmethodicalapproachispoisedtoexpeditethedevelopmentandrefinementofour model,allthewhileupholdingitsaccuracy andensuringtheoptimalutilization oftheavailabledataresources.

IV.RESULTSANDDISCUSSION

Uponacomprehensiveanalysisconductedonarestricted dataset, encompassing a total of 95 scans,our model has yielded aMean Intersection overUnion (Igou) score of 0.5692228. In forthcomingexperiments, we intend to harness the full datasetandadoptapatch-basedapproachtofurtheraugmentourmodel'sperformance.

Fig1.2PlottingTrainingandvalidationloss

Furthermore, we plan to delve into the applicationandevaluationofthe"SegmentAnythingModel"[7]developedbyMETA.Thismodel,whilenotoriginally designed for medical images, presents anoteworthyavenueforexperimentation.Aninherentchallenge in this endeavor pertains to adapting theinputlayertoaccommodateallthreetypes ofscans.

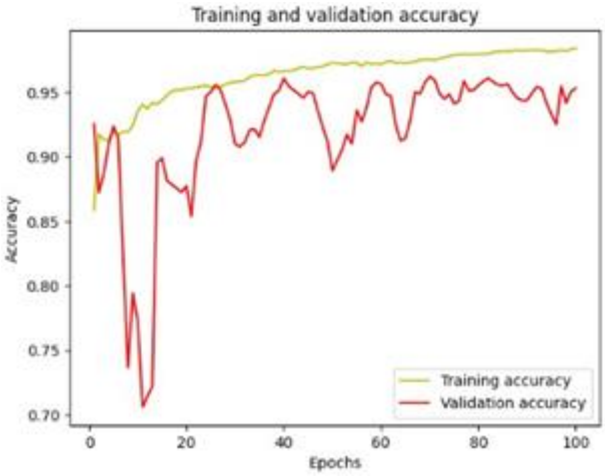

Fig 1.3PlottingTrainingandvalidationaccuracy

Followingtheimplementationoftheseexperiments,wewillundertakeacomprehensivecomparativeanalysisthatpitsthe"SegmentAnythingModel" against our custom Unet architecture. AnticipationssuggestthatourcustomUnet,bolsteredbytheutilizationofthecompletedataset,willlikelyoutperformthe"SegmentAnythingModel,"yieldingsuperiorresults.

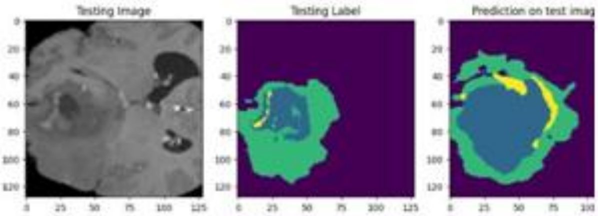

Fig 1.4 Plotting Testing image, Testing Label andPredictionontestimage

In addition to these specific experiments, our paperoffersathoroughandexhaustiveanalysisofsemanticsegmentationusingwell-establishedmodels, namely UniverSeg, FCT, and Meds AM.These research findings furnish invaluable insightsfor both researchers and practitioners operating inthe intersection of medicine and machine learning.Ourstudyhighlightstheeffectivenessandresilienceof these models, underscored by their applicabilityin addressing diverse segmentation tasks within thedomainofmedicalimageanalysis.

V. FUTUREWORK

In the field of medical image analysis, thesegmentationoftumors,mitochondria,orotherstructuresofinterestoftenreliesontheutilizationofdeeplearningarchitecturessuchasUNet,VNet,andvariousencoder-decodernetworks.Notably,continuous advancements have been made in thedevelopmentofUNet-basedarchitectures,includinginnovationslikeAttentionUNet,whichaimtoenhance the precision and efficacy of segmentationtasks.

Theprimaryobjectiveofthepresentresearchpaperistoestablishafoundationalframeworkthatwillserveasacornerstoneforforthcoming experiments. These experiments willrevolvearoundthecomparativeanalysisofstate-of-the-art machine learning models, including but notlimited to UniverSeg[3], FCT[1], and MedSAM[2],specificallyinthecontextofmedicalimagesegmentation. It is important to note that althoughnumerousnovelandpromisingmodelshaveemerged in the machine learning community, theirdirect application to medical image segmentation isimpeded by the distinct nature of the data they wereoriginallytrainedon.

One pivotal avenue of exploration in thisstudy involves the application of transfer learningtechniques. The aim is to adapt and fine-tune thesecutting-edgemodelsonmedicalimagedatasets,therebyenablingameaningfulcomparisonoftheir segmentationperformanceagainstconventional,established architectures. The intent is to ascertainwhethertransferlearningcanbridgethegapbetweenthesedisparatedomainsandpotentiallyleveragetherich representationslearnedbystate-of-the-art models in more general image analysis tasksforthespecificdomainofmedicalimagesegmentation.

Additionally, an important innovation inthis research involves extending the input modalityof the models. Rather than operating solely on 2Dimages, we intend to equip these models with thecapabilitytoprocess3Dstackedarrays.Thismodificationismotivatedbytheinherentadvantages of 3D information in capturing spatialrelationships andcontextualdetails.By allowingthesemodelstooperateinathree-dimensionalspace, we anticipate that they will acquire a morecomprehensiveunderstandingofmedicalimagedata,thusfacilitatingtheextractionofpertinentfeaturesandimprovingsegmentation accuracy.

Inconclusion,thisstudyendeavorstoprovide a solid foundation for future investigationsin medical image segmentation. By adapting state-of-the-art machine learning models to the medicaldomainthroughtransferlearningandenhancingtheircapacitytoprocess3Ddata,weaimtoadvancethestateoftheartinthiscriticalfieldandcontributeto the development of more accurate and effectivetools formedicalimagesegmentation.

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