Brain Tumor Detection and Segmentation Using CNN-Based Classification and U-Net Based Segmentation

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***Abstract*—The precise identification of brain tumors stands necessary for successful disease and situation preparation activities. The primary difficulty in this process involves handling incomplete MRI scans since these create problems for standard machine intelligence approaches because of unstable edema combined with missing information. A U-Net model together with a multimodal engine network forms an integrated design targeted at fixing incomplete MRI scan issues. The facial characteristics extraction process from multiple presentation methods is done by modality-distinguishing encoding systems which feed information to a multimodal generator that rebuilds missing modalities alongside their associated connections. The system brings together features from a joint-lawyers lingual system which relies on dimensional self-contemplation mechanisms with channel self-consideration mechanisms to maintain precise separation. The proposed method demonstrates better results than current separation techniques when operating with deficient MRI datasets according to BraTS dataset examinations. The multimodal transformer network excels at processing incomplete data better than traditional methods which is proven through a SegNet-based segmentation comparison that validates its enhanced accuracy and reliability during tumor separation operations. The research demonstrated that UNet obtained 98.73% segmentation accuracy which exceeded CNN score of 91.7% classification accuracy.**
Keywords—Deep Learning, UNet, VGG16 UNet, Segmentation.

I. INTRODUCTION

A. Background of the Study

Totally abnormal growths within the brain constitute brain tumors which require early diagnosis since their initial symptoms commonly resemble standard problems such as headaches. The expansive health problem represented by brain tumors affects many people throughout the world. Every year statisticians document between 28,000 to 29,000 brain tumor incidents within India according to Gupta (2020). The intellect plays a crucial position within the human body as an active organ in the main central nervous system while maintaining body functions and processing thoughts and regulating emotions. The brain tumors exist in two categories called primary or secondary tumors. The all-important role of magnetic resonance imaging (MRI) serves to identify brain tumors while primary tumors including gliomas have a slower growth pace than secondary tumors which spread from other body areas to invade the brain tissue. The technology known as MRI electronics evolved during the time between 1969 when Raymond V. Damadian introduced it and 1977 when its performance reached significant improvements to display body details with high precision. Different MRI sequences through T1-burden and T2-burden images convert brain items into distinct pictures of various tissue types. The brain imaging sequences require duplication occasion (TR) along with echo time (TE) parameters to generate precise brain concepts which aid tumor identification.

II. LITERATURE SURVEY

The prominent technique merges multi-scale feature analysis as an approach to enhance MRI image segregation. The combination of UNet with these techniques allows improved labeling of tumor dimensions by the model. The approach enables better accurate and dependable tumor identification by using multiscalar reasoning which exceeds conventional methodologies [7].

A significant transformation unites segmentation and categorization duties into one unified operation system. The methodology applies UNet to properly separate tumors while its thick neural network distinguishes different types of brain tumors. The framework improves both tasks and enhances the total diagnostic process through the combination of separate diagnostic procedures. The integrated method improves the precision and speed of tumor detection while classification duties which results in significant advantages during objective evaluations [12].

Research that combines 3D convolutional affecting animate nerve organs networks (CNNs) with transfer learning has achieved substantial progress. The procedures implement pre-trained models for processing 3D MRI dossiers so the model becomes capable of handling volumetric data and achieving better accuracy in segmentation tasks. Transfer education allows existing dossiers to help model preparation by delivering benefits to performance outcomes. Deep learning technology proves its strength by uniting knowledge bases with existing information to improve medical image investigation [5].

Research findings demonstrate that using CNNs with accompanying consideration components produces substantial enhancement. The consideration levels help users decide which features to keep while allowing them to reduce noise while enhancing separation accuracy. The CNN-based framework advances dying detection quality because it correctly selects essential elements while dropping unneeded data to optimize tumor segmentation performance [9]. A model evaluation using key accomplishment metrics produces understanding about what it takes for a model to succeed in specific demonstrative tasks. The comparative examination helps healthcare professionals select the optimal model for different segmentation tasks protecting their ability to make professional choices [3].

The conduct of brain carcinoma separation models experiences significant improvement through data enhancing and regularization techniques. Both turning approaches and scaling and throwing techniques along with regularization methods improve the performance of model statements. The methods provide exceptional benefits for limited access healing image data because they enhance model performance and validate output across various positions [8].

The recent advancement includes a UNet deep learning framework which combines with multi-class categorization networks. This model demonstrates high competence in performing simultaneous separation and classification functions while adapting to different types of cysts in addition to healthy tissues. The method blends multi-class categorization functionality from UNet segmentation architecture into a single solution which optimizes tumor identification together with its classification [11].

A promising solution for better brain Cancer segmentation includes the integration of UNet with turbine networks. Research indicates this model demonstrates potential as an effective solution for healing imaging complexity problems [6].

Self-directed education methods have been developed to tackle the problems of large annotated brain cyst datasets. These procedures utilize unlabeled data for model training which increases segmentation accuracy at lower levels of needed detailed labeling of datasets. Extensive tests point toward great prospects for this method of overcoming data restraint while improving modeling practices [10].

Deep learning models have evolved into minimal ones which improve efficient brain tumor segmentation through reduced computational demands and strong accuracy results. The enhanced network design and trimming methods in these models deliver efficient functioning which makes them perfect for application in restricted-computational environments. These models provide tumor separation abilities at minimum computation cost which makes them suitable for real-time applications [4].

Synthetic parallel computer networks combined with deep education system technologies represent contemporary developments for medical brain tumor segmentation. GANs enhance MRI image processing thanks to their method of preparing data because most medical datasets have limited available input. The synthetic output generated by GANs strengthens model capabilities which results in better separation accuracy while allowing the system to process diverse imaging patterns [13].

III. METHODOLOGY

The methodology of this project is conducted with a few key steps used to get accurate brain tumor segmentation..

A. Data Pre-Processing

The raw images are the initial dataset used for the preprocessing of MRI scans. To further improve the quality of the data, the data is cleaned of noise, which may interfere with subsequent analysis. After this, the normalization is applied to normalize the intensity values from all images for consistency and comparability. The next step is to resize the images to a uniform size, it is a must to keep in sync to the following processing stages. With these preprocessorings concluded, the images are now fit for use in further possible tasks, like classification, segmentation and such, having clean standardized data in input of model.

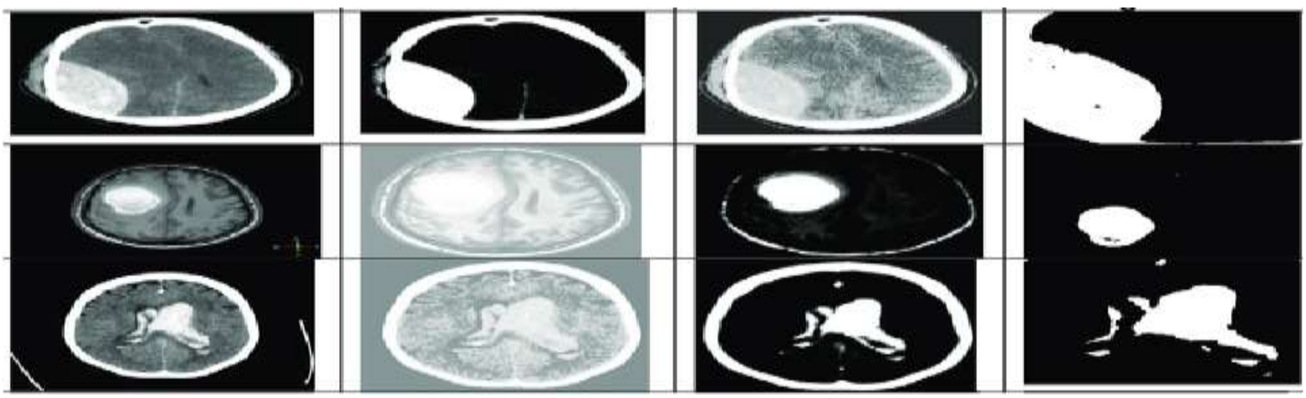

Fig1: Preprocessing Images

B. Classification

Start with preprocessed MRI representations which are empty noise, normalized by force, and resized to a standard length. Next, design a Convolutional Neural Network (CNN) model by outlining allure construction, such as the number of layers and where convolutional and combining coatings will be inserted as well as the location of each. Prepare the model and judge the effectiveness on hidden concepts via test dossier. Once the CNN model is prepared, produce forecasts by resolving new MRI images coming along with the prepared CNN model to determine if a lump is present ("Yes") or if the countenance is normal ("No.").

i. CNN Model

The proposed system integrates two deep learning models with the aim of classifying as well as segmenting those data in c d. For classifying MRI images to tumor or non tumor we make use of a Convolutional Neural Network (CNN). U-Net is used to perform the segmentation task in which it is able to identify and draw the boundaries of the tumor regions in the MRI scans. That combination of models ensures that, for both identifying that a tumor is present and pinpointing a tumor's location, processing is both efficient and accurate.In the brain tumor classification case, CNN model is built to distinguish between the MRI images of tumor and non tumor images, and generates a binary classification prediction - Yes if the tumor is present or No if there is no tumor present. Then the model follows a standard deep learning architecture subject to a set of several convolutional layers which extract the essential features of the input images. It generates increasingly abstract and complex features which help in tumor identification and is the reason behind the network deepening. The output of the entire CNN architecture is a full connected layers that take in the extracted features and predict if there is existence or not of a tumor and outputs a binary value. A softmax or sigmoid activation function takes all these scores and returns the final decision, outputs a probability score that classifies the image to the 'Yes', or 'No' category. The model learns to minimize the loss function typically cross entropy during training via back propagation; hence, it gets more accurate in discriminating between the tumor and non tumor images. Applying this CNN based approach is able to achieve very good performance in the brain tumor classification and reliable performance in tumor classification of medical imaging.

CNN model's architecture is such that it automatically extract features from MRI scans and hence removing the burden to create features manually. The model learns from the large datasets and is able to learn from subtle differences between the tissues which indicate a tumor. Thus, this model is capable of making fast and accurate classifications which is crucial to clinical decisions as well as early detection of brain tumors.

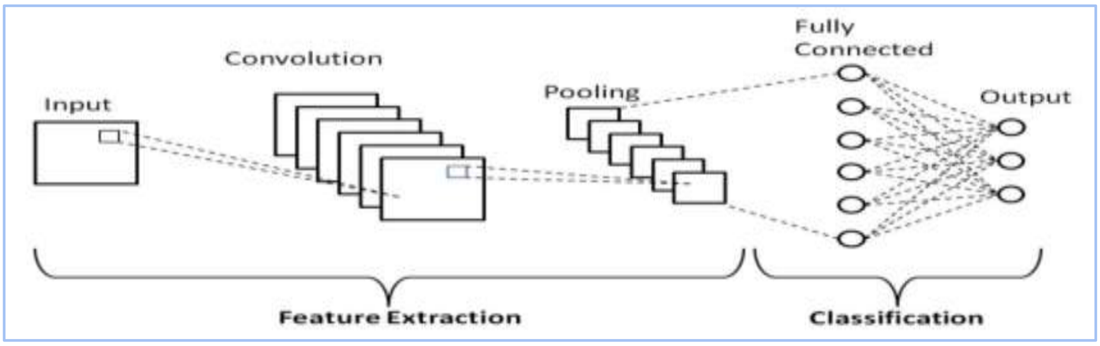

Fig2: CNN Architecture

ii. Comparative analysis

Comparative analysis of the CNN and VGG16 models' performance metrics is conducted when they are used for classification. Both models exhibit superior capability of tumor classifying, while the CNN being a shallower architecture, possesses weaker capability to learn the intricate features, can provide higher accuracy at the cost of the harder to learn the features in some cases as VGG16; see Figure 3 for the ROC curve of two: the CNN and VGG16 models. In the case of AUC metric, the VGM16 model provides a better field under the curve (AUC).

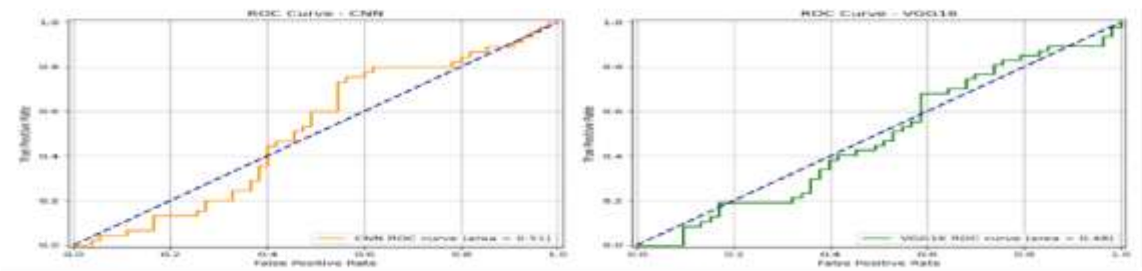

Fig 3.ROC Curve Comparison: (a) CNN Model, (b)VGG16 Model

The CNN model, even though exhibiting a lower AUC, still shows able accomplishment accompanying a good balance of subtlety and particularity. Both models are productive in detecting tumors, as rooted by their ROC curves.

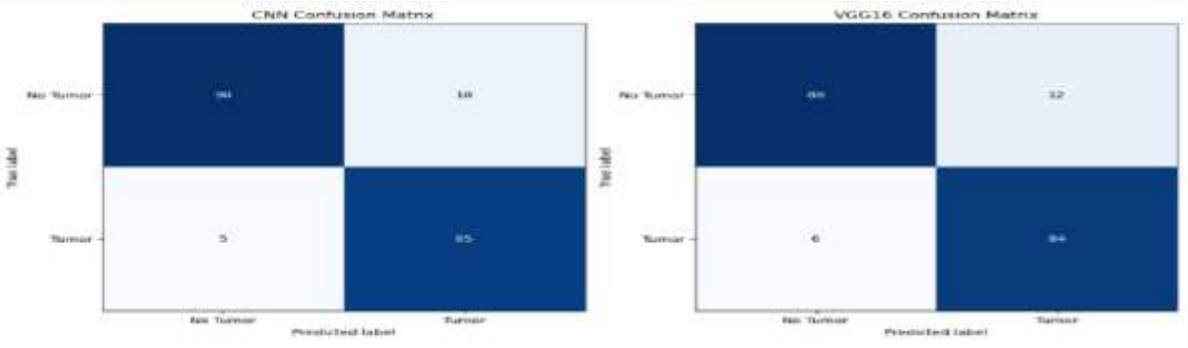

Fig 4. Confusion Matrix Comparison: (a) CNN Model, (b)VGG16 Model

In the Figure 4 presents the disorientation cast for the VGG16-UNet model, contribution a itemized view of allure act in classifying tumor and non-lump figures. The VGG16 model shows a most of correct classifications, containing two together real a still picture taken with a camera and valid contradiction, signifying its powerful strength.

C. Transformation and Segmentation

Preprocessed MRI images are used in the process that includes steps like noise reduction, intensity normalization and resizing to a standardized size. The second step is transformation of the images for example, transforming into T2 weighted images to capture given features of the brain tissue. After pre-treating the MRI representation, the next step entails characterizing how to separate. For instance, we describe the layers composition, which consists of convolutional, combining and upsampling pieces in a U-Net construction. The model starts from selecting the best optimizer, defining a specific deficit function specifically suitable for the separation tasks, and creating appropriate evaluation versification to some extent Dice cooperativism, verity, and sensitivity, as well as accuracy.Training the model is done by augmenting it with a predefined dossier, allowing it to tune the weights and bounds by underrating the misfortune and increasing segmentation accuracy. The model is prepared and then subjected to be confirmed over a confirmation dataset to measure allure ability; place versification such as Dice cooperative and Intersection over Union (IoU) are utilized to evaluate to how many places to accurately cover Cancer regions. Finally, the prepared model is used to process new MRI scans, and produce separate outputs which precisely annotate tumor fields aiding in two together imagination, and estimate of tumor diameter, and district.

i U-Net Model

Special case of UNet model architecture, designed for the image segmentation problem is very effective at detecting complex structure such as river networks. Taking the form of an encoder decoder model, the Contracting Path (Encoder) and Expansive Path (Decoder) jointly induce contextual as well as spatial information for precise segmentation. The model starts in the Contracting Path (Encoder) accepting 512 x 512 x 3 input color images. It consists of two initial 3x3 convolutions with Leaky ReLU activated, then followed by their max pooling of 2x2 reducing spatial dimension into 64 feature maps of 256x256. Successive layers follow this pattern: in the second layer, 128 feature maps of dimension 128 x 128 are produced by the second layer, second layer outputs 256 feature maps of dimension 64 x 64 and the third layer produces 512 feature maps of dimension 32 x 32. The core of the model is a bottleneck layer with two 3x3 convolutions using Leaky ReLU activations with output size of 1024. This bottleneck layer learns different levels of features so it can do well at identifying complex patterns and structures in the data.

The Expansive Path (Decoder) reads the spatial details reconstructed from the encoded data. We take full advantage of the CNNs first up convolution block, and up sample from dim. 32 x 32 to 64 x 64 while concatenating the encoder path feature maps. This is then followed by two 3x3 convolutions that reduce to 512 feature maps. By reversing in subsequent blocks, the decoder up samples to 128 x 128 with 256 feature maps, to 256 x 256 with 128 feature maps and to 512 x 512 with 64 feature maps.

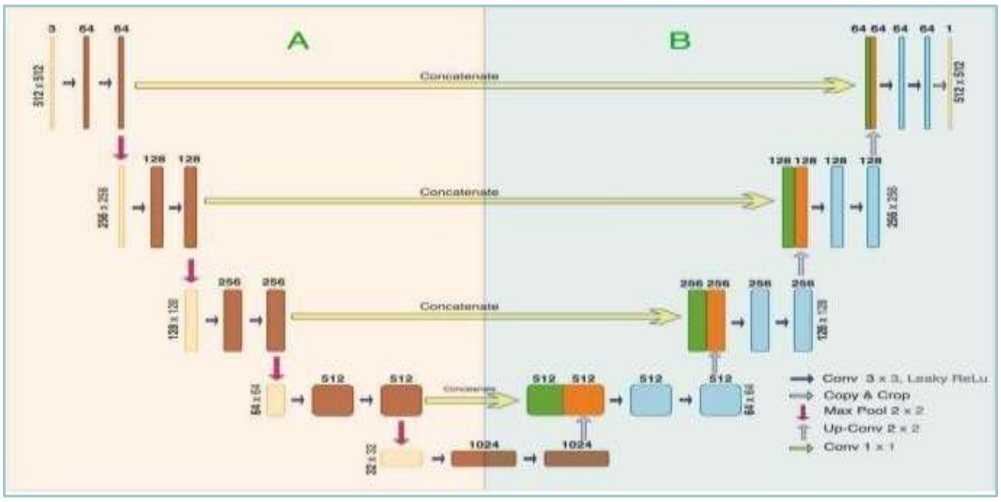

Fig 5. Architecture of UNet

Originally used for biomedical segmentation, the U-Net architecture (Fig. 5) [1] is very effective for detecting river networks. Its encoder-decoder framework has a contracting path with contextual info and an expansive path with spatial details. Skip connections enable accurate localization. This design facilitates the efficient segmentation of intricate structures through the use of limited data, and is general enough for application to other image segmentation problems.

ii. Segmentation Comparison

On comparing the U-Net and SegNet models, for segmenting figures, there are distinct differences between the two as they make up and described. Both are similarly created to classify figures on the pel pyramid, and the U-Net model is superior at detecting the details of cystic domains. This is because avoid relations, a term in the sense of allure for the use of which geographical facts are preserved throughout the process of knowledge. However, where the available dossier is limited, SegNet is less correct, and remains to be active when other complex constructions like tumors are present.

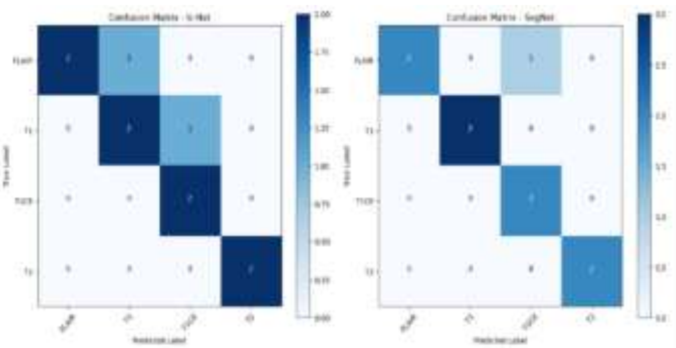

Fig 6. Confusion Matrix Comparison: (a) UNet Model, (b)SegNet Model

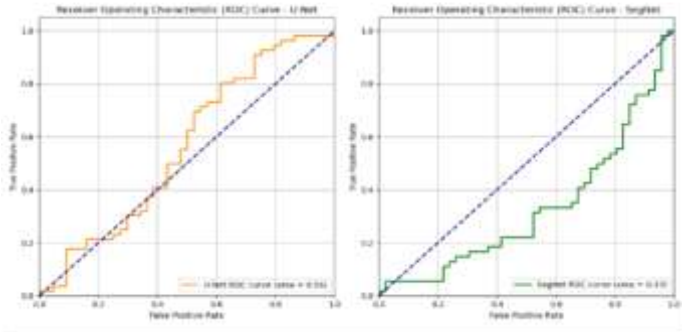

Fig 7.ROC Curve Comparison: (a) UNet Model, (b)SegNet Model

The confusion matrices for U-Net and SegNet model .It is observed that U-Net model captures more true still pictures taken with a camera that is representative of better veracity in detecting the Cancer domain. Regarding ROC curves, U-Net has a higher valid helpful rate and more balanced sense and precision than SegNet, which means that it has to deal more with wrong positive and falsehood contradiction. The results of this demonstrate that U-Net in general offers higher efficiency in tasks of separation. Although SegNet performs well, the allure region under the curve (AUC) from the distinctive middle from two point lump and lump domains is lower, which means that it is not as persuasive as one lump in the middle. From these results, it can be said that U-Net is a better model for Cancer segmentation tasks than SegNet in tumor segmentation tasks.

IV. RESULTS AND DISCUSSION

A. Performance Measures

A True Positive (TP) occurs if the model correctly identifies a tumor, a True Negative (TN) means that the model correctly recognizes the lack of a tumor. False Positive (FP) means when model predicts presence of tumor in healthy brain and False Negative (FN) means that model fails to identify tumor in brain, which is actually there. Accuracy: This is the best measure to get the percentage of pixels which are correctly recognized in entire data set by how many pixels are right recognized.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

Precision:Precision shows the dimension of valid a still plan of how trustworthy the model's beneficial classifications .

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

Recall (Sensitivity): Assessment for Recall (Sensitivity) : Evaluating how well the model captures all true positive cases denoting accurate identification of river pixels.

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

F1 Score: F1 Score: F1 Score balances accuracy and recall and is a more uniform measure to the model’s ability to correctly categorize.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{4}$$

B. Brain Tumor Segmentation

In the second step, classification is followed by the process of brain tumor segmentation. During this phase, the recommendation images are resolved by bureaucracy to decide whether the domain of interest has swelling tissue. The following step entails separation of the system to mark its district specifically related to the tumor. This ensures that the sanitary brain tissue surrounding the carcinoma will be given up responsibility by the carcinoma and bureaucracy everything that other types of MRI scans, T1, T1c, T2. We painstakingly analyze each scour type so as to distinguish it from another, and it admits the model of distinguishing these districts from the rest of the intellect. If the system segments the lump correctly in these distinguishing domains it draws a detailed map in the location of this lump in the brain; what the end result concerning this segmentation is, a clear outline of the tumor, which will help healing experts come up better understanding to the size, district and affect of this lump. It claims to have more knowledge running on the business of situation planning and other diagnostic stages.

V. CONCLUSION

The classification of the brain tumor process starts with a primary step of segmentation. In this phase, the bureaucrat resolves the recommendation images to see if the domain of interest contains swelling tissue. The separated districts are then recognized to be the exact districts that match the tumor. This ensures that the carcinoma will let go of responsibility for the nearby healthy brain tissue, and in the segmentation step we bureaucratise everything encompassing various types of MRI scan, T1, T1c and T2. By painstakingly analyzing each scour type, a model is admitted that can distinguish these districts from the rest of the intellect. A correct recognition of this lump within these decoupled domains enables the system to provide a highly detailed map of where it's located inside the brain, which we're able to correlate back to yield a definitive shape of the tumor, to aid the healing experts to better believe its size, district and possible impact. It admits to conducting more informed charge of situation planning and further diagnostic steps.

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