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DeepNeuroNet: A Novel Multiclass Model to classify Brain Tumors and Neurodegenerative Diseases using Machine Learning

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Abstract— **One of the most important applications of machine learning is the use of deep learning models in medical diagnosis and treatment. This application is particularly valuable in the early diagnosis of brain tumors and neurodegenerative diseases because earlier intervention leads to better prognosis and prevention of more fatal conditions. Among the most widely affected brain disorders are brain tumors, Alzheimer's disease (AD), and Mild Cognitive Impairment (MCI). These diseases have a high incidence of 11.3% and a high mortality rate of 40% [6]. Therefore, this study aimed to help with the early diagnosis of these diseases through the development of a new multiclass convolutional neural network (CNN) model to classify glioma tumors, meningioma tumors, pituitary tumors, AD, and MCI from normal patients with an overall accuracy of 88.33%. DeepNeuroNet was the first model that used brain MRIs to classify both brain tumors and neurodegenerative diseases. This model would have many applications including brain tumor detection and possible treatment research in clinical settings and the potential to be used for the early diagnosis of brain diseases.**

I. INTRODUCTION

Each year, millions of people worldwide are diagnosed with brain tumors, Alzheimer's disease (AD), and Mild Cognitive Impairment (MCI) [6]. These diseases can cause gradually worsening motor and cognitive functioning capabilities in patients and can ultimately result in death. Doctors and radiologists seek early diagnosis of these diseases in order to treat patients with the medications while the disease is still in mild stages to slow down progression. Before deep learning models, classical imaging techniques had limited accuracy and capabilities to classify multiple diseases. Furthermore, the previous techniques had longer runtimes and were often misdiagnosed at a higher rate. With the advances in machine learning, healthcare practitioners can now use deep learning models to fasten the diagnosis of these brain diseases. The advantage of deep learning models over traditional methods is that deep learning models are more accurate, faster, cost-efficient, and easier to implement in diagnosing diseases. This enables deep learning models to be able to detect even subtle brain abnormalities in MRI images faster and more accurately increasing the likelihood of early diagnosis.

Recently, there have been new models developed to help with the early diagnosis of brain tumors. For instance, Irmak proposed a new multiclass model that classified brain tumors by location in the brain and the specific neural cell affected. The study focused on diagnosing glioma, meningioma, pituitary, and metastatic tumors from healthy patients with a very high accuracy of 92.66% [2]. The study also showed that the new convolutional neural network (CNN) model had a higher accuracy in classifying the tumors than VGG16 or ResNet. Another study by Marghalani and Arif developed a 3-class model that classified AD, brain tumors, and healthy normal patients (unaffected by any neurological disorder) with an average accuracy of 97% [4]. There have also been developments in differentiating between AD and MCI from normal patients. Basaia et.al developed a deep learning algorithm that achieved a 75.4% accuracy for AD versus cMCI classification [5].

Even though there have been multiclass models that classify brain tumors as well as neurodegenerative diseases, there was no model that combined the two models into a 6-class model with a high accuracy, which would be highly useful in clinical diagnosis because of a wider range of disease classes.

Therefore, the purpose of this study was to create a 6-class CNN model which could detect glioma tumor, meningioma tumor, pituitary tumor, AD, and MCI. This would be the first such model to combine the classification of the different types of brain tumors as well as two of the most common neurodegenerative diseases. This model would have great potential in the early diagnosis of patients.

II. METHODS

The images for the brain tumors and normal patient MRIs were collected from the Kaggle database [1] and the images for the AD and MCI images were taken from the Alzheimer's Disease Neuroimaging Initiative (ADNI) [3]. In total, 200 images were collected for each disease and split into training (60%), validation (30%), and test subsets (10%). The number of images by disease class is shown below in table 1.

TABLE 1: NUMBER OF MRI IMAGES BY DISEASE CLASS

Data Folder	Disease Class					
	AD	*MCI*	*Glioma*	*Pituitary*	*Normal*	*Meningioma*
Training	120	120	120	120	120	120
Validation	60	60	60	60	60	60
Test	20	20	20	20	20	20

The images were scaled and normalized to improve accuracy. Data augmentation was applied to all the images including sharing, zooming, and flipping them. The images were trained in the DeepNeuroNet model for 20 epochs with the Adam optimizer and the categorical cross entropy loss. The DeepNeuroNet model consisted of 12 layers including convolutional layers, max-pooling layers, dropout layers, and batch normalization layers followed by a flatten and a dense layer. The total number of parameters was 346,374.

III. RESULTS

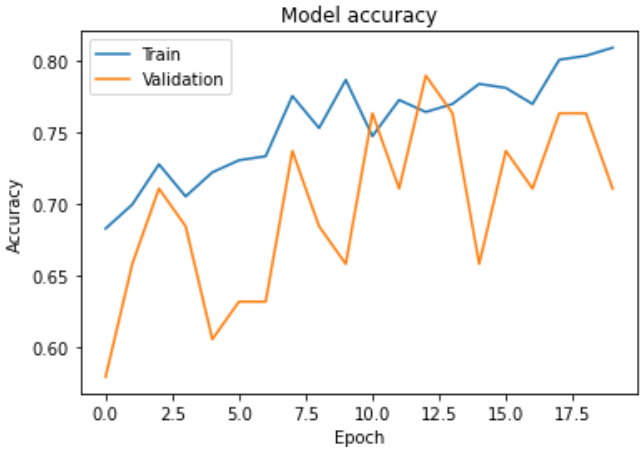

Figure 1: Model Accuracy for Training and Validation

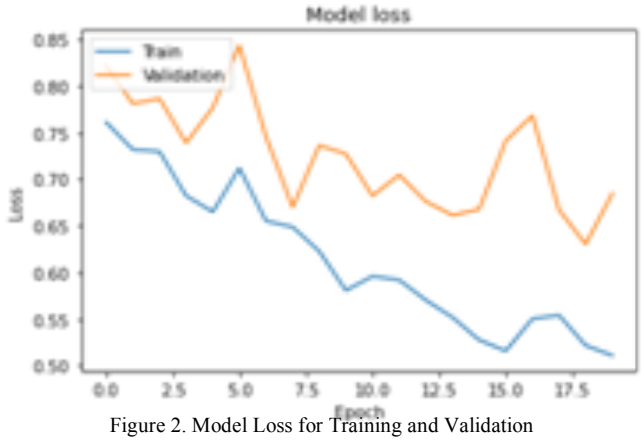

Figure 2. Model Loss for Training and Validation

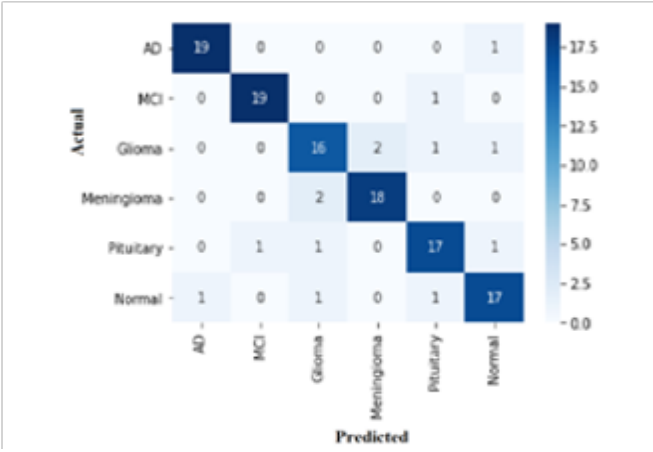

Figure 3. Confusion Matrix for DeepNeuroNet

After running the DeepNeuroNet model for 20 epochs, the model accuracy and loss graphs were generated as shown in Figure 1 and Figure 2 respectively . Then, the training set was run on the model. The model correctly classified 106 images from the original 120 MRI images as shown in Figure 3. Thus, the overall test accuracy was 88.33%, a relatively high accuracy for a 6-class model [4].

The classification report on the precision, recall, support, and f1-scores of each of the 6 classes was also generated (Table I) . The model recognized AD and MCI the best with a 95% precision for both classes. This could be a result of the more prevalent features of AD and MCI compared to the 3 classes of tumors which were hard to distinguish from each other.

	Precision	***Recall***	***F1-Score***	***Support***
AD	95.00%	95.00%	95.00%	20
MCI	95.00%	95.00%	95.00%	20
Glioma	80.00%	80.00%	80.00%	20
Meningioma	90.00%	90.00%	90.00%	20
Pituitary	85.00%	85.00%	85.00%	20
Normal	85.00%	85.00%	85.00%	20

Figure 3: Confusion Matrix for DeepNeuroNet

Overall, the model performed well and achieved high training and testing accuracy with fewer parameters than many other studies meaning that the model was quicker and more efficient in classifying more diseases. Although there have been many multiclass models for brain diseases like a 4-class model developed by Singh et.al [6], the DeepNeuroNet model proposed in this study was the first model to conduct a 6-class diagnosis of neurological disorders with such a high accuracy.

IV. CONCLUSION

The DeepNeuroNet model was proposed and shown to achieve a high accuracy in classifying glioma tumors, meningioma tumors, pituitary tumors, AD, and MCI from normal patients making it the first model to use a novel CNN architecture to achieve a 6-class diagnosis. This model has the potential to help with the early diagnosis of brain tumors and neurodegenerative diseases and therefore, save millions of lives worldwide. Further studies could enhance this model by adding more classes of diseases including PSP, MSA, and CBD as well as using non imaging data like gene expression to help the model be able to classify at a higher accuracy through a wider range of data.

V. REFERENCES

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