JNEST EISSN: 2961-8738 ● PISSN: 2961-8916 ● DOI: 10.56741/jnest.v3i03.567
Article Received 7 April 2024. Revised 25 May 2024.

Performance Optimization of Brain Tumor Detection and Classification Based MRI by Using Batch Normalization Algorithms in Deep Convolution Neural Network

Thein Aung Tin, Mya Mya Aye, Ei Ei Khin, Thandar Oo, Hla Myo Tun*, Devasis Pradhan

***Abstract*—Brain tumor is represented as an essential part of critical cancers around the world. These cells multiply and accumulate uncontrolled, forming a mass or lump that can interfere with normal brain function. Primer detection systems not only took too must time in analyzing and setting error, but also extended more datasets to become overfitting, more computation time, and lack accuracy. Supervised ML and traditional CNN are not convenient for estimating the vita feature engineering in larger datasets and they need to be modified using normalization techniques in deep convolutional Neural Networks (CNNs) architectures. The proposed of the research MRI image datasets were evaluated and combined with two popular benchmark data sets, Kaggle, and BRATS. This main objective is to reduce the computational cost avoid overfitting and underfitting and then improve the classification accuracy. In addition, this paper follows the concept of the CNN model and evaluates the modified DCNN with six normalization layers benefits acceptable results with batch normalization techniques and the average number of epochs in a limited time. In this regard, we exploited to extend inside the layer DCNN for the problem of brain tumor classification. This model achieved the best result for the enhanced dataset, with a training accuracy of 99.9%, 98.9% in validation accuracy, 0.0074 in training loss, and a validation loss of 0.0566 in validation loss.**

***Index Terms*—Batch normalization, Brain Tumor, Classification accuracy, DCNN, Manual detection, MRI**

I. INTRODUCTION

UNNORMAL development of cells surrounding the brain called Brain Tumor. This can be analyzed into two main classes: no tumors and different types of tumors. Two crucial types of brain tumors have been recognized, one of which is predicated on the place of the initial stage of the tumor and the other one is the development types of tumor. MRI scanning can discover the microscopic features in the body [1]. To discover brain tumors also through biopsy or diagnostic image processing is achievable. Several detection systems are used in brain tumors including CT and MRI for brain cancer diagnosis [2]. Detecting brain tumors is believed to be a complete test and is needed to transfer biopsy observation [3].

In the case of Considering the classification of brain tumor class, some researchers have applied several supervised learning algorithms. There are SVM, LR, KNN, RF, ANN, and naive classifiers. The recent evolution in image classification techniques has shown significant progress, especially the deep convolution neural networks (CNNs), which have succeeded in this area. For brain tumor condition classification, various researchers have expended pre-trained CNN architectures and well-tuned them [4]. These classification algorithms consisted of four stages, there are collected data, selected the important feature, SVM classified the type of tumor and obtained 95.62% [5]. Eventually, extracted features are fed in the SVM classification to be categorized as benign or malignant with an average 95.62% precision. The weak point of traditional learning algorithms is required to improve computational time and learning capacities in diverse datasets [6][7]. DWT is used to classify in CNN and has obtained 93.94% accuracy.

Ref. [8] proposed (VGG16 and VGG19) and extortion with CNN-SVM, 98.22% accuracy is obtained by using 3000 images in datasets. Ref. [9] proposed tuning the hyperparameters by promoting Bayesian optimization and solving with accuracy between 84.19% and 96.13% for the identical dataset. Ref. [10] applied different models, Inception, VGG16, MobileNet, and ResNet models for each model such as the design model was 98.28, 99.86% in VGG16 [11], 98.14% in ResNet50, 99.88% in InceptionV3 and 88,98% in MobileNet. Ref. [12] presented an MCNN for the classification and segmentation of the location of the tumor area. Red. [13] based on the architecture model, applied (ML) and (CNN) techniques achieve 96% precision and classification accuracy scores. Ref. [14] implemented the complex pre-trained model that clinical images (>98%) T2 (>98%), and T1C (>97%). Ref. [15] proposed that WHHO is fabricated by incorporating the HHO and WOA algorithm with an absolute accuracy of 0.816. Ref. [16] applied VGG19, such as 3D CNN (convolutional neural network) architecture, operated for searches and confirmation and scored an accuracy of 98.32, 96.97, and 92.67%, particularly using BRATS datasets 2015, 2017, and 2018. Ref. [17] proposed ML algorithms, 28% in MLP and 86% in KNN concluded that people experiencing poverty and leading accuracy rates. The next one applied autoencoder in the internal networks was 94% and 95% in 2D CNN. Ref. [18] solved deep learning algorithms with mathematical modeling by using the features and characteristics of relative models, which provided the prediction results but needed to solve a generic technique. Proposed CNN architectures are

Thein Aung Tin, Mya Mya Aye, Ei Ei Khin and **Thandar Oo** are with the Department of Electronic Engineering, Yangon Technological University, Gyogone, Insein PO, 11011, Yangon, Myanmar. **Prof. Dr. Hla Myo Tun** (Corresponding Author) is with the Department of Research, Yangon Technological University, Gyogone, Insein PO, 11011, Yangon, Myanmar. **Devasis Pradhan** is with the ECE Department of Acharya Institute of Technology, India. The corresponding author's email address is hmt.ytu@gmail.com.

© 2024 IISTR

compared with further trendy DCNN models like ResNet-50, AlexNet, Inceptionv3, GoogleNet, and VGG-16 by tuning hyperparameters to find optimized results and get a higher accuracy of 92. 66%. Ref. [11] discussed manual diagnosis detection problems and time-consuming problems, solving them with machine learning and another conventional classifier. This result achieved precision, f1 scores, and recall, 99.2%,99.2%, and 99.1%, respectively, using the VGG Stacked Classifier Network (VGG-SCNet) [19]. In the previous research are widely used machine learning algorithms such as logistic regression, SVM, KNN, DT, and novice classifier. The studied machine learning model achieved 80% in logistic,88% in Random Forest, 82%in SVM,72%in KNN, and 45% in Naïve Bayes. This model has caused some problems in medical images or instructed data, leading to poor generalization to new or unseen data, and struggling to scale to larger datasets due to computational limitations or inefficiencies. This research needed to optimize the classification accuracy in a large number of diverse datasets and apply different types of CNN models. Both MRI and CT Scans are widely used in the detection of brain tumors but MRI serves to analyze anatomical parts of the brain images, providing clinicians to visualize the spots, and features of tumors in images with high structural resolution. Currently, MRI detection techniques by using diffusion-weighted imaging (DWI), perfusion-weighted imaging (PWI), and magnetic resonance spectroscopy (MRS), can support high-resolution images for clinicians, and these raw images are also applied in diverse testing datasets. Traditional CNN can be efficient in certain tasks or simple pattern recognition. This model is suitable for structured data analysis and classification. This model can limit its ability to generalize to complex datasets and its ability to learn complex representation patterns or images. After the improvement of dataset imaging, this model occurred overfitting and underfitting between the target and prediction results. In the previous work, the different type of traditional DCNN model and architecture was applied for classification. This paper proposes the modified Deep CNN with a Batch Normalization (BN) technique to stimulate convergence and training performance. The core objective following batch normalization is to adjust the inputs of a layer well by scaling and adjusting the activations. By normalizing the inputs, BN aims to achieve a faster and more stable optimization process. This work discussed the label image reader, training the traditional CNN model, and training the proposed new DCNN model.

II. Materials and Methods

This paper presents the convolution neural network model and evaluates the existing model with normalization techniques in the six-convolution hidden layer. Firstly, instead of using human-level prediction in medical images and CNN model is more effective and accurate. Classification models are focused on sizeable public health image databases from medical images such as Kaggle. This research is divided into three stages, the first one is to study the previous work and follow up algorithm testing. The second one is to collect larger datasets and construct the optimization model based on the previous research experimental. The last stage is to collect one-year image data including various ages and genders from the local MRI Center in Defense Service Orthopedic Hospital.

A. Traditional Convolution Neural Network

Five layers can be classified in the CNN; The Convolutional Layer detects the features from the image by applying a convolution layer using the following step: Input Layers would generally be a sequence of images dataset. The initial stage considers the input data w x h x d (32, 32, and 3) and extracts the feature from the input dataset image. Depending on the input shape different styles of filters are usually applied in 2×2, 3×3, or 5×5 shapes of various dimensions. Moreover, the segmentation of input images and the linking of weight and bias by calculating with dot product. Activation Layer (ReLu) transforms the target value by passing through a convolution layer, eliminating unwanted value by using the boundary values 0 and 1. Pooling layers continuously moderate the input image, maintaining the essential features and preparing some features. It can accommodate the reduction of overfitting and the calculation of parameters in the layer. Subsequently, with numerous propagations passing through the layer, there is a traditional multilayer neural network from the complete network process. FC layers convert to collect the type of flattened image pixels from the feature extraction layer. Moreover, the softmax layer is dedicated to the outputs concerning the deep layers, providing the expectation of an individual type of image. The final layer predicts the target output by using a binary function (softmax) inside the hidden layer that translates the individual type of tumor. Analysis of the previous CNN model and evaluation of the optimization algorithms applied in the hidden convolution layer. To overcome the problem of computational limitations or inefficiencies, this research needed to optimize the classification accuracy in a large number of diverse datasets and apply different types of TCNN and DCNN models. A manual detection system can only obtain different types of images for clinicians and this research also supports demonstrating the type of tumor or not in images.

B. Proposed Deep convolutional neural networks (DCNN) Architecture

The larger DCNN can be computationally intensive to train and require significant computational resources after applying higher computational costs. For this reason, the optimization model with a suitable layer and new contribution BT within the hidden layer. Applying BT to normalize the activations process within each layer, helped to stabilize the training process, reduced overfitting, and accelerated convergence, leading to more effective DCNN. DCNN model could effectively capture the raw input data and understand the images of the underlying structure. It reduces the number of input feature parameters in the hidden network and supports learning larger datasets efficiently. This model saved computational costs and training time while achieving optimization performance.
DCNN accepted the input images dataset and applied the different features to activate a classifier. Four types of layers are classified in the architecture of a convolutional

network, such as convolution for feature extraction, pooling like max-pooling technique, activation estimate of the target value, and fully connected for flattening.

In the proposed model, we include five steps in the following. The first step is to collect brain images from the BRTS, Kaggle dataset. It contained 10287 images, including 2820 images in glioma tumors, 2720 images in meningioma tumors, 2720 images in pituitary tumors for brain tumor type images, and 2027 images without brain tumors. Secondly, the data preprocessing action involves scanning and resizing the vital parts of images. The detection of images with a variable labeled the image with individual images and estimate the size of images for DCNN. Thirdly, we created the training and testing set and then these steps generated a training set with type of tumor labels (Glioma, Meningioma, Pituitary, No tumor) images situation. It classified the MR images of the brain without or with various kinds of tumors individually. The fourth stage is to run the DCNN architecture and train the neural network. It builds with six Conv2D layers, a normalization layer, and supporting the pooling layer, and then flattens the data value after that is fully connected and the SoftMax layer is utilized. This model is evaluated using batch normalization and sparse explicit cross-entropy, and the model training is suitable in 30 epochs. In the final stage, the network will decide whether the addicted MR image includes the type of tumor or not.

The mean and the standard deviation of this hidden activation using the following equation, the mean value in the hidden layer comes from the total average summation of the batch input layer in equation (1).

$$\mu = \frac{1}{m}\sum h_i \tag{1}$$

The prediction of optimal values from the learnable parameters γ,β and batch input from the layer is shown in equation (2).

$$h_i = \gamma h_{i(norm)} + \beta \tag{2}$$

The total average value σ is estimated as the prediction and target value from the learnable parameter in equation (3).

$$\sigma = \left[\frac{1}{m}\sum\left(h_i - \mu\right)^2\right]^{\frac{1}{2}} \tag{3}$$

This traditional model was predicted to be 0.1948, 88%, 0.6263, and 71% in the last epoch's prediction, respectively, as shown in Table I.

TABLE I
PERFORMANCE ACCURACY AND LOSS IN TCNN

Learning Rate	Epochs	Batch Size	Loss	Validation Loss	Accuracy	Validation Accuracy
0.0001	5	64	0.5712	0.8780	0.7859	0.6536
0.0001	10	64	0.4871	0.8311	0.8211	0.6562
0.0001	15	64	0.4005	0.7904	0.8528	0.6901
0.0001	20	64	0.3634	0.7440	0.8717	0.6927
0.0001	25	64	0.3060	0.7234	0.8899	0.7188
0.0001	26	64	0.2948	0.7068	0.8970	0.7189
0.0001	27	64	0.2594	0.6968	0.8870	0.7189
0.0001	30	64	0.1948	0.6263	0.8770	0.7080

The updated batch input from the layer is divided by the total prediction and the total average using equation (4).

$$h_{i(norm)} = \frac{\left(h_i - \mu\right)}{\sigma + \varepsilon} \tag{4}$$

In this research work, the New DCNN model was trained using the following hyperparameter turning, such as several epochs, which tuned the best optimization accuracy and minimum loss for individual images as shown in Table II.

TABLE II
PERFORMANCE ACCURACY AND LOSS IN DCNN

Epochs	Loss	Val-Loss	Accuracy	Val-Accuracy
2	0.7076	1.4517	0.7354	0.3555
4	0.2567	0.3349	0.9005	0.8719
6	0.1736	0.1570	0.9398	0.9508
8	0.1164	0.1023	0.9599	0.9625
10	0.0732	0.1017	0.9745	0.9680
12	0.0584	0.1630	0.9808	0.9391
14	0.0355	0.0801	0.9877	0.9734
16	0.0245	0.0854	0.9931	0.9766
18	0.0244	0.0742	0.9930	0.9805
20	0.0138	0.0613	0.9965	0.9820
22	0.0103	0.0876	0.9977	0.9758
24	0.0120	0.0565	0.9972	0.9828
26	0.0097	0.0566	0.9991	0.9845
28	0.0074	0.0596	0.9981	0.9852
30	0.0102	0.0666	0.9975	0.9820

This TCNN model is constructed with six hidden layers in feature extraction and four prediction layers in the classifier as shown in Fig 1.

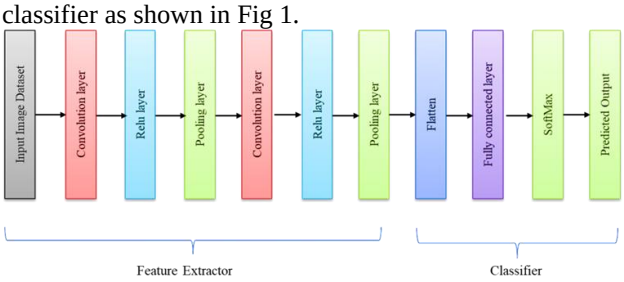


Fig.1. Constructing two layers for the Traditional Convolution Neutral Network Model

In this system, using a brain tumor image dataset, DCNN architecture and prediction results are shown in Fig 2.

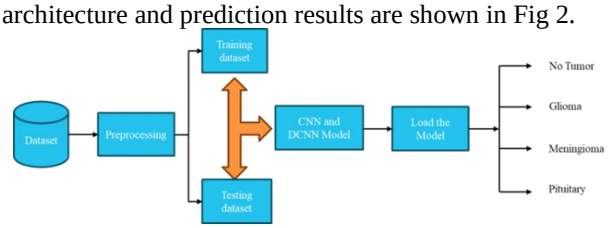


Fig. 2. General Block Diagram for Traditional and Deep Convolution Model

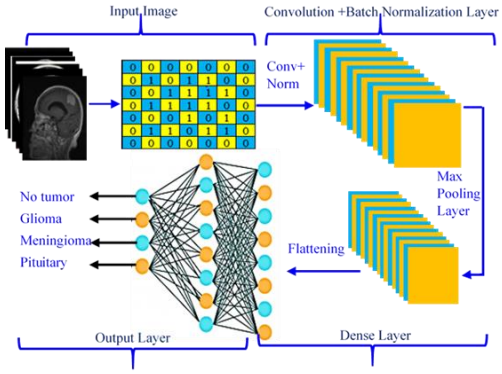


Fig. 3. Layer for Deep Convolution Neutral Network model

This research idea is constructed on the concepts of the advanced CNN model and evaluated six layers of CNN and each layer inserts the batch normalization algorithms for reducing computation cost as shown in Fig 3. The

structure of the internal hidden layer and prediction layer are illustrated in Fig 4.

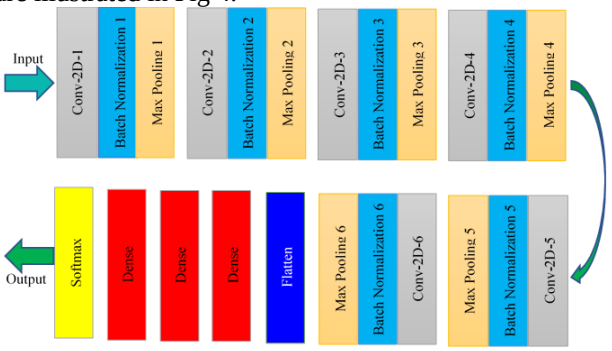


Fig. 4. System Process for Deep Convolution Neutral Network Model

III. Results and Discussions

In this experimental part, three results are demonstrated in this paper. These are linking the dataset's images from the individual datasets, training the CNN model and collecting the loss and accuracy depending on the learning rate testing the proposed new DCNN model, and estimating the prediction and target loss and accuracy depending on the number of epochs. This model applied the two combinations of Kaggle BRAT datasets and Colab Notebooks software.

A. Results Analysis of Four Types of Tumor

These results showed the linking images between the individual tumor types and relative datasets. The label name (Glioma, Meningioma, Pituitary) identified the relative of the images shown in Fig 5.

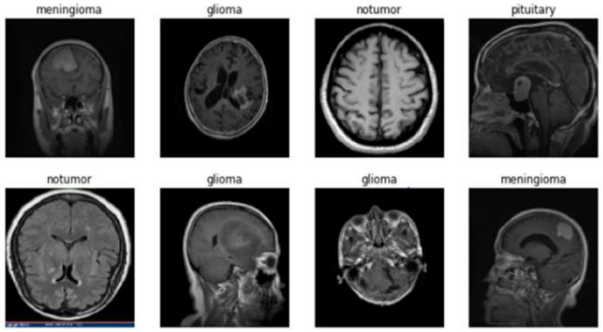


Fig. 5. Label Images for four types of brain tumors

B. Traditional Convolution Neural Network (TCNN)

The TCNN model was trained using the following hyperparameter turning, there is the learning rate, forward and backward propagation, and batch size, which tuned the parameter to obtain the optimization estimate results for individual images.

Fig 6 indicated the higher overfitting model between the training data and validation data, whereas training data was estimated to have nearly 90% accuracy, and validation data was predicted to have nearly 70% accuracy. To overcome the overfitting problem, we needed to extend the convolution layer, choose optimizer and normalization techniques, and tune the hyperparameter to get prediction results.

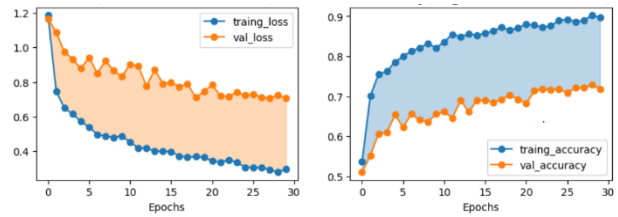


Fig. 6. Optimization Accuracy and cost using TCNN in 30 Epochs

If the model will achieve the best prediction, it is essential to receive the minimum loss. However, this CNN model showed a higher prediction loss than the estimation results.

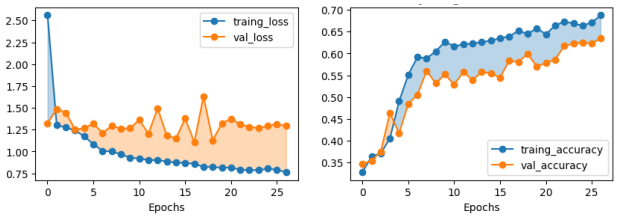


Fig. 7. Optimization Accuracy and Cost using TCNN in 25 Epochs

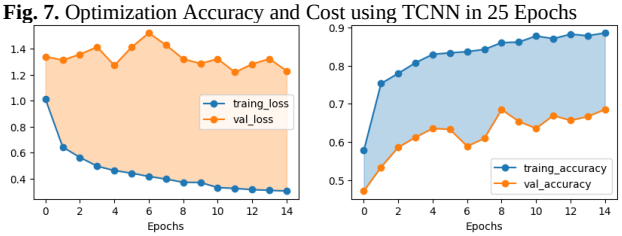


Fig. 8. Optimization Accuracy and Cost using TCNN in 14 Epochs

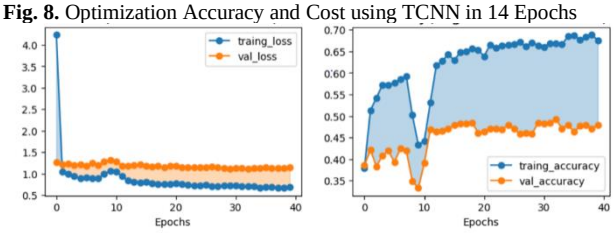


Fig. 9. Optimization Accuracy and cost using TCNN in 40 Epochs

Although the propagation time was extended for this model, the loss prediction accuracy did not change. This model obtained the minimum loss prediction of 0.1948 in training loss and 0.6263 in validation loss. This model extended the training epochs (15 to 25,40) and the prediction results compared with previous epochs (30), as shown in Fig 7,8,9.

The DCNN model predicted the best optimization performance and the lowest loss from the target prediction, as shown in Fig 10. The prediction results had nearly the same target results (99.89%) and optimization loss (0.0074).

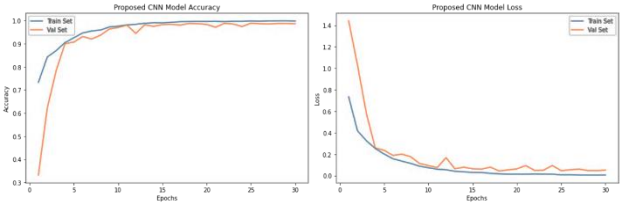


Fig.10. Optimization Accuracy and Cost using DCNN in 30 Epochs

This model extended the training epochs (15 to 25, 40) and the prediction results compared with previous epochs (30), as shown in Fig 11, 12, and 13.

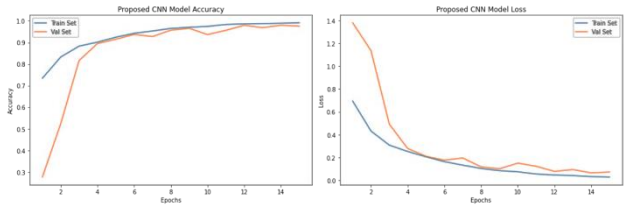


Fig.11. Optimization Accuracy and Cost using DCNN in 14 Epochs

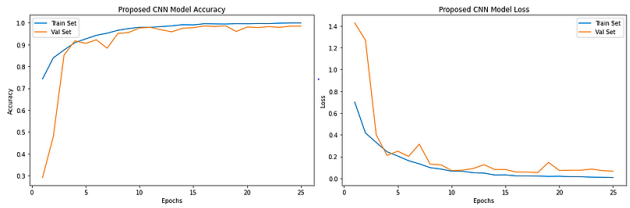


Fig.12. Optimization Accuracy and Cost using DCNN in 25 Epochs

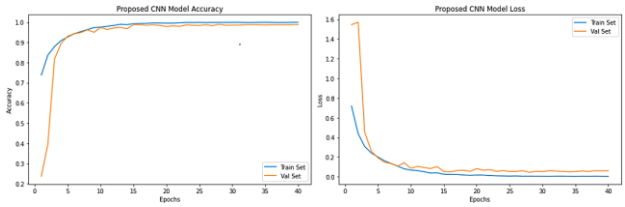


Fig.13. Optimization Accuracy and Cost using DCNN in 40 Epochs

In the previous research experiments Navie Classifier, the dataset contains 3146 MR images of the brain, including 900 images for glioma tumors, 896 images for meningioma tumors, 500 images for pituitary tumors, and 850 images without brain tumors. In the detection of 194 glioma images,164 images corrected and 30 images missed, and then 55 images for no tumor can be detected 51 corrected and 4 missed, and then 18 images for meningioma can be detected 169 images corrected and 3 images missed after that 150 images for pituitary tumor can be detected 14 images corrected and 4 images missed. This model achieved lower prediction between the target and prediction results as shown in Fig 14.

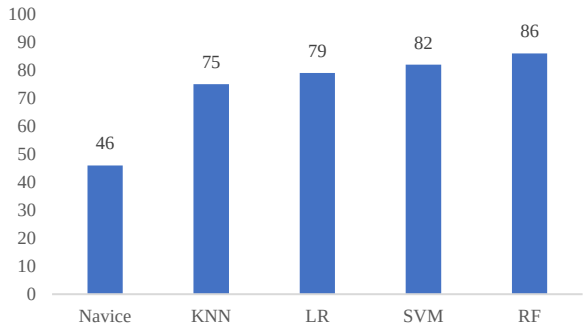


Fig.14. Performance accuracy in Machine Learning Classifier

These datasets contained 10287MR images of the brain, including 2820 images for glioma tumors, 2720 images for meningioma tumors, 2720 images for pituitary tumors, and 2027 images without brain tumors. In the detection of 157 glioma images,155 images were corrected and 2 images were missed, and then 82 no tumor images can be detected fully corrected, and then 172 images for meningioma were detected 169 images were corrected and 3 images were missed after that 150 images for pituitary tumor can be detected fully corrected. The model guided to powerful accuracy and avoided the problem of overfitting and computation loss as shown in Fig 15.

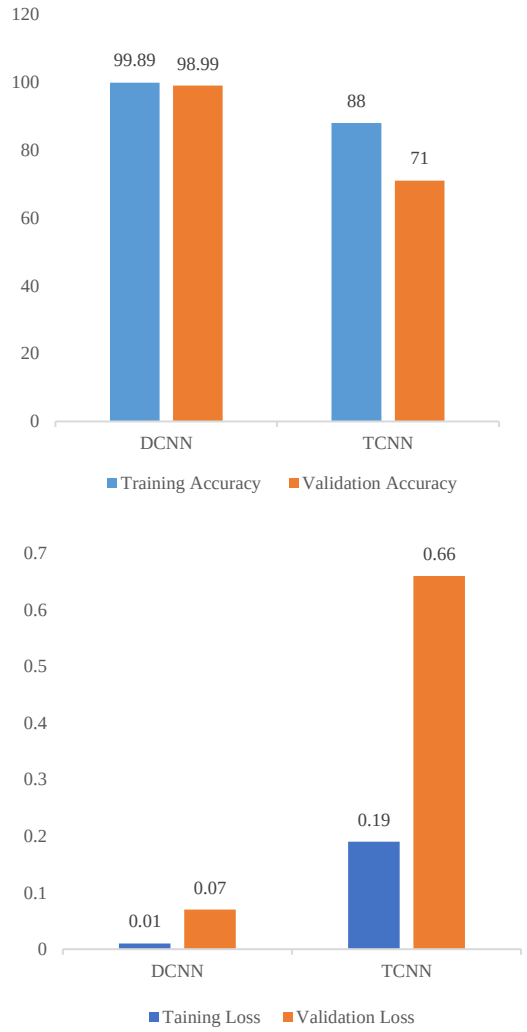


Fig.14. Performance Accuracy and loss in DCNN and TCNN

In the previous research, testing with the different types of CNN models and different types of hidden layers, and some are training with such as VGG16, VGG19, and AlexNet. And then ResNet50 and ResNet101 (>99%) obtained higher classification accuracy in ResNet50 and ResNet101 [20]. Moreover, clinical images (>98%) T2 (>98%), and T1C (>97%). [15], [14] and DWT obtained 93.94% prediction accuracy and other machine learning respectively. Based on the analysis of the previous CNN layer and learning process and follow up the custom CNN model obtained lower optimization learning and evaluated the new DCNN model to achieve higher accuracy and lower loss.

This model applied the traditional and deep convolutional neural network using different types of hidden layers and hyperparameter tuning. Analyzing the simple CNN model using fixed hyperparameters and validation accuracy did not improve (70%), and loss estimation was higher (0.6263). Implemented DCNN achieved the best accuracy in training and validation and lower loss optimization by using normalization techniques. Batch Normalization (BN) reduced the model's dependence on the initialization of weights. It allows higher learning rates without the possibility of varying over training. It reduces overfitting and can remove the essential for another regularization technique.

V. CONCLUSION

In this research, deep neural convolution network (DCNN) architecture with an optimum normalization approach is advanced and applied to observe different brain tumors from obtained MRI images automatically. This architecture involves individual blocks. This model contained six layers, there is the convolution layer, (ReLU) for boundary function, the normalization layer, the pooling layer, the Dense layer, and the SoftMax layer. Our model has achieved the best result for the enhanced dataset, with a training accuracy of 99.9%, 98.9% in validation accuracy, a training loss of 0.0074 for training loss, and 0.0566 in validation. This proposed model is better than the traditional CNN model because it is dedicated that the highest accuracy and lowest loss can be utilized to detect the ease of a tumor in the brain. We discussed with medical clinicians about the detection of MRI and the capture of brain images. Currently, the detection techniques do not include the demonstration of various types of tumors, and then they support local real images but are mentioned with patient ID. This research is based on the two online access Kaggle, and BRTS Datasets and then created larger datasets. We discussed with the medical clinician about ethical considerations and patient privacy concerns in medical diagnostics. They advised instead of using the patient name mentioned with individual patient ID. This research easy to classify various types of tumors and supports neurologists. This research prefers the improvement of medical diagnostics findings and faster support of the patient in treatment. In the future, we will construct larger training datasets from open access and local images after that test with the local images for real-time applicability effectively.

NOMENCLATURE

μ = the value of the mean and the standard deviation
h_i = predicted the optimal value
γ,β= the value from the learnable parameters
σ= estimated the prediction value
$h_{i(norm)}$= updated batch input from the layer

AUTHOR'S CONTRIBUTION

This paper contributes to the Deep Convolution Neural Network Layer modified by using the normalization techniques between the convolution and max pooling layer. After that, we evaluate the dataset images from the modified DCNN model and these results are comparable with previous research work. This paper was guided and supervised by Dr. Mya Mya Aye, and reviewed and edited by Dr. Ei Ei Khin and Dr. Thandar Oo, and supervised and validated by Dr. Hla Myo Tun.

REFERENCES

[1] Z. Zulkoffli and T. A. Shariff, "Detection of Brain Tumor and Extraction of Features in MRI Images Using K-means Clustering and Morphological Operations," 2019 IEEE Int. Conf. Autom. Control Intell. Syst. I2CACIS 2019 - Proc., no. June, pp. 1–5, 2019, doi: 10.1109/I2CACIS.2019.8825094.

[2] D. Suresha, N. Jagadisha, H. S. Shrisha, and K. S. Kaushik, "Detection of Brain Tumor Using Image Processing," Proc. 4th Int. Conf. Comput. Methodol. Commun. ICCMC 2020, no. Iccmc, pp. 844–848, 2020, doi: 10.1109/ICCMC48092.2020.ICCMC-000156.

[3] W. Wang, F. Bu, Z. Lin, and S. Zhai, "Learning Methods of Convolutional Neural Network Combined with Image Feature Extraction in Brain Tumor Detection," IEEE Access, vol. 8, pp. 152659–152668, 2020, doi: 10.1109/ACCESS.2020.3016282.

[4] D. DIvyamary, S. Gopika, S. Pradeeba, and M. Bhuvaneswari, "Brain Tumor Detection from MRI Images using Naive Classifier," 2020 6th Int. Conf. Adv. Comput. Commun. Syst. ICACCS 2020, pp. 620–622, 2020, doi: 10.1109/ICACCS48705.2020.9074213.

[5] A. El Kader Isselmou, G. Xu, and S. Zhang, "Improved methods for brain tumor detection and analysis using MR brain images," Biomed. Pharmacol. J., vol. 12, no. 4, pp. 1621–1631, 2019, doi: 10.13005/bpj/1793.

[6] R.Vinoth and Chunchu Venkatesh, "MRI images Using CNN and SVM Classification," 2018 Conf. Emerg. Devices Smart Syst., no. March, pp. 21–25, 2018.

[7] P. Sharath Chander, J. Soundarya, and R. Priyadharsini, Brain Tumour Detection, and Classification Using K-Means Clustering and SVM Classifier. Springer Singapore, 2020. doi: 10.1007/978-981-13-8323-6_5.

[8] A. S. Musallam and A. S. Sherif, "A New Convolutional Neural Network Architecture for Automatic Detection of Brain Tumors in Magnetic Resonance Imaging Images," IEEE Access, vol. 10, pp. 2775–2782, 2022, doi: 10.1109/ACCESS.2022.3140289.

[9] M. Alshayeji, J. Al-buloushi, A. Ashkanani, and S. Abed, "Enhanced brain tumor classification using an optimized multi-layered convolutional neural network architecture," 2021.

[10] H. R. Almadhoun and S. S. A. Naser, "Detection of Brain Tumor Using Deep Learning," vol. 6, no. 3, pp. 29–47, 2022.

[11] M. S. Majib, M. D. M. Rahman, T. M. S. Sazzad, N. I. Khan, and S. K. Dey, "VGG-SCNet: A VGG Net-Based Deep Learning Framework for Brain Tumor Detection on MRI Images," IEEE Access, vol. 9, pp. 116942–116952, 2021, doi: 10.1109/ACCESS.2021.3105874.

[12] T. K. Das, P. K. Roy, M. Uddin, K. Srinivasan, C. Chang, and S. Syed-Abdul, "Early Tumor Diagnosis in Brain MR Images via Deep Convolutional Neural Network Model," 2021, doi: 10.32604/cmc.2021.016698.

[13] B. Shetty, R. Fernandes, A. P. Rodrigues, and P. Vijaya, "Brain Tumor Detection using Machine Learning and Convolutional Neural Network," Int. Conf. Artif. Intell. Data Eng. AIDE 2022, vol. 13, no. 7, pp. 86–91, 2022, doi: 10.1109/AIDE57180.2022.10060254.

[14] V. Rajinikanth, A. N. J. Raj, K. P. Thanaraj, and G. R. Naik, "A customized VGG19 network with concatenation of deep and handcrafted features for brain tumor detection," Appl. Sci., vol. 10, no. 10, 2020, doi: 10.3390/app10103429.

[15] D. Rammurthy and P. K. Mahesh, "Whale Harris hawks optimization based deep learning classifier for brain tumor detection using MRI images," J. King Saud Univ. - Comput. Inf. Sci., vol. 34, no. 6, pp. 3259–3272, 2022, doi: 10.1016/j.jksuci.2020.08.006.

[16] A. Rehman, M. A. Khan, T. Saba, Z. Mehmood, U. Tariq, and N. Ayesha, "Microscopic brain tumor detection and classification using 3D CNN and feature selection architecture," Microsc. Res. Tech., vol. 84, no. 1, pp. 133–149, 2021, doi: 10.1002/jemt.23597.

[17] S. Saeedi, S. Rezayi, H. Keshavarz, and S. R. Niakan Kalhori, "MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques," BMC Med. Inform. Decis. Mak., vol. 23, no. 1, pp. 1–17, 2023, doi: 10.1186/s12911-023-02114-6.

[18] J. Amin, M. Sharif, A. Haldorai, M. Yasmin, and R. S. Nayak, "Brain tumor detection and classification using machine learning: a comprehensive survey," Complex Intell. Syst., vol. 8, no. 4, pp. 3161–3183, 2022, doi: 10.1007/s40747-021-00563-y.

[19] E. Irmak, "Multi-Classification of Brain Tumor MRI Images Using Deep Convolutional Neural Network with Fully Optimized Framework," Iran. J. Sci. Technol. - Trans. Electr. Eng., vol. 45, no. 3, pp. 1015–1036, 2021, doi: 10.1007/s40998-021-00426-9.

[20] C. Someswararao, R. S. Shankar, S. V. Appaji, and V. Gupta, "Brain Tumor Detection Model from MR Images using Convolutional Neural Network," 2020 Int. Conf. Syst. Comput. Autom. Networking, ICSCAN 2020, pp. 1–4, 2020, doi: 10.1109/ICSCAN49426.2020.9262373.



Mr. Thein Aung Tin received his B.E. (Electronics) from Technological University (Hppa-An) in 2014, and an M.E. (Electronics) Degree from Yangon Technological University in 2016, respectively. He joined Technological University (Hppa-An) as a tutor at the Department of Electronic Engineering in 2014. She is now a PhD candidate at the Department of Electronic Engineering of Yangon Technological University. (email: ecdepartment.ytu@gmail.com).



Dr. Mya Mya Aye is an Associate Professor at the Department of Electronic Engineering at Yangon Technological University. With extensive experience and expertise in her field, she plays a crucial role in educating future engineers and advancing research in electronic engineering. (email: mamyamyaaye.ytu@gmail.com).



Dr. Ei Ei Khin is a Professor at the Department of Electronic Engineering at Yangon Technological University. In addition to her teaching responsibilities, she manages the Remote Sensing and GIS Research Centre at YTU, contributing significantly to research and development in these advanced technological fields. (email: maeieikhin.ytu@gmail.com).



Ms. Thandar Oo received her B.E. (Electronics) from Technological University (Myitkyina) in 2012, her M.E. (Electronics) Degree from Mandalay Technological University (MTU) in 2015, and PhD (Biomedical Engineering) from Prince of Songkla University in 2019, respectively. She joined Yangon Technological University as a tutor at the Department of Electronic Engineering in 2021. (email: mathandaroo.ytu@gmail.com).



Dr. Hla Myo Tun is a Leading Pro-Rector for Research and Engineering Higher Education at Yangon Technological University (YTU). He specializes in professional training for Engineering Higher Education leaders, heads of departments, and faculty members. He also directs Research and Development programs and workshops and has worked as a certified Quality Assurance Evaluator of the Myanmar Engineering Council (MEngC) since 2019. (email: hmt.ytu@gmail.com).



Mr. Devasis Pradhan has worked as an Assistant Professor in Grade 1 and Dean of Research and Development at Acharya Institute of Technology, Bengaluru, Karnataka, from 2017 onwards. His current research includes the effectiveness of 5G Green Communications, mmWave antenna design, UWB antennas, and its implementation. With 16+ years of experience in the Academic and Research field, he has published 76 research papers and eight papers submitted to IEEE Access and Reputed Book and 4 Authored Books and 3 Edited Books (CRC, ISTE, Bentham Science) with a reputed publishing house. (email: devasispradhan@acharya.ac.in).