A NOVEL HYBRID APPROACH OF DEEP LEARNING NETWORK ALONG WITH TRANSFER LEARNING FOR BRAIN TUMOR CLASSIFICATION

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Abstract : Brain tumors occur mainly due to the abnormal and uncontrollable partitioning that happened in the cell. In recent times, the DL[deep learning] method has helped the medical field by diagnosing the medical image process of several disease types. Among which brain tumor-based medical image classification is the most common one. It is done through Deep NN[neural Networks], where the TL[transfer Learning] on the MR image for brain tumor image classification helps in improving the metrics of classification by developing image-level stratified and patient-level models. In this research, almost 3640 T1-based MR[Magnetic Resonance] images from 233 patients with different types of tumors such as the [glioma, meningioma, pituitary] have been collected for research purpose. The image views are based on three views known as the sagittal, coronal, and axial views, respectively. The average brain image in all three views was found to be 14. Image classification is done with the help of cross-trained data with the use of the already trained Inception V3-model. In the MR imagimg dataset, the 3-image-level and 1-patient-level have been a model to proceed with the process. The evaluation process during image classification is based on loss, accuracy, recall, kappa, precision, and AUC. The validation process is done through 4 methods: 10-fold cross-validation, holdout validation, group 10-fold cross-validation, stratified 10fold cross-validation. With the use of the cropped and uncropped dataset, the capacity of the generialization and its improvement process is detected. A siginificant result was gained with the utilization of 10-fold cross-validation, where it acquired an accuracy of 99.82%. The brain tumor classification from the MR image can be done with the help of DNN along with the transfer learning process. Our patient-level organization model noticed the best outcomes in arrangement to improve exactness.

Keywords: Deep learning, MR-imaging, Inception V3, brain tumor, Transfer learning, multi-class classification.

1. Introduction

The headway in clinical advances helps clinical specialists work with more proficient e-medical care frameworks to the patients. There are various clinical spaces where e-medical care frameworks are helpful [1]. PC vision-based biomedical imaging utilization is acquiring significance as they give acknowledgment data to the radiologist for player therapy-related issues. Diverse clinical imaging strategies and techniques that incorporate Ultrasound, and Computed Tomography (CT), X-ray, Magnetic Resonance Imaging (MRIs) have tremendous significance over the treatment and diagnosis process.

The development of abnormal gatherings of cells inside the cerebrum or close to it prompts a brain tumor's introduction. The unusual cells unexpected the preparation of the cerebrum and influence a patient's wellbeing [4]. Brain imaging investigation, determination, and therapy with embraced clinical imaging strategies are the principal focal points of examination for specialists, radiologists, and clinical specialists [5]. The examination of brainimages is viewed as basic since infections of the brain called brain tumors are deadly and liable for an enormous number of passings in created nations; for example, as per the National Brain Tumor Foundation (NBTF), 28,000 individuals are determined to have a brain tumor in the United States (US) with brain tumor and 12,000 of those patients bite the dust per annum [6].

This research aims to investigate the DNN effect along with TL on the MRI images for brain tumor classification. Through which there will be an improvement in the classification process. Classification is done by developing image-level stratified and patient-level models. The outcome of the process is compared with the other method with a similar dataset of brain tumor images and the identical approach to the proposed method's superiority. In this research, almost 33,640 T1-based MR[Magnetic Resonance] images from 233 patients with different types of tumors such as the [glioma, meningioma, pituitary] have been collected for research purpose.

The image views are based on three ideas: the sagittal, coronal, and axial views. The validation process is done through 4 methods: 10-fold cross-validation, holdout validation, group 10-fold cross-validation, stratified 10fold cross-validation. The evaluation process during image classification is based on loss, accuracy, recall, kappa, precision, and AUC. Finally, the comparison performance was made by studying the state-of-the-art method to show the proposed method's superiority.

2. Literature Survey

[8] trained a convolutional neural network to classify three specific brain tumor classes, namely Meningioma, Glioma, and Pituitary, which achieved 98.51% training accuracy and 84.19% validation accuracy. [9] also trained a CNN model with an image processing technique to identify various brain tumor types and achieved 94.39% accuracy with an average precision of 93.33%. [10] presented a radiomic machine learning approach to predict tumor grades and nodal status from CT scans of primary tumor lesions and got the highest accuracy of 92.9% by Naive Bayes and k-nearest neighbor. [11] used the ResNet34 pre-trained CNN model, a transfer learning approach, and Data Augmentation to classify normal and abnormal brain MRI images and got 100% accuracy. [12] used three different pre-trained CNN models (VGG16, AlexNet, and GoogleNet) to classify the brain tumors into pituitary, glioma, and meningioma. During this Transfer learning approach, VGG16 acquires the highest accuracy that is 98.67%. [13] proposed a framework by modifying the pre-trained process of the Res_net-50 CNN model. Where the proposed model was compared with the AlexNet, GoogleNet, ResNet50, the updated Res_net-50 CNN model showed an accuracy of 97.1%.

The unavailability of labeled data is one of the major obstacles in the penetration of deep learning in medical healthcare. As recent development of deep learning applications in other fields has shown, the bigger the data would be, the better accuracy. Data segmentation and data augmentation are done using deep learning in the mentioned literature, and different pre-trained CNN Models using the transfer learning approach to classify brain tumors had been used. Most of the literature addresses the classification efficiency using transfer learning approach. The pre-trained models that are mostly used in the mentioned literature are VGG-16, ResNet-50 and Inception-v3, which are pre-trained on a mass amount of datasets such as ImageNet. And for radiology research and experiments, we have to do fine-tuning by freezing the layers to reduce parameters if the dataset is small, we also have to replace the fully connected layers according to the dataset labels, Besides transfer learning requires high processing power from specialized processors (GPUs) to train smoothly, which is cost consuming, and one of another drawback in transfer learning is that the image input size is fixed so, we have to adjust our images according to the pre-trained model's input size. so in our experiment, we took a very small dataset of Brain MRI Images.

The evaluation process during image classification is based on loss, accuracy, recall, kappa, precision, and AUC. The validation process is done through 4 methods: 10-fold cross-validation, holdout validation, group 10-fold cross-validation, stratified 10fold cross-validation. With the use of the cropped and uncropped dataset, the capacity of the generialization and its improvement process is detected. A siginificant result was gained with the utilization of 10-fold cross-validation, where it acquired an accuracy of 99.82%. The brain tumor classification from the MR image can be done with the help of DNN along with the transfer learning process. Our patient-level organization model noticed the best outcomes in arrangement to improve exactness.

3. Present Methods for datamodels

3.1 Proposed dataset for the model

[12] initially used image data for tumor type classification. The present MRI image dataset has a 2-dimesional image of 3 types of brain tumors known as the [1. Glioma, 2. Meningioma, 3. Pituitary]. The image views are based on three ideas: the sagittal, coronal, and axial views. Table 1 describes the details of the almost 3640 T1-based MR[Magnetic Resonance] images from 233 patients. The MRI image dimension was considered to be 775x713 pixel images. Further details regarding the MRI image dataset is shown in table 1 as follows:

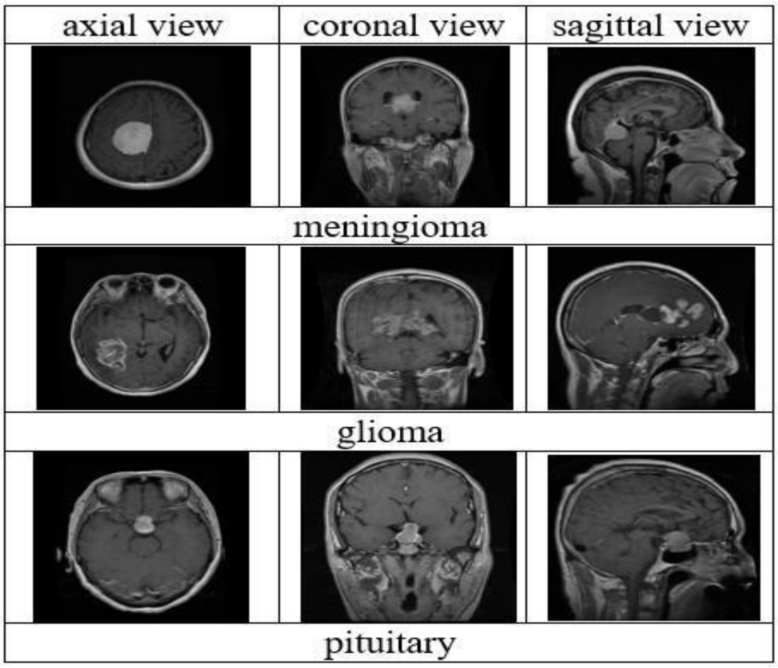

Fig. 1. Types of Brain Tumor in a different viewpoint

Table 1. The description of T1-based weighted Magnetic Resonance Imaging

Type of Tumor	**MRI View**	**Number of MR images**	**Number of patients**
Meningioma	Axial	209	82
	Coronal	268	
	Sagittal	231	
Glioma	Axial	494	89
	Coronal	437	
	sagittal	495	
Pituitary	axial coronal	319	62
	sagittal	320	
	Total	3640	233

3.2 Implemented technique

3.2.1 Techniques for pre-process

Two types of the dataset have been generated for the original image dataset. 1-dataset is about the cropping operation near the brain view in the Magnetic Resonance Imaging. The second one is the one that takes place without any sort of cropping process. They are the uncropped image. The variation of the cropped and the uncropped image is illustrated in fig 2 &3. The dataset has been normalized to a 313x313 pixel image. In this process, almost two sizes of the image have been implemented for the input process of the networking. The enhancement accuracy of the classification process was not noted. Because it obtained more resources by processing time and memory of the dataset of 313x313 pixel images compared to that of the 775x715 pixel images.

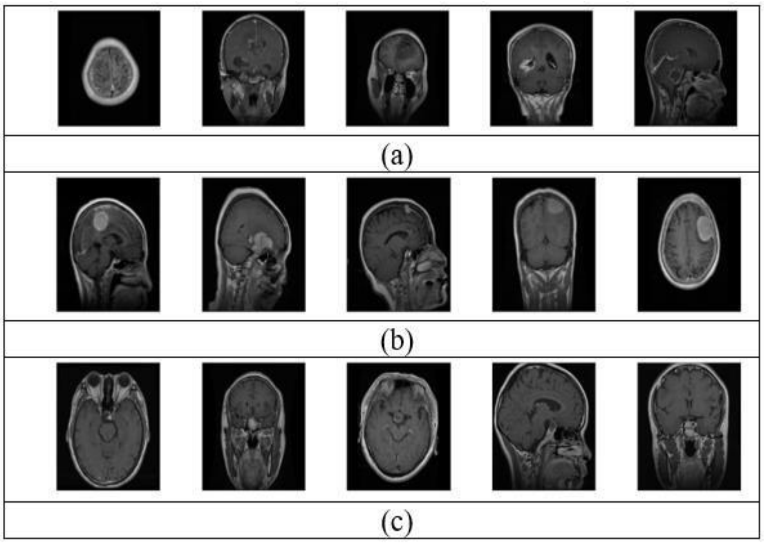

Fig.2 image of the uncropped dataset for [1. Glioma, 2. Meningioma, 3. Pituitary]

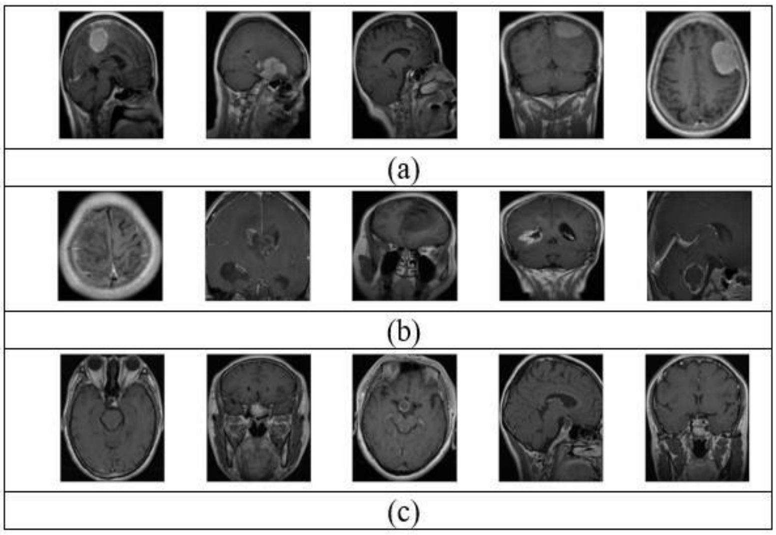

Fig.3 image of the cropped dataset for [1. Glioma, 2. Meningioma, 3. Pituitary]

3.2.2 Convolutional Neural Networks [CNN]

The Convolutional Neural Networks are commonly used for image recognition, classification, and detection of object. DL-based CNN, known as the DCNN, has a variety of layer panels with a different set of filters. These filters are used for dimensional reduction and feature extraction. The input in the DCNN is passed in a series manner to the CL [COventional Layer] with Kernel Filters' use. This process is used for classifying the object. This model creates a probability value that ranges from zero to one for the given input value. CL layer of the DCNN is made of pooling, filters, ReLu, Dropout, and entirely connected layers. The softmax and the sigmoid function present in the DCNN are used for the classification process. The classification in DCNN is done in 2 ways. The multiclass classification is done with the help of softmax, and the binary classification is done with the help of sigmoid function. The extraction and automatic feature extraction in CNN will always yield better results employing performance.

In this paper, DCNN along with TL is employed along with the Inception V3. The Inception V3 is trained already. Fig 4 explains the TL process in detail. The Inception V3 consist of 312 layers. This process requires more datasets for the purpose of optimizing the result as well as for training. In the case of the medical sector, it is challenging to get a large amount of dataset where the smaller dataset faces the problem of overloading.

[24] there are 3 types of DCNN model known as the GooLeNet also known as the Inception V1, which is mostly used for decreasing the error rate and the computation time. Which is otherwise called Inception V2. Fig 5 describes the Inceptionv3 model in detail. In this, the proposed process takes less time for computation, and the

error rate will also be reduced. The present DCNN adapts different complications through which it only takes less time for computation.

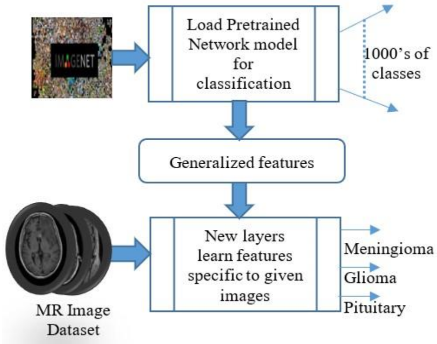

Fig.4 DCNN with TL

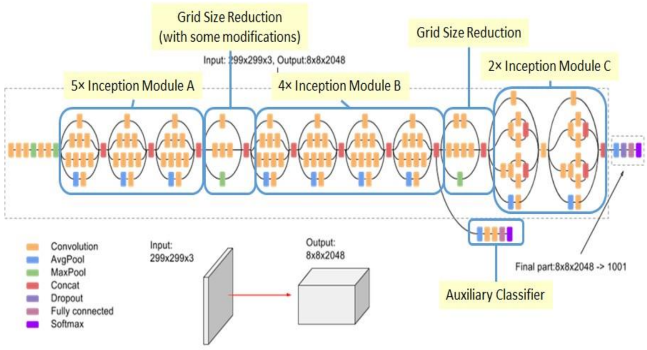

Fig.5 Architecture of Inception Version 3

3.2.3 Present Conventional Neural Network Process

In this paper the Conventional Neural Network was created in tensor flow and keras. The inception V3 model has set of pretrained data which was obtained from ImageNet-311-layer. This layer was entirely connected to the neurons. Totally 256 neurons are present in the ReLu function. 20% of it is connected to the dropout layer. Softmax is used for output and classification. From the pre-prepared model general image highlights removed to the completely associated layer. This extraction gives great discriminative portrayal for prepared images. These overall image highlights joined with MRI image highlights from the completely associated layer. In the final layer the total no. of hidden unit will be equal to the no. of the brain tumor class. Fig 6 explains the detail of the proposed CNN. In the final layer of Inception V3 one clould find almost thousand no. of hidden units, which is represented in the ImageNet database. Therefore, the last layer of InceptionV3 was replaced with a layer with 3 hidden units according to the MRI image dataset classes.

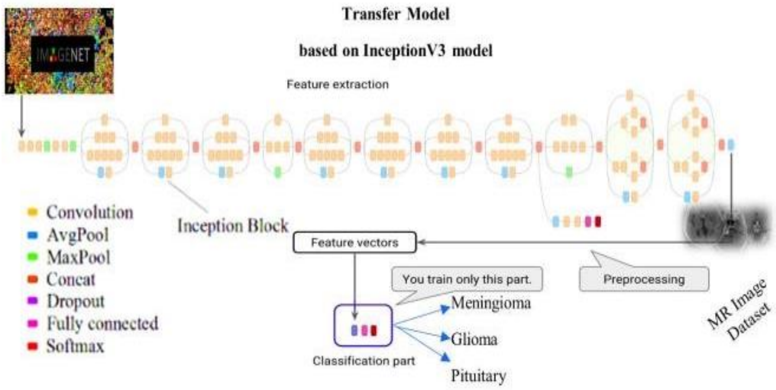

Fig. 6. Description of TL based technique

The TL is popular in recent times due to its capacity to reduce the time for training, and it also requires less amount of data for the train through the efficiency can be enhanced. All the layers have been used for pre-processing other than the final layer, represented by ImageNet data. The trained data was made to freeze by which it can fully understand the MRI brain tumor images. The misfortune metric and streamlining agent in the model are categorical_crossentropy and RMSprop with a learning pace of 0.0001 individually. While passing the contribution to the model, pictures were resized to 256x256 pixels structure unique size (312x312 pixels). we have tweaked the organization with the above-said hyperparameters and accomplished an exactness of 98.82% from chose dataset.

3.2.4 Evaluation process

Some of the commonly used classification methods are CNN, SVM, Decision Tree, RF Random forest, RNN[Recurrent Neural Neywork]. Evaluation of classification can be done in various forms. The following the method of classification evaluation:

For accuracy the TP[true positive], TN[true negative], and FN[false negative] is interrelated.

The confusion matrix is the most important requirement in the classification process. The rows and columns of confusion matrix are represented using predicted and actual class. The correct prediction and misclassification are described in the confusion matrix in the diagonal and non-diagnal elements. In the confusion matrix, the dimension is defined in the form of no. of classes multiplied by no.of classes. The TP, TN, FP, FN are the elements of the confusion matrix. All these elements are used for calculating the recall, precision, accuracy, sensitivity, and specificity of the estimated classification process.

Classifcation of accuracy:

$$\text{Accuracy} = \frac{(TP)+(TN)}{\cdot(TP)+(FP)+(TN)+(FN)} \quad (1)$$

Precision is calculated with the help of the below equation

$$Precision = \frac{\text{True Positive }(TP)}{\text{True Positive }(TP)+\text{ False Positive }(FP)} \quad (2)$$

The recall is calculated with the help of below equation

$$\text{Recall} = \frac{\text{True Positive }(TP)}{\text{True positive }(TP)+\text{ False Negative }(FN)} \quad (3)$$

F1-Score is calculated with the help of below equation

$$\text{F1} - \text{Score} = \frac{2* \text{precision} * \text{recall}}{\text{precision} + \text{recall}} \quad (4)$$

Kappa is calculated with the help of the below equation

$$\text{Kappa} = \frac{\text{Accuracy} - \text{randomAccuracy}}{1 - \text{randomAccuracy}} \quad (5)$$

$$\text{randomAccuracy} = \frac{(\text{TN+FP})\times(\text{TN+FN})+(\text{FN+TP})\times(\text{FP+TP})}{\text{Total} \times \text{Total}} \quad (6)$$

The region under the bend (AUC): A total proportion of a paired classifier's execution overall conceivable limit esteems. AUC ascertains the territory under the ROC [recursive operating characteristic curve]. ROC is a plot that shows the presence of a parallel classifier that removes the edge. AUC is the likelihood that the model positions an irregular positive perception more exceptionally than an arbitrary negative perception. The higher AUC estimation of a model can give better outcomes.

4. Analysis of Outcome

4.1 Experimental setup

In this process, 4-types of validation are done with the help of 2-set of database which is the cropped and the uncropped dataset. Table 1 and 2 describes the types of the validation process.

1. The databse was divided by means of 30:70, which is almost $1/4^{th}$ the ratio. Among which seventy % of it is utilized for the training process, and the leftover thirty % is used for testing. The 10-fold validation was carried out for the 3 variations for the stratified image level, patient level, and image level only. The comparison of the proposed method with the state-of-the-art method is discussed in section.5.
2. The proposed model was created using the Keras and the tensor flow platform. This is implemented on the colab pro-environment. For sharing the work in such a case, google Colab is used. Where the other users can write and exit on the web without any configuration. This can be done with free GPU access and can be shared easily as well through Google Drive.

3. Training for the transfer model is given using the optimizer and the loss matric. The batch was taken in small size with 20. Nos where the highest nos. of epochs was 25. The validation of the proposed model is done using similar hyper-parameters on the 2 sets of the database for 4 types of validation.

4.2 Results

Tables 2 and 3 are used for summarizing the outcome of the proposed model. Fig 6 and 7 also illustrates the effect of the proposed model. In this process, 4 types of validation technique has been employed using the 2 types of dataset known as the cropped and the uncropped dataset. The outcome of the uncropped dataset yields better results when compared to the cropped dataset. It has proceeded through the group10-fold patient-level cross-validation model. It achieves better results when compared to the other combinations. The obtained values for precision, AUC, accuracy, recall, kappa, f1 score were found to be 97.57, 94.60, 99.82, 99.47, 94.60, 98.40, respectively. The 2nd most satisfying combination was with the uncropped dataset using the stratified 10-fold image-level cross-validation. These values are detailed in table 3 as follows. Other datasets such as the Figshare would have helped the recall and precision attain better performance in the uncropped image process with the stratified 10-fold cross-validation and 10-fold cross-validation. From the performance evaluation, it is clear that the TL has benefitted from reducing over-loading and increased computing speed. The DCNN based-TL model does not need the cropped image dataset for classifying the brain tumors.

Fig 7 and 8 represent the performance of the 4 classes of validation process on the cropped as well as an uncropped dataset. In fig 7 [a1,a2,a3] indicates the holdout validation confusion matrix. Where the validation accuracy vs. training accuracy & the validation accuracy vs. training loss is discussed. Likewise, fig 7 [b1,b2, b3] indicates the stratified 10-fold, 10-fold, group 10-fold cross-validation for the cropped database's training process. The validation and training progress curve for the accuracy and loss indicates no change for the overloading action in the model. Fig 8[a1,a2,a3], [b1,b2,b3], [c1,c2,c3] and [d1,d2,d3] indicates the validation and training progress curve for the classification process for the Uncropped image dataset of MRI image.

Table 2. 4-type validation performance metrics of the cropped dataset

Validation Type	Accuracy	Precision	Recall	F1-Score	Kappa	AUC
Hold out	95.07	91.53	92.05	91.77	88.38	98.89
10-fold (Image Level)	99.10	98.85	98.38	98.57	97.92	99.88
Stratified 10-fold (Image Level)	99.23	98.60	98.82	98.68	98.20	99.84
Group 10-fold (Patient Level)	99.27	98.67	99.53	99.07	99.70	99.70

Table 3. 4-type validation performance metrics of the un-cropped dataset

Validation Type	Accuracy	Precision	Recall	F1-Score	Kappa	AUC
Hold out	96.7	95.70	93.98	94.69	92.43	99.55
10-fold (Image Level)	99.10	98.11	98.71	98.33	97.85	99.82
Stratified 10-fold (Image Level)	99.32	98.95	98.87	98.88	98.42	99.85
Group 10-fold (Patient Level)	99.82	97.57	99.47	98.40	94.60	99.50

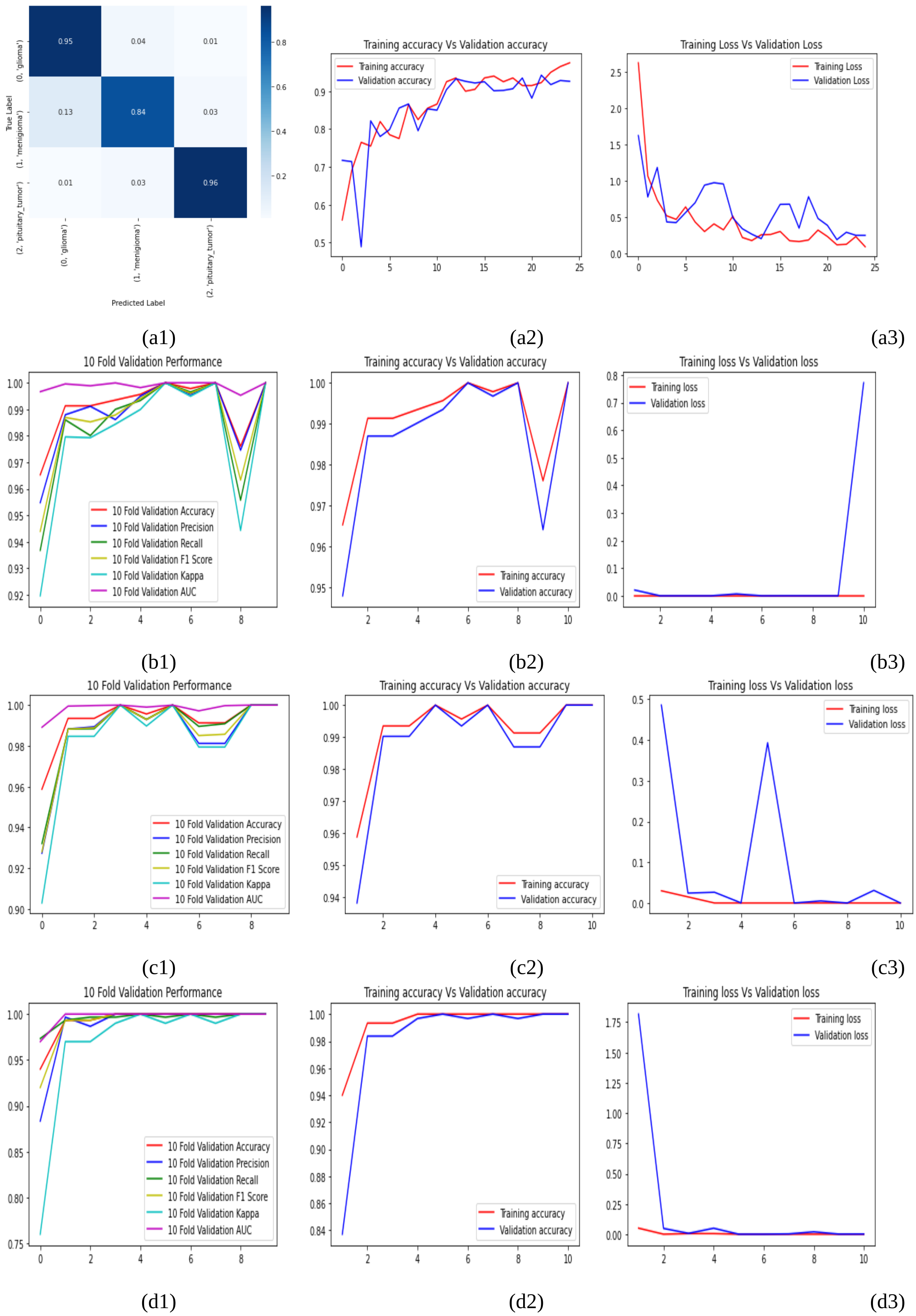

Fig.7 Performance of the Present Model based on loss history, accuracy, of the cropped dataset, for [a1,a2,a3] Holdout-validation, 10-fold Cross Validation in B series, and Stratiifed 10-fold process in C series, and group 10-fold process in D-series

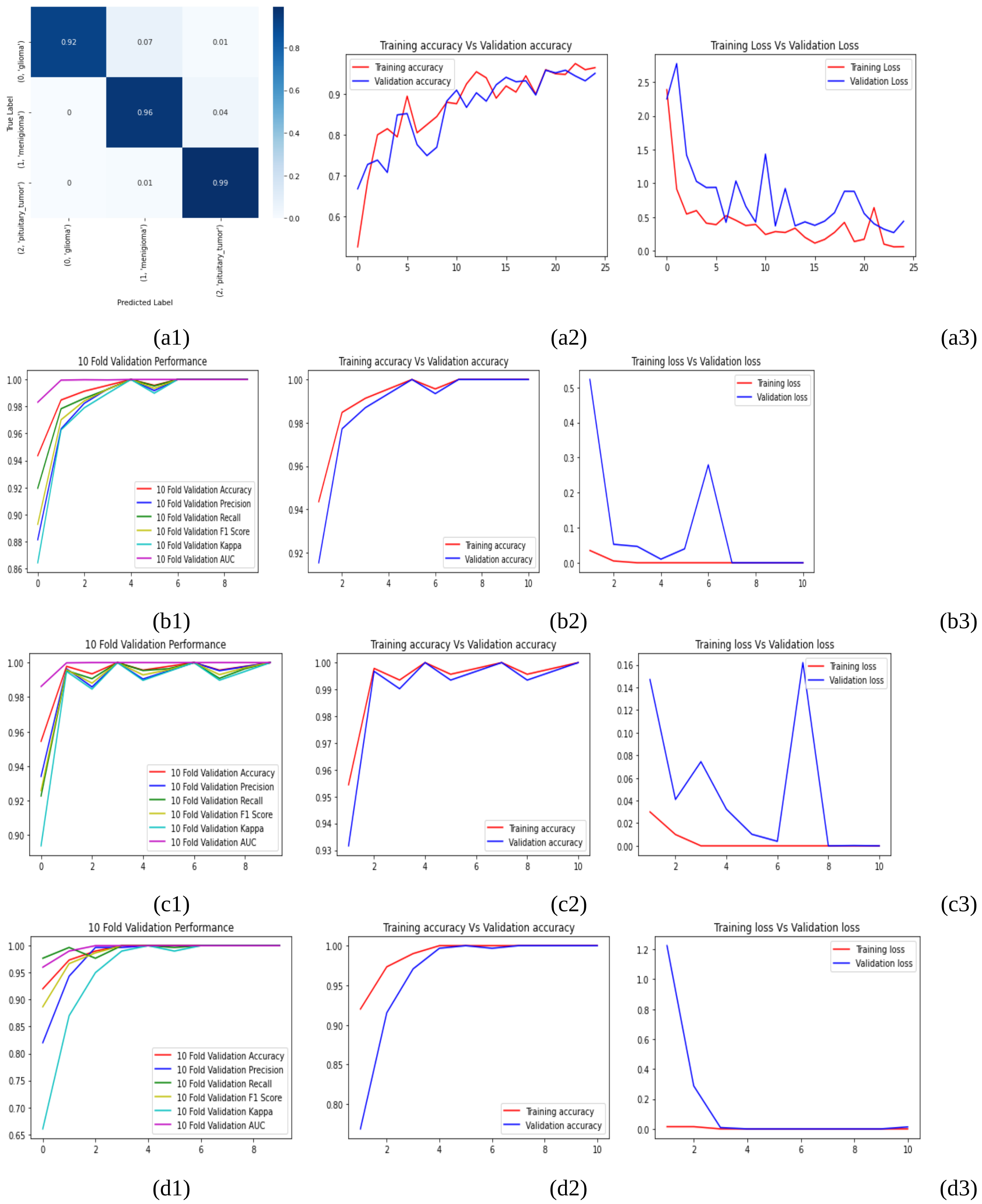

Fig 8 Performance of the Present Model based on loss history, accuracy, of the uncropped dataset, for [a1,a2,a3] Holdout-validation, 10-fold Cross Validation in B series, and Stratiifed 10-fold process in C series, and group 10-fold process in D-series

4. DISCUSSION

Table 4.Outcome Comparison of the present state-of-the-art through Figshare dataset

Existing Reference	Accuracy	Precision	Recall	F1-Score	AUC
[3]	86.56	-	-	-	-
[8]	95.03	-	-	-	-

[11]	96.13	96.06	94.43	-	-
[12]	92.16	-	-	-	-
[15]	93.68	94.60	91.43	93.00	-
Proposed (cropped dataset)	99.27	98.67	99.53	99.07	99.70
Proposed (uncropped dataset)	99.82	97.57	99.47	98.40	99.50

The comparison is made to know the significant performance for the similar dataset for classification of the brain image. The DCNN model is compared with the state-of-the-art method with the help of the past literature. For this process, only specific papers have been selected for comparison. Above table 4 indicates the comparison outcomes of the past studies along with the present proposed method. From the table's results, it is clear that the state-of-the-art method's accuracy was 96.7% and 99.8% for the 10-fold cross-validations and holdout.

6. Conclusion

While comparing the proposed DCNN model with the other model for the classification of MRI brain tumor images. The present model attained more standard than the other by means of classiifcation and pre-trained data for the inception V3. In the proposed model there is no need for separate pre-processing or segmentation required. The proposed model has an excellent execution speed of about 15 secs/per epoch. in order to know the performance efficiency, both the cropped as well as the uncropped images have been used for in 7:3 ratio with the 10-fold cross-validation at the patient level and image level. The patient-level model increased its performance in accuracy when compared to the other model. The present model has 99.8% of accuracy for classification of MRI dataset through Figshare dataset.

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