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Brain tumor classification of magnetic resonance images using a novel CNN-based medical image analysis and detection network in comparison with AlexNet

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ABSTRACT

Aim: This research work aims at developing an automatic medical image analysis and detection for accurate classification of brain tumors from a magnetic resonance imaging (MRI) dataset. We developed a new MIDNet18 CNN architecture in comparison with the AlexNet CNN architecture for classifying normal brain images from brain tumor images.

Materials and methods: The novel MIDNet18 CNN architecture comprises 14 convolutional layers, seven pooling layers, four dense layers, and one classification layer. The dataset used for this study has two classes: normal brain MR images and brain tumor MR images. This binary MRI brain dataset consists of 2918 images as the training set, 1458 images as the validation set, and 212 images as the test set. The independent sample size calculated was seven for each group, keeping GPower at 80%.

Result: From the experimental performance metrics, it could be inferred that our novel MIDNet18 achieved higher test accuracy, AUC, F1 score, precision, and recall over the AlexNet algorithm.

Conclusion: From the result, it can be concluded that MIDNet18 is significantly more accurate (independent sample t-test $P<0.05$) than AlexNet in classifying tumors from brain MRI images.

Keywords: *AlexNet, binary classification, brain tumor image, convolutional neural network, deep learning, novel medical image analysis and detection network*

INTRODUCTION

Brain tumor disease[5,11,18] is increasing day by day due to various factors. Nowadays, upon early diagnosis, the usage of modern tools and technology helps to increase the survival rate/period of brain tumor patients. Age groups between 20 and 39 years have a high percentage of survival gain. Few brain tumor categories show less survival rate in young and older age groups.[3–5,18] Poor diagnosis and classification of the tumor also decreases the survival rate. Early diagnosis and proper severity classification help to reduce the mortality rate of a large population[8] to an extent.

Artificial intelligence (AI) in machines has human-like intelligence to learn, solve, and reason any disease when presented with an enormous variety of data.[4,27] Of late, the impact of AI in diagnosis and treatment of brain tumor-related diseases has been increasing drastically. AI is used for brain tumor surgery, pediatric brain tumor imaging,[9] brain tumor segmentation,[21] and differentiating brain tumor from non-neoplastic lesions.[1] Therefore, AI has been adopted for brain tumor classification for effective treatment and early diagnosis.

Kesav and Jibukumar (2021) have used two channel, CNN and RCNN, models to classify glioma and normal brain magnetic resonance images.[13] Also, this work detected meningioma and pituitary tumors with high average confidence levels. Tandel et al. (2021) used brain tumor grading methods with deep learning and machine learning techniques.[23] This work also compared the same with five different CNN models. Özcan et al. (2021) introduced customized CNN for grading the degree of malignancy in brain tumor.[20] Clinical cases and augmented dataset were used for training the data. The work was effective and robust in classification of low-grade and high-grade gliomas. Khan et al. (2021)[14] performed brain tumor segmentation using the K-means clustering algorithm and classification of MR images using the VGG19 CNN model. Khan et al. (2021)[14] and Kang et al. (2021)[12] applied transfer learning-based deep CNN to extract features from brain MR images. A support vector machine with radial basis function outperforms the CNN model. Ismael (2018)[10] designed a CADD system to classify abnormal growth in brain images. A set of features are obtained from discrete wavelet transform and Gabor filter method. Stacked sparse autoencoder and softmax classifier is used for identifying three brain tumors. Ismael (2018)[10] and Lotlikar et al. (2021)[21] presented a review work that presents preprocessing techniques, deep learning techniques and machine learning algorithms used by researchers with challenges encountered in performing analysis.

MATERIALS AND METHODS

The study was conducted in the AI research laboratory in Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences. The dataset was downloaded from Kaggle (“Kaggle: Your Machine Learning and Data Science Community” n.d.). Since it was downloaded from the public database, no ethical clearance was necessary. There are two groups involved in this study. Based on,[21] the sample size calculated for the study was 14 with parameters Alpha 0.05, beta 0.2, and g-power 0.8 (Figure 1).

The dataset consists of 2918 images belonging to two classes (presence of tumor and normal brain MRI) under the training folder. The validation folder consists of 1458 augmented images belonging to both classes. Further, 212 separate images belonging to both classes were kept in the test folder, which was duly marked by medical experts from the Saveetha Medical College and Hospital. This study was performed on a novel medical image analysis and detection network (MIDNet18) CNN architecture, and its results were compared with AlexNet architecture.

Hardware and Software

The study was conducted on a MacBook Air with an Apple M1 chip and 8 GB memory. All of

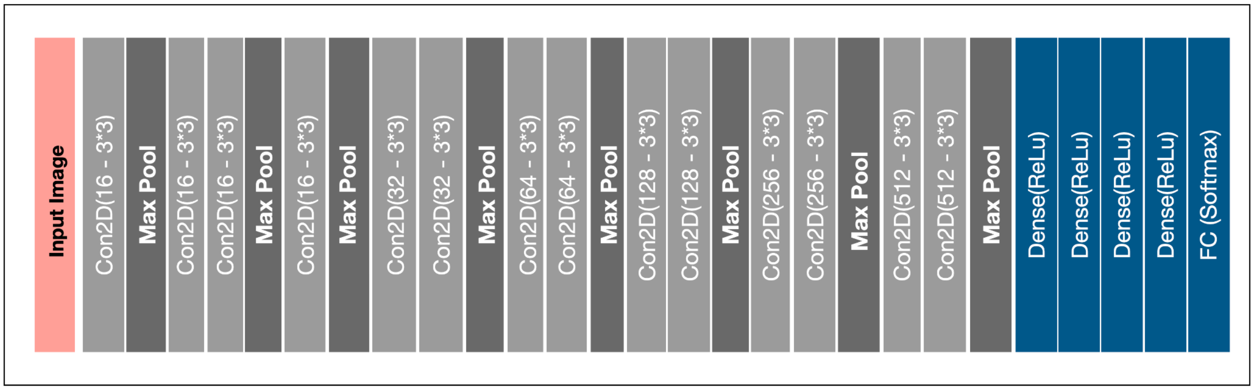

FIGURE 1. Proposed MIDNet18 architecture.

the CNN models were run in Google Colab, which provides a single 12 GB NVIDIA Tesla K80 GPU. All analyses are conducted using SPSS software.[15] Independent variables in this study are the input variables (brain tumor and nontumor MRI images. The dependent variables are output variables (accuracy, precision, recall, F1 score). Independent t-test is performed to compare the performance of algorithms.

Figure 1 shows the architecture of our proposed MIDNet18 model. The MIDNet18 model consists of 14 convolutional layers with a 3×3 kernel size. The ReLu activation function was used in all of the layers. These convolutional layers provide a feature map from the image. The input size of the image is maintained as 224×224. The model consists of seven max pooling layers with a pooling size of 2×2. Max pooling[19] in the MIDNet18 CNN model helps in highlighting the brighter pixels.[7] Batch normalization is performed in the MIDNet18 model, which helps in avoiding the overfitting of the model. In simple terms, batch normalization helps each layer to learn more independently. Four Dense layers with

AlexNet

The first convolutional network using GPU to boost performance was AlexNet. It consists of five convolutional layers, three max pooling layers, two normalization layers, two fully connected layers, and one softmax layer. The convolutional layers contain two convolutional filters and a ReLu activation function. The input size is generally 224×224×3, but due to the occurrence of padding, it is actually 227×227×3.

MIDNet18 algorithm

Begin
Step 1: Dataset consisting of normal and brain tumor images of size 224×224 is uploaded to the MIDNet18 model as input. Total data is split as training dataset for learning the images, validation dataset to validate the trained brain images, and test dataset which is data that is not learned by the model.
Step 2: The MIDNet18 input layer consisting of the training dataset is given to the convolutional layer of the CNN model.
Step 3: Fourteen convolutional layers are implemented in the MIDNet18 model. Each convolution layer is convoluted with a kernel size of 3×3 with one stride. Default padding is used in each layer. The convolutional layer uses ReLu activation function in order to obtain feature maps.
Step 4: Batch normalization is carried out for each convolutional layer in order to range the value between 0 and 1.
Step 5: The output after convolution is given to max pooling for selecting the best or the max value.
Step 6: Max pooling of all 14 convolutional layers gives feature maps as input to the dense layer.

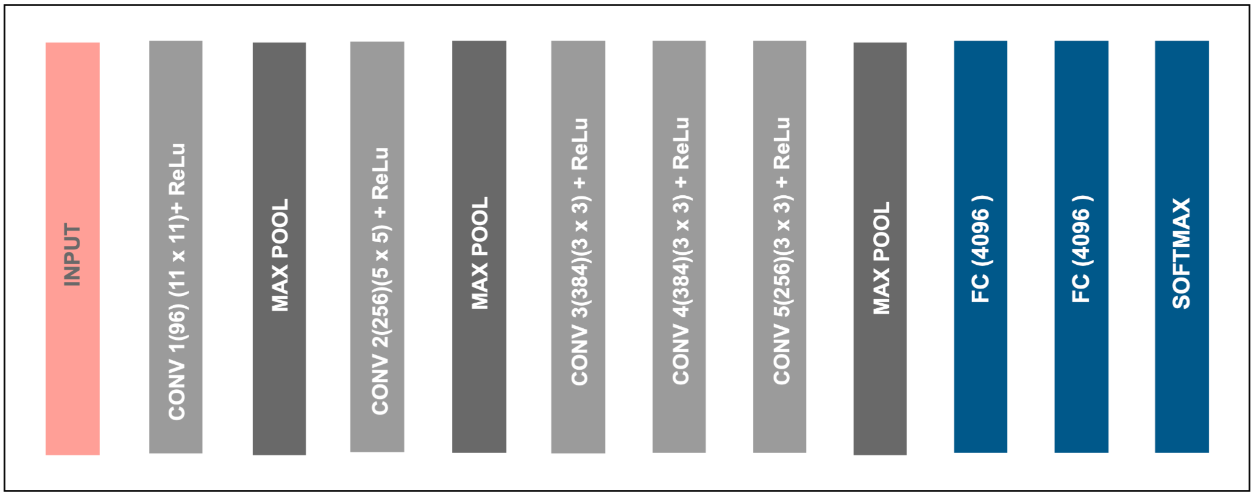

FIGURE 2. AlexNet architecture.

Step 7: The dense layer has three hidden layers and one output layer. The hidden layers in a fully connected network learn the brain images by updating the weights in 100 iterations.
Step 8: The output layer classifies the trained data as a normal or tumor brain image.
Step 9: The process is validated and tested with validation and test dataset for understanding the model performance.
End

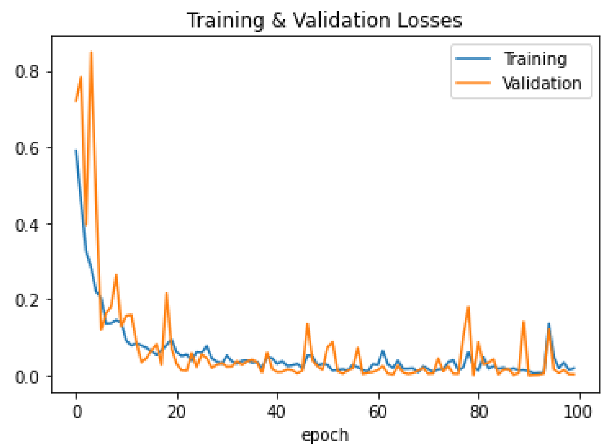

FIGURE 3. Representation of the training loss and validation loss performance of MIDNet18 in different iterations.

RESULTS

The training and validation loss of MIDNet18 is represented in Figure 3. It could be inferred from the figure that the loss was as high as 90% before the 15th iteration. But as the iteration increases, the learning capacity of the model with its weight updation algorithm reduces the loss parameter. This reduction in the training and the validation was maintained until the 100^{th} epoch.

Figure 4 represents the training and the validation loss of AlexNet. It is observed that the initial training loss in AlexNet was more than 70% and the validation loss was 60%. Around the 10th iteration, it could be noticed that there was a steep fall in the loss reaching around 15%. With the increase in the number of iterations, the loss percentage of both the training and validation was below 10% and was maintained till the 100th iteration.

Training and validation accuracy performance of MIDNet18 is represented in Figure 5. It can be observed that initially the training and validation accuracy of MIDNet18 was as low as 50% and 70%, respectively. But the training accuracy increased to 90% around the third or fourth iteration, and from the graph, it can be noticed that the training

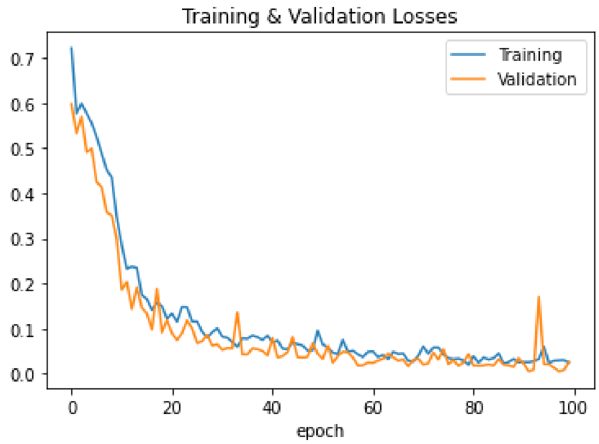

FIGURE 4. Representation of the training loss and validation loss performance of AlexNet in different iterations.

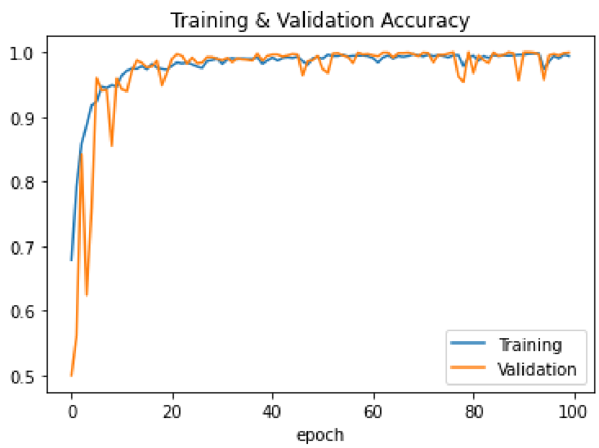

FIGURE 5. Representation of the training and validation accuracy performance of MIDNet18 in different iterations.

accuracy was maintained at around 99% until the 100th iteration. With respect to the validation accuracy, until 20 iterations, the accuracy shifted from 85% to 65% and then again increased to 96%, followed by a slight slip to around 88%. But from the 20th iteration, the accuracy of the validation dataset was maintained at around 99 for the remaining epochs.

From Figure 6, it can be inferred that the training accuracy of AlexNet was 70% initially, which

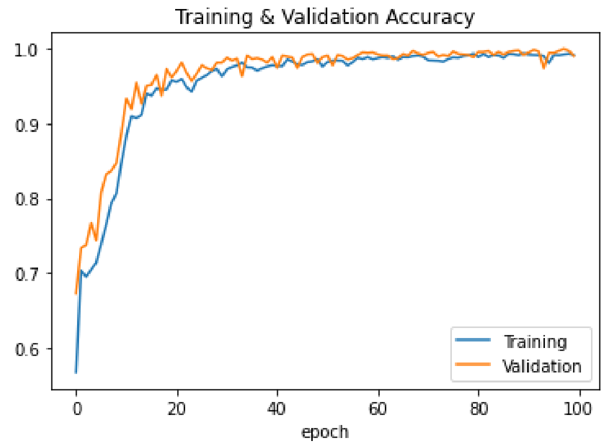

FIGURE 6. Representation of the training and validation accuracy performance of AlexNet in different iterations.

gradually increased to more than 90% at around the 18th iteration. AlexNet maintained the training accuracy of more than 98% for the remaining 82 epochs. The same pattern could also be seen for the validation accuracy, which also started with as low as 70% accuracy. But around the 20th iteration, it spiked above 90% and thereafter gradually built up the accuracy to more than 90%.

It can be observed from Figure 7, that the training AUC in MIDNet18 reaches 99% around the 5th iteration and remains constant throughout the entire iterations. Similarly, the validation AUC of MIDNet18 also increased after the 5th iteration, but there was a sudden drop in AUC around the 50th iteration, which was regained immediately to 99% in the following epoch due to the MIDNet architecture's resilient nature. For the rest of the epochs, the 99% AUC was maintained by the novel MIDNet model.

The training and validation AUC of AlexNet are represented in Figure 8. From the figure, it can be noticed that training and validation AUC of AlexNet started around 75% and 80%, respectively. As the number of epochs increased, both the training and validation AUC went up to around 97.5% and was maintained for the remainder of the 100 epochs.

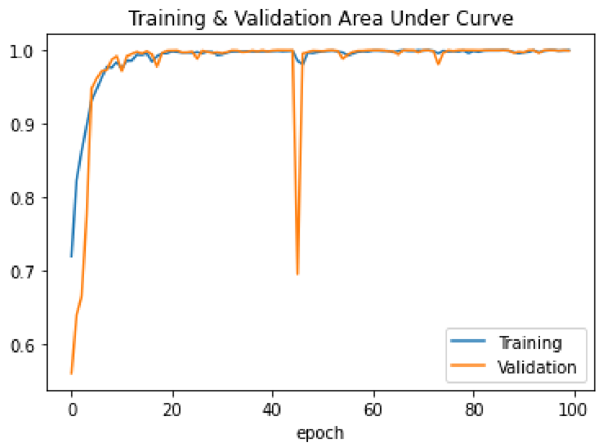

FIGURE 7. Training and validation area under curve (AUC) of the MIDNet18 model.

FIGURE 9. Training and validation: F1 score of the MIDNet18 model.

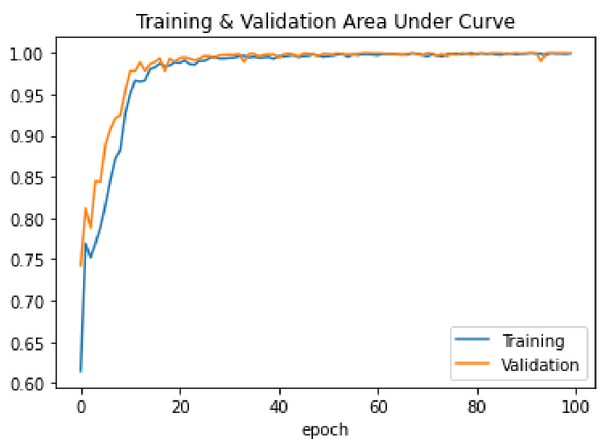

FIGURE 8. Training and validation AUC (area under curve) of the AlexNet model.

FIGURE 10. Training and validation F1 score of AlexNet.

Figure 9 represents the training and validation F1 score of the MIDNet18 model. From the figure, it can be inferred from the training and validation dataset that the F1 score reaches as high as 100% in the first few iterations itself. But around the 50th iteration, both the training and the validation F1 score became as low as 20% and 70%, respectively, which could also be noticed in the drop of AUC (Figure 7) around the same iteration. This sudden decrease was overcome by the model very shortly, and it regained close to 100%, maintaining it for the rest of the iterations. The training and validation F1_score of AlexNet (Figure 10) shows that the model reaches as high as 94.25% during the 20th iteration and maintains it stably thereafter till the last iteration.

The training and precision of MIDNet18 are represented in Figure 11. It can be inferred that the precision of MIDNet18 for training and validation dataset reached nearly 99% during the first few iterations. The precision of the validation dataset alone dropped at around the 50th iteration, but due to the batch normalization and learning rates of MIDNet18, the model was able to perform the weight adjustment appropriately, which not only helped in regaining the percentage back to 99% but also in maintaining it until the 100th iteration. This was well reflected in the test dataset where the MIDNet model achieved the precision score of 98.78% (Table 1) when compared with that of AlexNet model's 93.90%. It can be observed from Figure 12 that for both the training and validation, the AlexNet model established the precision score close to 100%, which remained constant with an increase in the number of iterations. But the model was able to achieve the precision score of 93.90% (Table 1) for the test dataset.

Figure 13 represents the recall of the MIDNet18 CNN model. It could be inferred from the figure that the recall of the model is similar to the precision. The MIDNet model maintained around 99% for the training and validation. During validation, the recall in MIDNet18 showed a sudden decrease around the 50th iteration but increased to 98% shortly after that. The model achieved a test recall of 98.78%, which was 5% higher than that of the AlexNet model (Table 1).

A comparison of MIDNet18 and AlexNet for all the performance metrics is given in Table 1. The proposed MIDNet18 model achieves a higher testing accuracy of 98.78% in comparison with AlexNet's testing accuracy of 93.90%. In comparison with the loss performance metrics, MIDNet18 achieved a low testing loss of 2.01 when compared with AlexNet's testing loss of 50.34%. Similarly, the area under curve (AUC) for AlexNet is 95.41%,

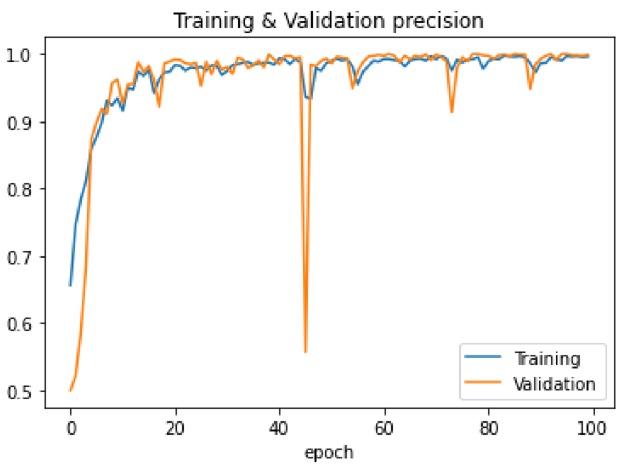

FIGURE 11. Training and validation: precision of MIDNet18.

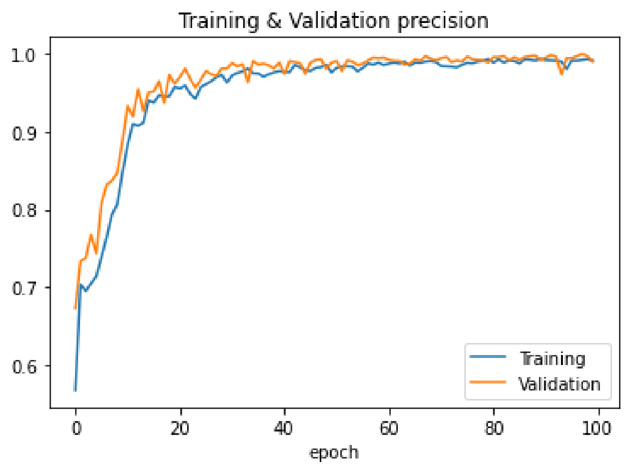

FIGURE 12. Training and validation precision performance metric of AlexNet.

TABLE 1. Comparison of MIDNet18 and AlexNet CNN on Various Metrics, Namely, Training Accuracy, Testing Accuracy, Training Loss, Testing Loss, AUC, F1 Score, Precision, and Recall Value, for Classification of Tumor from Brain MRI Images.

Architectures	Training Acc (%)	Testing Acc (%)	Testing Loss (%)	AUC (%)	F1 Score (%)	Precision (%)	Recall (%)
Our Novel MIDNet-18	99.42	98.78	02.01	99.98	98.79	98.78	98.78
AlexNet	99.07	93.90	50.34	95.41	94.25	93.90	93.90

FIGURE 13. Training and validation recall of MIDNet18.

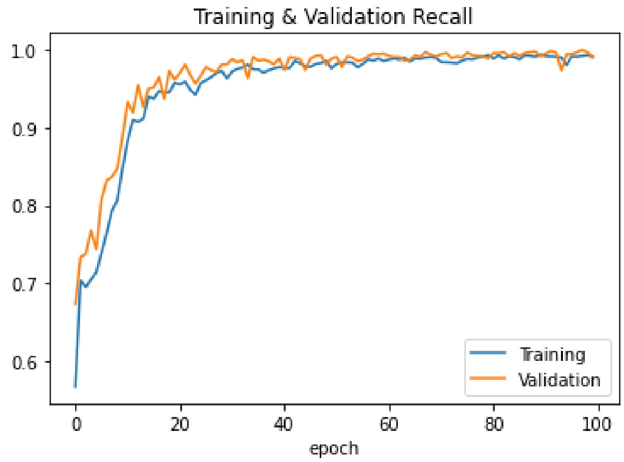

FIGURE 14. Training and validation recall performance metrics of AlexNet.

which is 4.57% lower than that of the MIDNet18 model. MIDNet18 achieved the F1 score of 98.79% in comparison with AlexNet, which displayed only 94.25%. MIDNet18 achieved higher precision and recall with a difference of 5% when compared with AlexNet. All of the performance metrics indicate that the accuracy of the MIDNet18 CNN model is better in classifying brain tumor images from the brain MRI dataset compared to the AlexNet model.

The training and the validation recall of AlexNet (Figure 14) indicate that the model maintained around 98% throughout the iterations. It could be inferred from Table 1 that the model achieved a recall of 93.90% for the test dataset (Table 1), which was lesser than that of the MIDNet18 model.

The bar chart (Figure 15) compares the mean accuracy of AlexNet and MIDNet convolutional neural network models for classifying tumor lesions from the brain MRI dataset.

We observe that MIDNet18 is significantly more accurate than AlexNet in classifying the tumors from brain MRI images, which can also be observed from the statistical test conducted (independent sample t-test $P<0.05$) indicating that the MIDNet18 model prediction accuracy is statistically significant, as shown in Tables 2 and 3.

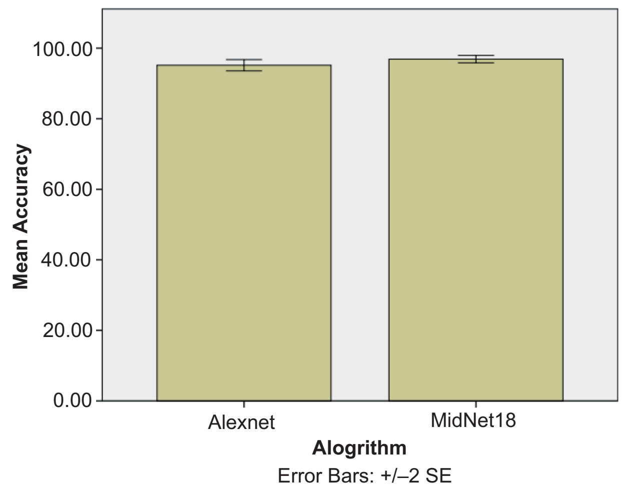

FIGURE 15. Bar chart comparing the mean accuracy of AlexNet and MIDNet convolutional neural network models shows that MIDNet18 is significantly more accurate than AlexNet in classifying tumors from the brain MRI images.

DISCUSSION

Liu et al. (2022)[16] distinguished benign inverted papilloma tumors using a three-dimensional CNN model. All-Net achieved accuracy of 77.9% and sensitivity and specificity of 66.7% and 81.5%, respectively. Wang et al. (2021)[26] identified nodal

TABLE 2. Comparison of the Accuracy of MIDNet versus AlexNet Algorithms in Detecting Cancer Lesions in Brain MRI Images (Independent Sample *t*-Test $P < 0.05$).

Independent Sample Test										
		Levene's Test For Equality of Variances		t-Test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Accuracy	Equal variances assumed	6.283	.013	–1.823	198	.070	–1.73310	.95087	–3.60824	.14204
	Equal variances not assumed			–1.823	172.345	.070	–1.73310	.95087	–3.60996	.14376

MIDNet18 superior accuracy in prediction over AlexNet is statistically significant.

TABLE 3. Statistical Comparison of AlexNet and MIDNet18.

Group statistics					
Algorithm		*N*	**Mean**	**Std. Deviation**	**Std. Error Mean**
Accuracy	AlexNet	100	95.1532	7.91519	.79152
	MidNet18	100	96.8863	5.26932	.52693

MIDNet18 Gives the Highest Mean Accuracy of 96.88% over AlexNet.

metastasis stage for lung cancer prediction using a multi-energy-level fusion model with principal feature enhancement. This fusion model achieved an accuracy of 93% and the kappa value of 86%. Arshad et al. (2021) performed skin cancer classification using ResNet-50 and ResNet-101. The standard models used achieved an accuracy of 91.7%. Gab Allah, Sarhan, and Elshennawy (2021) performed classification of brain tumors using VGG19 coupled with classifiers. This framework gave an accuracy of 98.54% with high computational time. Tazin et al. (2021) identified brain tumor with X-ray images using CNN and transfer learning techniques and achieved an accuracy of 92% in MobileNetV2, 91% in inceptionV3, and 88% in VGG19. Saba et al. (2021) used a DenseNet201-based CNN model for breast tumor diagnosis and obtained an accuracy of 92.8%. Saba et al. (2021)[22] and Wang et al. (2021)[25] used the ResNet34 model for classification of benign and nonbenign tumors. The overall accuracy obtained using this model was 75%. In observing these works carried out by other researchers, the proposed MIDNet18 model achieved a good accuracy of 98.5% in classification of brain tumors. Therefore, MIDNet18 performed significantly better than the AlexNet model and the other standard models that were discussed.

CONCLUSION

Our proposed MIDNet18 model outperformed the AlexNet model in brain tumor medical image classification of tumor and nontumor images. Our MIDNet18 model learned well and provided a high accuracy of more than 98% in binary classification, which is statistically significant (independent sample t-test $P<0.05$). MIDNet18 proves to be a high performer in all performance metrics with respect to the given dataset that was considered for this study.

CONFLICT OF INTERESTS

The authors have no conflicts of interest in this manuscript.

AUTHOR CONTRIBUTIONS

Ramya Mohan was involved in novel MIDNet18 CNN architecture development, implementation, data collection, analysis and interpretation of data, and manuscript writing. Kirupa Ganapathy was involved in conceptualization, manuscript writing, document editing and critical review of manuscripts, and interpretation of the results. Rama A was involved in data collection, data analysis, and data validation.

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