1.1 Motivation/purpose/aims/hypothesis:
The authors aim to build a model with a federated learning approach and another model with an ensemble learning consisting of the three best performing weak learners. They used transfer learning on pre-trained CNN architecture to find the best performing models. The primary goal was to use federated learning to create a privacy focused model. And an ensemble model which will outperform the individual model it is built on.

1.2 Contribution:
The authors built a federated learning model with an accuracy of 91.05% and an ensemble voting mode which achieved an accuracy of 96.68%. The researchers used a brand new combination of pre-trained CNN architectures to form new transfer learning models. The pre-trained architecture was followed by a max-pooling layer, flatten, dropout, dense layer and finally an output layer.

1.3 Methodology:
The dataset was from the UK Data Service which consisted of images from 22 brain tumor patients. Then they extracted 2D images from 3D scans. This was followed by the labeling of the dataset in accordance with the presence of brain tumor. After that min-max scaling was done on the images. For the model, the authors used six pre-trained CNN architectures to implement transfer learning. The six pre-trained CNN architectures are as follows VGG16, VGG19, Inception V3, ResNet50, DenseNet121 and Xception Net. Then using VGG19, Inception V3 and DenseNet121 a voting ensemble was created. Finally average federated learning was executed to incorporate the distributed approach.

1.4 Conclusion:
The authors developed two models primarily which addressed the problem of brain tumor detection, namely the federated approach and the ensemble approach. Both had different goals to achieve. Federated learning would give a distributed model which can be implemented on edge devices and an ensemble model with a superior performance.

2.1 First Limitation/Critique (15%)
The first limitation is that the dataset used in such health related problems are very hard to come by. This is because these are sensitive data which doctors or hospitals do not want to share with researchers. Also in most countries there are strict government regulations which forbids disclosing medical data to researchers. There are only two ways researchers mainly get quality dataset. Either they work directly with a research foundation dealing with such sensitive patients under them or patients sign a form which allows their medical data to be used. However, this limits the use of this data by most researchers.

2.2 Second Limitation/Critique (15%)
The next limitation is not handling the imbalance dataset. Any medical data related to brain tumors will have more cases of non-tumour. This will result in the tumor class to be a minority class. Not handling the minority class will result in a wrong metric value which does not give a proper reflection of the model performance.

3 Synthesis
The paper has opened a lot of future applications. The authors have shown keen interest to work on DNA images as genetic mutation causes brain tumour. Furthermore as this is a federated learning approach, this model can be used to predict brain cancer in local village clinics which lack enough dedicated doctors for diagnosis. The researchers also have shown the willingness to work with larger dataset to improve the model performance and improved image formatting to work with low quality images.