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Developing accurate predictive models for brain tumor growth using LSTM and GRU techniques

Rahul Namdeo Jadhav *
Department of Electronics and Communication Engineering
Bharath Institute of Higher Education and Research (Deemed to be University)
Chennai 600073
Tamil Nadu
India

and

Department of Electronics and Telecommunication Engineering
AISSMS Institute of Information Technology
Pune 411001
Maharashtra
India

G. Sudhagar †
Department of Electronics and Communication Engineering
Bharath Institute of Higher Education and Research (Deemed to be University)
Chennai 600073
Tamil Nadu
India

Abstract

Using Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) methods, this study aims to create accurate models that can predict the growth of brain tumours. We used a complete method that included steps like picture cropping, normalization, resampling, and improvement to prepare the BraTS dataset from the University of Pennsylvania. After that, we used the U-net model to do photo segmentation, which was very important for appropriately defining the rims of the tumour. We use LSTM to predict how a tumour will develop through the years and then enhance it with a blended LSTM-GRU model to make it greater correct and use less computing electricity. We checked how properly our models anticipated the future by using looking on the dice coefficient and Intersection over Union

* *E-mail:* **jadhavrn@gmail.com (Corresponding Author)**
† *E-mail:* **sudhagar.ece@bharathuniv.ac.in**

(IOU) measures for segmentation consequences. next, we checked the accuracy of our predictions the usage of suggest Absolute mistakes (MAE) evaluation The comparison of performance showed that the blend model not only minimizes losses better, but it also makes much better predictions about how tumours will grow, which suggests that it could be used in personalized treatment plans and keeping track of progress.

Subject Classification: *68T05, 92B20.*

Keywords: *Brain tumor prediction, LSTM and GRU models, Image segmentation, U-NET, Tumor growth analysis.*

1. Introduction

Predictive modelling has facilitated diagnosis and treatment of brain tumours greatly since it provides the doctor with more information on the growth patterns of the tumours. Although the conventional imaging methods are highly useful in the detection and tracking of tumours, the methods are not always effective in predicting how such complicated diseases can arise with time. This calls on the creation of complex models that will be able to accurately monitor the variations of tumours over time as regards their shape. Artificial intelligence (AI) has come a long way in recent times, partly due to Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, which have been promising to provide solutions to the problems mentioned above [1]. These deep learning models are the best in terms of simulating the changes in time as a tumour develops since they are quite good in the sequential data. The algorithms can be trained on time-series data of sequential medical imaging [2] to predict brain tumours. Identification of the best time and methods to treat tumours before they grow too large can be used to enhance the outcome of the patients. Moreover, hybrid models that are developed by incorporating LSTM and GRU networks simultaneously could be more effective than relying on either of them [3], [4]. The strategy has the advantageous characteristics of both architectures: the fast training and model performance of the GRU and the ability of the LSTM to maintain long-term associations. Combined with these techniques, the model will be able to perceive the complex tendencies of tumour development better and, therefore, allow making more accurate projections. According to this paper, [5], on the studies on how these advanced modelling techniques might apply in the real world, this article is titled Developing Accurate Predictive Models of Brain Tumour Growth with LSTM and GRU Techniques.

2. Methodology

The examine strategy, mostly, relies on the application of machine learning of techniques, such as LSTM and GRU models, to develop and test fashions capable of forecasting the surge of intelligence tumours [6]. The analyses start with the brain Tumour Segmentation (BraTS) data of the University of Pennsylvania. This data includes pre-operative MRI pictures of gliomas in various institutions, so it makes an excellent commencement point with regard to both learning and exploring the fashions [7]. Facts learning are step one inside

the approach and is fundamental for making gadget studying models work better. MRI photos are cropped to attention on essential areas, the sharpness of the scans is normalized, all of the photos are resampled to ensure they're all the equal, and essential features are superior to lead them to simpler to look [8], [9]. After the information is preprocessed, it is cut up into schooling and check sets so that the models can be evaluated effectively. The U-net neural network [10] is used to separate tumours. U-net is famous for how well it can separate components of clinical snap shots as it has a plan with a route that shrinks to document context and a direction that grows in a uniform thanks to permit for correct localization [11].

2.1 *Load Dataset*

The Figure 1 indicates distinctive MRI sorts from the intelligence Tumour Segmentation (BraTS) series, which includes T1, T1ce (T1 post-evaluation stronger), T2, and flair (Fluid-Attenuated Inversion restoration) images, in conjunction with a segmented mask that suggests the rims of the tumour.

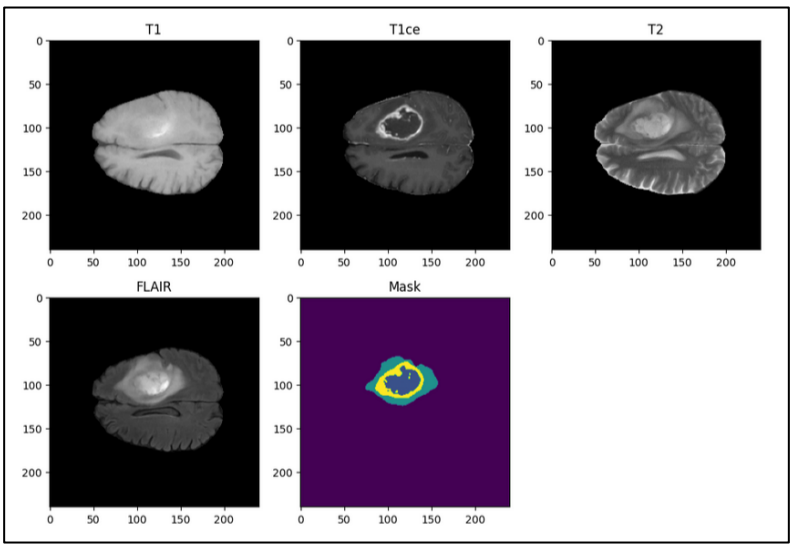


Figure 1
Representation of Dataset Sample

The coloration-coded mask indicates the center of the tumour and the swollen regions round it. Its miles an essential device for coaching gadget learning models how to correctly find and expect tumour sizes and growth.

2.2 *Data Pre-Processing*

The data pre-processing component of the BraTS dataset involves three steps, with the help of which MRI pictures are prepared to be analyzed further. To start with, images are cut in order to remove the unnecessary parts and center

on the brain. This enhances the speed of the computer and makes the model concentrate.

Pre-Processing of MRI images Data:

1. Cropping:

$$C\_i = I\_original[a:b, c:d] \quad (1)$$

To zoom in on pertinent parts of the original image, the pixel coordinates are used to select a particular area of the original image.

2. Normalization:

$$I_{normalized} = \frac{I_{original} - \mu}{\sigma} \quad (2)$$

Modifies the pixel values to mean (mu) and standard deviation (sigma) to make them standard.

3. Resampling:

$$I\_resampled = resize(I\_original, new\ dimensions) \quad (3)$$

Adjusts the image to a certain dimension, making it uniform in order to be analyzed.

Then, normalized values are achieved where the pixel intensities of all the scans are identical. This ensures that machine learning models receive the same data. Finally, resampling reforms the pictures to a conventional resolution. It is more straightforward to make comparisons of images and the quality of segmentation and prediction models is also enhanced by ensuring that all data share identical input dimensions.

2.3 *Image Enhancement*

Images which are made using image enhancement methods allow better viewing of MRI pictures, therefore programs can find and tackle tumours more easily. Typically, this involves adjusting the contrast and the brightness, applying filters to remove noise and make the edges be more prominent, or applying effects such as histogram equalisation to improve the dynamic range of the image.

Image enhancement algorithm–

1. Contrast Adjustment:

$$I\_adjusted = \alpha * I\_original + \beta \quad (4)$$

Adjusts the intensity where α controls contrast and β adjusts brightness.

2. Histogram Equalization:

$$H(v) = ((cdf(v) - cdf\_min)/(M * N - cdf\_min)) * (L - 1) \quad (5)$$

Increases contrast through dispersion of the most common values of intensity.

3. Gaussian Smoothing:

$$G(x,y) = \left(\frac{1}{2\pi\sigma^2}\right) * e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (6)$$

Removes noise and details with the help of a Gaussian kernel.

4. Laplacian Sharpening:

$$I\_sharpened = I\_original + c * (\Delta I) \quad (7)$$

Sharpening of edges through the incorporation of scale Laplacian operator in the original image.

5. Unsharp Masking:

$$I\_sharpened = I\_original + k * (I\_original - I\_blurred) \quad (8)$$

Refines through increasing contrast of edge with blurred copy of the picture.

Train Test Split: Train-test split is one of the most crucial processes in preparing data to be used in machine learning models, which can be seen in Figure 2. It is a process of dividing the dataset in two parts, one being the training set that is utilized to instruct the model on what to do and the other being testing which is utilized to verify the extent to which the model has performed. This is to ensure that the model will be effective with new data that it has not encountered previously and it is not overly reliant on the training data.

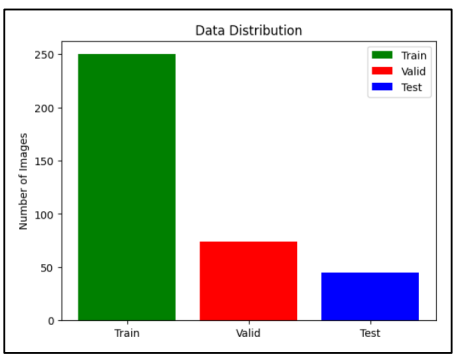


Figure 2
Representation of data distribution for training, test and validation

3. Image Segmentation Model

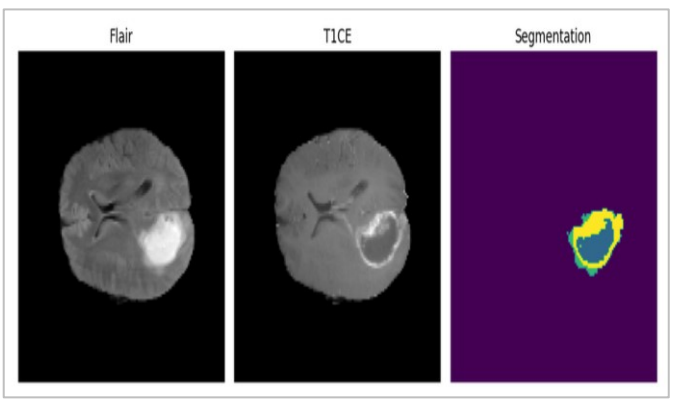
3.1 *U-NET Method*

The U-NET design is very important for separating brain tumours from MRI pictures because it helps find the exact edges of the tumours. Both of these paths are necessary for accurate and detailed segmentation results in brain tumour studies. Figure 3 shows a model representation that shows the design of a U-NET model, as represent it in Figure 3 (a), which is often used for tasks like picture segmentation. The model is made up of an input layer, then a set of

convolutional and max pooling layers that reduce the size of the picture while keeping the context. This U-net model is very beneficial for jobs that need a number of accuracy and element, like talent tumour segmentation. Figure 3 (b) shows how a talent tumour used to be damaged up the use of 2 sorts of MRI scans, aptitude and T1CE. The FLAIR picture helps find the peritumoral oedema, and the T1CE image, which has better contrast, shows the tumour core.

```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 256, 256, 1)       0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 256, 256, 64)      640
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 128, 128, 64)      0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 128, 128, 128)     73856
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 64, 64, 128)       0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 64, 64, 256)       295168
_________________________________________________________________
up_sampling2d (UpSampling2D) (None, 128, 128, 256)     0
_________________________________________________________________
concatenate (Concatenate)     (None, 128, 128, 384)     0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 128, 128, 128)     442496
_________________________________________________________________
up_sampling2d_1 (UpSampling2 (None, 256, 256, 128)     0
_________________________________________________________________
concatenate_1 (Concatenate)  (None, 256, 256, 192)     0
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 256, 256, 64)      110656
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 256, 256, 1)       65
=================================================================
Total params: 922,881
Trainable params: 922,881
Non-trainable params: 0
_________________________________________________________________
```

(a)



(b)

Figure 3

(a) UNET Model Summary (b)Tumor Segmentation using UNET Model

The segmentation panel clearly shows the tumour with a yellow border on a purple background. This exact segmentation makes it easier to analyse and measure the tumour correctly, which is important for planning treatment and keeping an eye on how well it's working in real life.

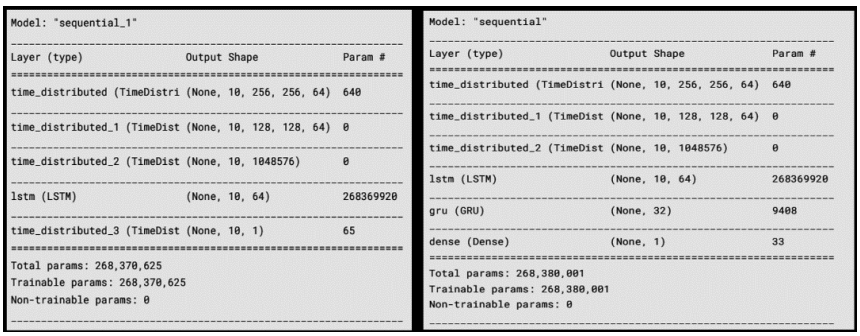
3.2 *Predicting Tumor Growth*

a. Sequence Modeling using LSTM

By looking at sequential MRI data, Long Short-Term Memory (LSTM) models are used to guess how big a tumour will get. They record how tumours change over time and how they change over time, which is very important for planning treatments and keeping an eye on them, as shown in Figure 4 (a).

b. Hybrid LSTM + GRU Model

This model uses both LSTM and Gated Recurrent Unit (GRU) algorithms to make predictions more accurate, the model represent in Figure 4 (b).



Model: "sequential_1"

Layer (type)	Output Shape	Param #
time_distributed (TimeDistri	(None, 10, 256, 256, 64)	640
time_distributed_1 (TimeDist	(None, 10, 128, 128, 64)	0
time_distributed_2 (TimeDist	(None, 10, 1048576)	0
lstm (LSTM)	(None, 10, 64)	268369920
time_distributed_3 (TimeDist	(None, 10, 1)	65

Total params: 268,370,625
Trainable params: 268,370,625
Non-trainable params: 0

Model: "sequential"

Layer (type)	Output Shape	Param #
time_distributed (TimeDistri	(None, 10, 256, 256, 64)	640
time_distributed_1 (TimeDist	(None, 10, 128, 128, 64)	0
time_distributed_2 (TimeDist	(None, 10, 1048576)	0
lstm (LSTM)	(None, 10, 64)	268369920
gru (GRU)	(None, 32)	9408
dense (Dense)	(None, 1)	33

Total params: 268,380,001
Trainable params: 268,380,001
Non-trainable params: 0

(a) (b)

Figure 4
(a) Represent sequence modeling using LSTM (b) Represent the Hybrid LSTM + GRU Model

4. Result and Discussion

Figure 5 probably shows how well segmentation models work when measures like the Dice Coefficient and Intersection over Union (IOU) are used. The Dice Coefficient measures how similar the expected segmentation is to the real segmentation.

Higher Dice scores mean that the model worked better. The IOU, or Jaccard Index, measures how much the expected and real segments meet. A higher IOU also means that the segmentation is more accurate. When segmentation algorithms like U-NET are used on MRI images to find and define tumours, these measures are very important for figuring out how well they work. Comparing these measures helps to make sure that the segmentation process is reliable and accurate.

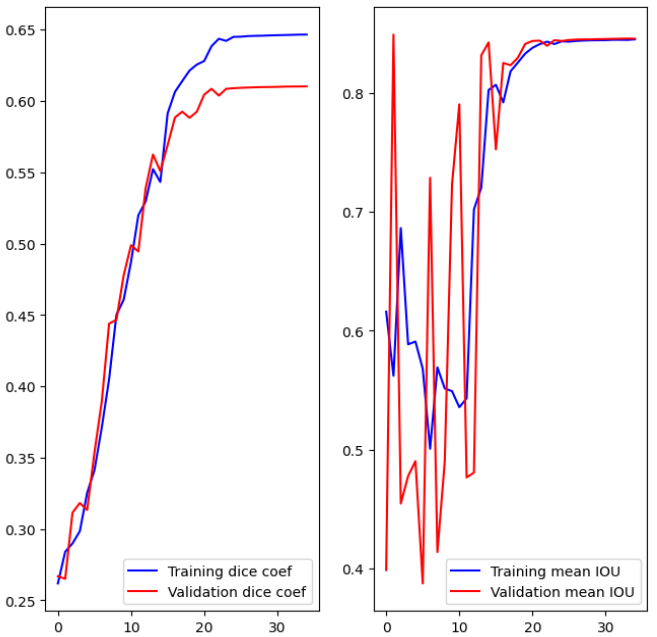
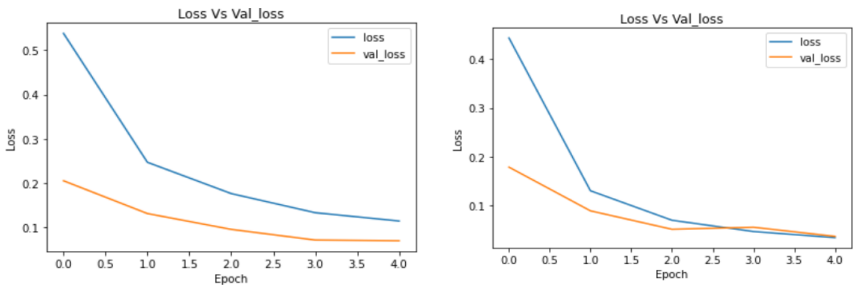


Figure 5
Dice Coef and IOU comparison Graph

4.1 *Tumor Grow Prediction*

Figure 6 shows plots that compare the loss for (a) LSTM models and (b) Hybrid LSTM-GRU models. The training loss (blue line) and validation loss (orange line) both go down a lot over epochs, which show that learning is happening. The Hybrid LSTM-GRU model (b), on the other hand, has a more stable convergence in validation loss than the LSTM model (a), which suggests that it can generalize better and learn better.



(a) (b)

Figure 6
(a) LSTM Loss Comparison Graph (b) Hybrid LSTM - GRU Loss Comparison Graph

In Table 1, demonstrate two different machine learning algorithms—LSTM and a Hybrid LSTM-GRU predict the growth of tumours. For each model, the Training Loss and Validation Loss are shown.

Table 1

Performance metrics for Models

Algorithm	Training Loss	Validation Loss
LSTM	0.1139	0.0708
LSTM + GRU	0.0699	0.0514

With a Training Loss of 0.1139 and a Validation Loss of 0.0708, the LSTM algorithm can learn from the information, but it could still do a better job of making predictions. The Hybrid LSTM-GRU model, on the other hand, does better, with a smaller Training Loss of 0.0699 and a Validation Loss of 0.0514. This big drop in loss measures shows that the mixed model does a better job of capturing the complex time data, making the model more accurate and usable in more situations, comparison illustrate in Figure 7. Combining the most useful aspects of long-term memory of LSTM and the speed of GRU, the mixed method obviously enhances model performance, which is why it is a preferable option whenever it comes to tasks that require extreme accuracy, such as medical assessment and design of treatment plans.

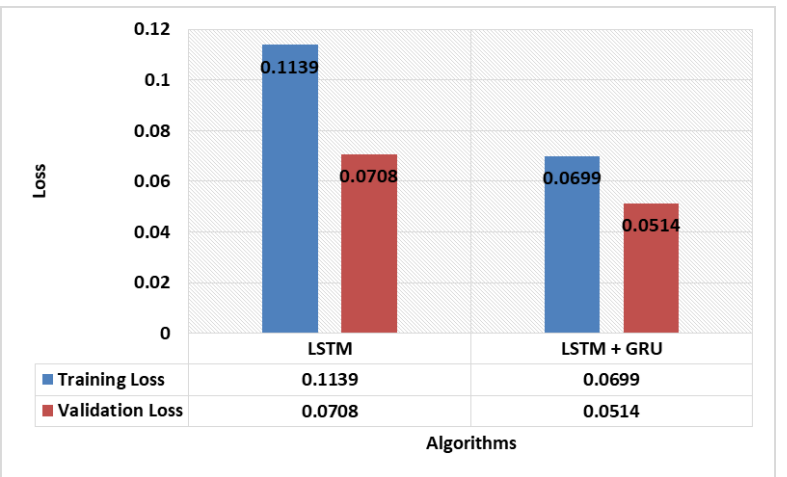


Figure 7

MAE Loss Comparison Graph

5. Conclusion

In the study, the BraTS dataset was used to demonstrate that the LSTM and GRU-based models can be used to make accurate predictions about brain tumour growth. The researchers revealed significant variations in the quality of

the predictions in case they applied a full approach that encompassed preprocessing, U-NET-based picture segmentation and sequential modelling. The hybrid LSTM + GRU model was better than the single LSTM model, and it had lower losses in terms of training and testing. This demonstrates that it can be useful to combine these two potent recurrent neural network technologies. This research introduces the possibility of a brain tumour treatment that will be more personalised and fast. It may enhance the outcomes of patients as it will allow physicians to make better guesses regarding tumour development.

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