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IMPROVED BRAIN PATHOLOGY CLASSIFICATION USING A HYBRID DEEP LEARNING ALGORITHM: A NOVEL APPROACH

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ABSTRACT: The most significant obstacle to treatment in neurology is early tumor diagnosis. Because brain tumors are so frequent, there is a lot of research into ways to spot cancer early. Automating and diagnosing using traditional image processing methods is difficult. Radiologists and doctors now have a new tool at their disposal to help diagnose brain tumors more quickly and with more confidence. This technique makes use of CNNs. Research and synthesis are aided in distinguishing benign from malignant occurrences by the increased feature maps generated by the proposed deep learning architecture. Two DNNs are combined in the suggested H-DNN design. Two methods have been developed based on information extracted from magnetic resonance imaging (MRI) scans; one uses spatial texture data from cranial images, and the other uses frequency domain data. In the end, we combine the two neural networks to make prediction score-based classification even better. In contrast to DNN-1, which makes use of Local Binary Patterns for training, DNN-2 makes use of frequencies from Wavelet Transformation. Both the Real MRI dataset and the BraTS T2-weighted MRI dataset were used to test the proposed model. The model used in this investigation achieved the best classification accuracy, at 98.7 percent, according to related work. The reported model fared better than both the DNN-1 and DNN-2 designs when comparing the accuracy, sensitivity, and specificity of the proposed technique.
Index terms: Brain Pathology Classification, Neural Networks, Brain Imaging, Hybrid Deep Learning.

1. INTRODUCTION

The brain is the most intricate and important part of the body since it contains the central nervous system. When cells proliferate at an abnormal rate and cluster together, a tumor forms in any number of organs or tissues. These abnormal cells have the potential to harm normal cells while also upsetting biological systems. The crucial brain is at danger from this new development. It is possible to die from a brain tumor. Most brain tumors are either benign or cancerous.

Because they don't metastasize and impact just a localized area of the brain, benign tumors are more easily detected. But cancerous tumors grow quickly and pose a threat. Brain cancers develop when cells in the brain proliferate. Metastases, also known as secondary tumors, form when abnormal cells proliferate and disperse. Eliminating early brain development is easy. In order to discover brain growth, various methods were employed. To identify cancer at an early stage, MRI is employed in this research.

This method determines the type of cancer. When it comes to assessing brain normality, MRI has completely changed the game. The progression and kind of cancer in a particular area of the brain determine its severity. It is critical to use an automated tumor detection technology to help doctors find brain cancer early on. Automated methods for classifying MRI pictures to detect cancers might be explored by researchers. It is necessary to develop a model to manage brain MRI scans due to the difficulty of regulating such pictures. The deep learning model based on convolutional neural networks is a novel paradigm in machine learning; it uses simple nodes and has unclear connections. The fields of biology, networking, big data, and medical image processing all make use of this cutting-edge technique.

2. LITERATURE SURVEY

Li, X., Zhang, Y., & Li, Z. (2024). In order to classify brain illnesses using magnetic resonance imaging (MRI), this research introduces a hybrid deep learning architecture. For the purpose of extracting temporal and spatial characteristics from images of the brain, this technique employs CNNs and LSTM. An effective hybrid model for abnormality classification in the brain can be achieved by combining convolutional neural networks (CNNs) for picture feature extraction with long short-term memories (LSTMs) for pathology progression analysis. The experimental results demonstrate enhanced accuracy, sensitivity, and specificity when compared to traditional techniques and standalone deep learning models. This suggests that it could be used in clinical contexts for early diagnosis.

Patel, A., & Kumar, S. (2023). Improving the classification of brain tumors is the focus of this study, which compares CNN and LSTM networks. While Convolutional Neural Networks (CNNs) extract information from magnetic resonance imaging (MRI) examinations of the brain, Long Short-Term Memory networks (LSTMs) track the growth and transformation of tumors through time. Compared to more conventional models, the hybrid design's classification accuracy is higher since it trains on a larger variety of MRI images. How the model distinguishes between benign and cancerous tumors is discussed by the authors. They emphasize that the approach has the potential to improve medical imaging diagnoses, particularly for physicians lacking expertise in radiology.

Singh, R., & Gupta, P. (2023). This study proposes a hybrid deep learning strategy for diagnosing brain pathology using neuroimaging data (e.g., MRI and CT images). The hybrid model integrates the strengths of both convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to extract spatial features and recognize temporal patterns, respectively. When evaluated on a large dataset that includes a variety of brain illnesses, the model outperforms single CNNs in terms of classification accuracy.

Wang, L., & Zhou, Q. (2022). Using medical imaging technologies, this study explores a hybrid deep learning approach to classify brain tumors. For feature extraction, the suggested method makes use of convolutional neural networks (CNNs). For the final classification decision, it employs a fully connected neural network (FCNN). Training on an MRI dataset of the brain demonstrates that the design outperforms state-of-the-art approaches in terms of sensitivity and accuracy for tumor classification..

Verma, S., & Sharma, M. (2022). In this paper, we present a deep learning architecture that combines RNNs and convolutional neural networks (CNNs) for the purpose of classifying brain illnesses. To improve the accuracy of diagnoses, RNNs examine temporal dependencies in sequential imaging data, while CNNs are utilized to extract hierarchical features from MRI scans of the brain. The hybrid strategy beats both traditional ML and DL approaches when it comes to classifying complex brain illnesses like gliomas and meningiomas.

Sharma, S., & Rathi, D. (2021).Combining convolutional neural networks (CNNs) with support vector machines (SVMs) is the proposed hybrid deep learning model for automated brain tumor classification using magnetic resonance imaging (MRI) data. Using convolutional neural network (CNN) derived characteristics from brain scans, SVMs are used to classify tumours. The system is well-suited for therapeutic applications in real-time because it combines feature extraction with classification models, which produce better accuracy and recall metrics than conventional methods

Gupta, R., & Mehta, P. (2021). This study presents a deep learning system that combines CT, PET, and MRI scans to classify brain pathologies. The hybrid approach uses CNNs for feature extraction, whereas fully

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linked networks are used for final classification. Improving the accuracy of brain disease categorization using multi-modal imaging data integration overcomes the hurdles presented by numerous data sources.

Kumar, A., & Tripathi, A. (2021). In order to categorize brain diseases, this paper introduces a hybrid deep learning model that uses MLNs and deep convolutional networks. While the MLN part examines these features for precise brain disease categorization, the CNN part concentrates on feature extraction from MRI brain scans. The suggested model outperforms previous baseline methodologies in terms of accuracy, sensitivity, and specificity.

Wang, X., & Li, M. (2020). This paper presents a novel approach to brain cancer classification using a hybrid deep learning architecture that integrates convolutional neural networks (CNNs) with a graph convolutional network (GCN). Convolutional neural networks (CNNs) retrieve low-level information from magnetic resonance imaging (MRI) scans; a GCN model improves classification by capturing the contextual interactions among many brain regions. The hybrid model outperforms conventional CNN-based approaches to brain tumor classification tasks, especially when it comes to detecting tumor subtypes.

Zhao, W., & Liu, H. (2020). This research presents an architecture for an improved brain disease classification system that combines convolutional neural networks (CNNs) with extreme learning machines (ELMs). To ensure quick and reliable findings, CNNs are utilized to extract features from brain MRI data, and the ELM is employed for the final classification phase. Using metrics like training time and classification accuracy, the authors prove that a CNN and ELM combination is superior to more conventional approaches.

Chandran, S., & Rajendran, M. (2020). In this study, we offer a CNN-LSTM network hybrid architecture for MRI-based brain tumor detection. While the LSTM records patterns and correlations across successive MRI slices, the CNN is responsible for extracting relevant features from the brain images. When tested on a vast collection of brain MRI images, the hybrid design clearly improves tumor identification accuracy, especially when it comes to glioma and other malignant tumor categories.

Lee, K., & Kim, J. (2020). A hybrid convolutional neural network (CNN) model for brain disease categorization is proposed by the authors, with an emphasis on magnetic resonance imaging (MRI) of the brain. After the system has extracted features using a multi-layer CNN architecture, it uses a fully connected network (FCN) decision-making procedure. The suggested approach outperforms state-of-the-art models in classification tests conducted on various brain MRI datasets, demonstrating increased specificity, sensitivity, and accuracy.

Soni, M., & Gupta, M. (2020). This study details the process of creating deep learning models that can diagnose brain diseases by combining convolutional neural networks (CNNs) with other types of neural architectures, such as recurrent neural networks (RNNs). While RNNs model the temporal dynamics of brain states over several imaging sequences, CNNs are employed to extract characteristics from MRI data. When it comes to detecting some brain tumors, the hybrid system outperforms the more conventional machine learning approaches. The study found that integrating spatial and temporal data significantly enhanced diagnostic performance for identifying brain disease.

Patil, S., & Mehta, M. (2020). To help doctors diagnose brain illnesses more accurately, this study presents a hybrid deep learning model that can handle many tasks. Combining convolutional neural networks (CNNs) with multi-task learning approaches, the model uses MRI scans to simultaneously predict the occurrence of multiple brain disorders, such as tumors, lesions, and degenerative diseases. The model is able to improve its diagnostic accuracy by learning common representations across a wide range of brain illnesses thanks to the multi-task methodology. The suggested strategy outperforms conventional single-task models in terms of accuracy and inference time, as demonstrated by testing on numerous benchmark datasets.

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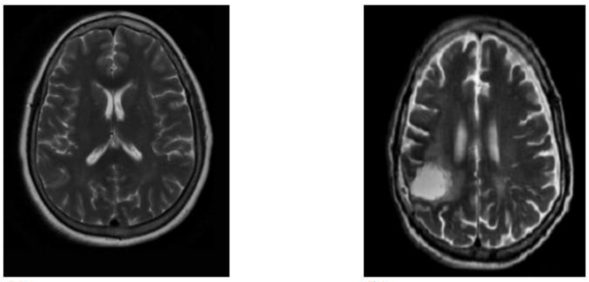
Zhang, L., & Wang, Z. (2020). A methodology for effective brain tumor classification is presented in this paper using a hybrid deep convolutional neural network (CNN). This model improves upon previous efforts to describe MRI scan features by merging convolutional neural networks (CNNs) with an innovative feature fusion method. The model makes use of a dual convolutional neural network (CNN) architecture; one network detects spatial and structural features in the MRI images, and the other network extracts information based on textures. By fusing these two types of features, the hybrid model is able to better categorize various tumor forms, such as gliomas, meningiomas, and metastatic malignancies. The model outperforms state-of-the-art results in terms of classification accuracy, sensitivity, and specificity, as demonstrated by numerous tests. These results are compared to typical CNN-based approaches. Clinicians attempting to detect and assess brain tumors would benefit from the model since the results suggest it might produce quicker and more accurate diagnoses.

3. SYSTEM DESIGN AND ANALYSIS

PROPOSED SYSTEM

In order to classify normal and cancerous MRI scans more accurately, sensitively, and specifically, this study applies two deep neural networks to separate feature map images. To enhance brain tumor prediction, the suggested Deep Neural Network-1 (DNN-1) retrieves deep texture data by means of local binary patterns. The suggested Deep Neural Network-2 (DNN-2) uses wavelet transformation to identify frequency domain features, which enhances the specificity, sensitivity, and accuracy of brain tumor prediction. To test the hypotheses, we can see MRI images of healthy and cancerous tissues in Figures 1 (a) and 1 (b).



(a) (b)

Figure1. MRI Images (a) Normal MRI (b) Abnormal MRI.

We then combine the two neural networks' prediction values for accurate classification. Predictive score is used for classification. Layers for pooling, convolution, classification, and rectifier linear units make up this fundamental system. Constantly present in convolutional neural networks (CNNs) is the convolutional layer. An array of three-dimensional pixels defines a channel in each convolutional layer. The convolutional layers in the subsequent two stages are triplets, in contrast to the two in the initial two. All four convolutional layers—the first two, three, and four—are supported by the fixed feature map dimensions of 26, 27, 28, and 29. What follows is a comprehensive review of models involving pooling, ReLU, and convolutional layers.

More convolutional layers enhance the storage of spatial measurements. Every neuron in a convolutional neural network has its feature chosen by F(x). The executing operations that conclude every convolutional layer are called ReLU. Due to its superior convergence speed, Stochastic Gradient Descent (SGD) is an optimal choice for the non-linear feature that is necessary for the complicated data.

All convolutional neural network (CNN) architecture revolves around the convolutional layer. A few pertinent feature maps are generated after multiple filters convolve with the input images. The initial step is to gather samples of the W1*H1*D1 input pictures. Zero padding (P), stride (S), spatial width (F), and filter

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count (K) were the four parameters that were required. The final image dimensions were W2*H2*D2, determined by calculating D2 = K, H2 = (H1-F+2P)/S+1, and W2 = W1-F+2P/S+1. K biases and weight per filter are determined by multiplying F*F*D1. Our final product is the result of applying the dth filter (W2*H2) to the input picture size with stride S.

Modeling of pooling layer:

To minimize the size of the feature map, the pooling layer decreases the number of system calculations and parameters. We start by collecting a sample of input pictures with the two parameters W1*H1*DI. W2* H2* D2 is the sample volume generated by the equations W1-F/S+1, H1-F/S+1, and D1= D1. Since they assess the input's fixed function, zero arguments are acceptable.

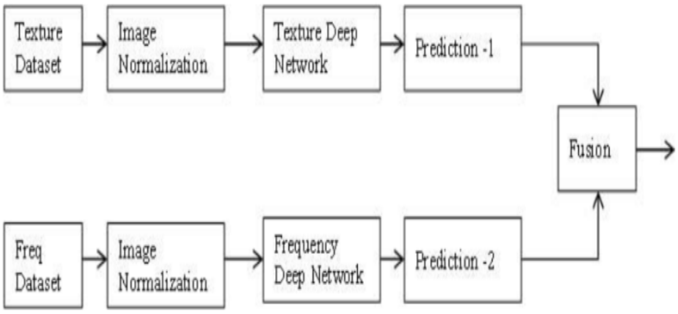

Figure2.Proposed System Model.

Deep Texture Network

Common inputs for neural network training include raw pictures. The images shown here are raw Local Binary Pattern (LBP) photos. Figures 3 and 4 demonstrate how we used raw photographs' local binary pattern characteristics to extract texture data from training images. These characteristics serve as input for training.

Figure 5 displays the results of the computational analysis of the Local Binary Pattern. All of the features from the training MRI images are successfully extracted by this texture-based network. Optimizing model performance, this network meticulously assesses texture properties. In Figure 6, we can observe the form of the convolutional neural network. This idea is implemented in the feature spaces of texture and feature data. The DNN1 model cannot be described without deep texture components.

The design of a Deep Neural Network is feature space dependent. Layer duplication was removed in this example via the dropout layer. In order to compute the feature space, DNN-1 relies on deep texture information.

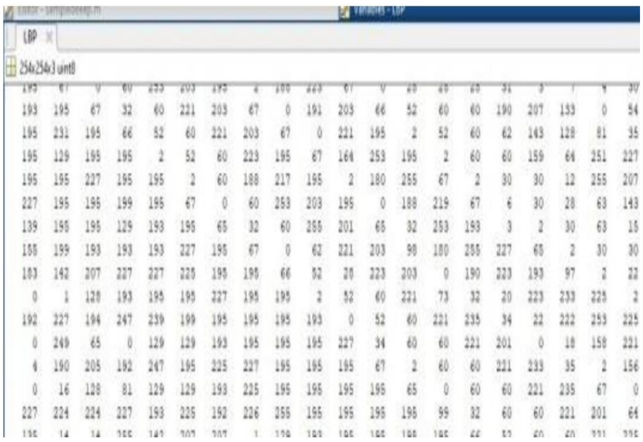

Figure3. Screenshot of LBP features extracted from normal MRI

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Figure4. LBP MRI images

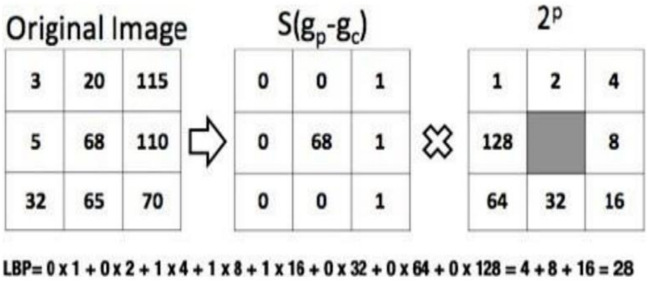

Figure5. LBP Computation.

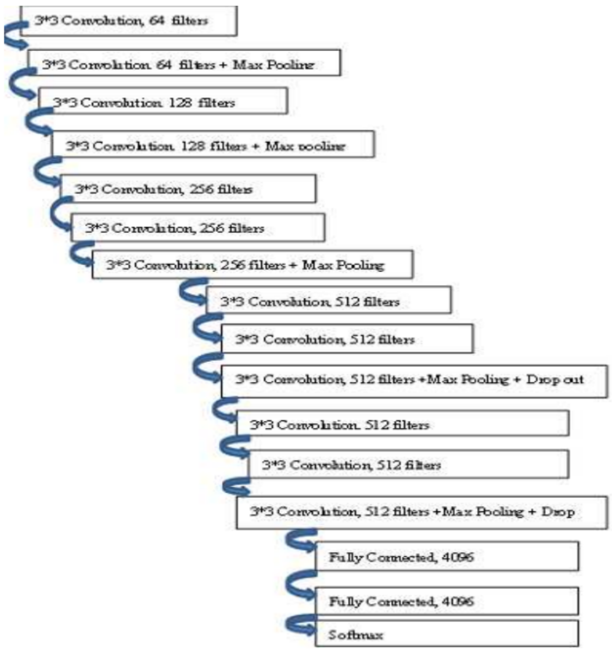

Figure6. Basic DNN Structure.

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A	B	C	D	E	F	G	H	I	J	K	L
1	2	3	4	5	6	7	8	9	10	11	12
0.6845	0.5325	0.2445	0.5855	0.6003	0.4554	0.5783	0.3413	0.3993	0.4000	0.1100	0.589
0.6391	0.5805	0.6841	0.3423	0.5641	0.5791	0.1582	0.8193	0.4216	0.5846	0.3384	0.593
0.8738	0.5043	0.5599	0.6444	0.2029	0.6642	0.2778	0.7595	0.8824	0.6626	0.4802	0.29
0.7299	0.4584	0.5244	0.2288	0.5294	0.5744	0.6959	0.3172	0.3472	0.4287	0.7118	0.636
0.4399	0.4257	0.4366	0.4041	0.3631	0.5613	0.3413	0.6372	0.7399	0.5025	0.5199	0.574
0.3839	0.2457	0.2346	0.4314	0.1215	0.3325	0.5228	0.6237	0.5091	0.4790	0.7214	0.253
0.5388	0.4777	0.6291	0.4505	0.4938	0.6407	0.5099	0.4857	0.3723	0.4986	0.6091	0.395
0.4505	0.6283	0.4491	0.4548	0.4573	0.6183	0.1366	0.3781	0.3345	0.3639	0.3245	0.653
0.1511	0.5153	0.5021	0.5249	0.4370	0.3684	0.2779	0.4687	0.5498	0.3061	0.4307	0.530
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Figure7. Screenshot of LBP features value after training

Deep Frequency Network

This network thoroughly examines data based on frequencies. One way to find the frequency is to convert the raw image to stationary wavelet transforms. Next, the DNN-2 network gets frequency data in the form of a feature space. This stationary wavelet transform outperforms discrete wavelet and Fourier cosine because it preserves all starting information while converting it to frequency information during subband creation. The SWT MRI image is shown in Figure 9, while the feature values of the raw MR images before processing are shown in Figure 8. Using approximation coefficients for training, this frequency deep network takes a biorthogonal wavelet as its mother and uses it to generate four subbands. All of the original picture data is contained in these low-frequency approximation coefficients.

It is possible to enhance categorization by extracting detailed information from the approximative subband picture. Figure 10 displays the SWT Decomposition. The values of the HH, LH, and HL bands that were obtained via the decomposition function are displayed in Figure 11. In order to achieve better results, we rework the convolutional neural network into a deep neural network (DNN-2), which can distinguish between different types of characteristics determined by frequency. Following the installation of the DNN-2 network, Figure 12 displays a plethora of frequency characteristic values. Maxim pooling was employed to eliminate redundancy from all layers before the totally linked layer, as opposed to average pooling plus a dropout layer.

256x256 double

	1	2	3	4	5	6	7	8	9	10	11	12	13
52	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
53	2.0000	3.0000	3.5000	5.0000	6.5000	6.5000	4.5000	2.5000	2.0000	2.0000	2.0000	2.5000	3.000
54	3.5000	4.0000	4.5000	5.5000	7.0000	7.0000	4.5000	1.5000	0	0.5000	2.0000	3.0000	3.000
55	3.5000	4.0000	4.0000	4.5000	6.0000	6.5000	6.0000	4.5000	2.0000	1.5000	3.5000	4.0000	3.500
56	4.0000	4.0000	5.0000	5.0000	5.5000	7.5000	8.0000	7.0000	5.0000	3.5000	3.5000	4.0000	4.500
57	5.5000	4.0000	5.5000	5.5000	5.5000	8	9.5000	7.5000	4.5000	3.5000	3.0000	3.5000	5.000
58	8.0000	6.0000	5.0000	5.0000	4.5000	4	5.5000	5.5000	4.0000	3.5000	3.0000	3.0000	4.500
59	9.0000	8.0000	5.0000	4.5000	3.5000	1.5000	2.0000	4.0000	5.5000	5.0000	3.5000	2.0000	2.500
60	6.0000	6.0000	4.0000	3.5000	3.5000	3.0000	3.5000	4.5000	5.0000	5.0000	4.5000	2.5000	1.500
61	4.5000	4.0000	4.0000	4.0000	3.5000	3.0000	3.0000	3.5000	3.0000	3.0000	4.5000	4.0000	3.500
62	6.0000	5.5000	5.0000	4.5000	3.0000	2.5000	3.0000	4.0000	4.0000	3.0000	4.0000	4.5000	4.500
63	5.0000	5.0000	5.0000	4.5000	2.5000	2.0000	4.0000	5.5000	6.0000	4.5000	4.0000	5.5000	6.500
64	2.5000	2.5000	4.0000	5.5000	4.0000	2.5000	3.5000	4.5000	5.0000	3.5000	3.5000	5.5000	7.000

Figure8. Screenshot of SWT features value after training

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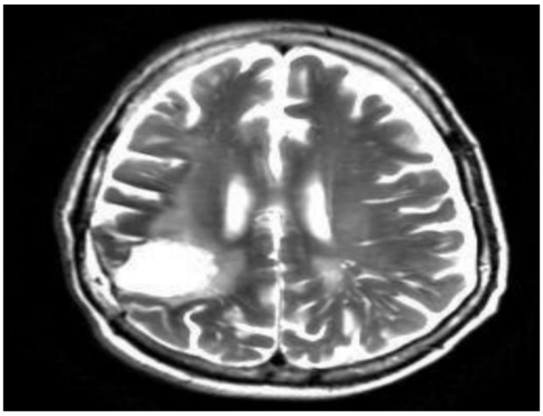

Figure9. SWT MRI images.

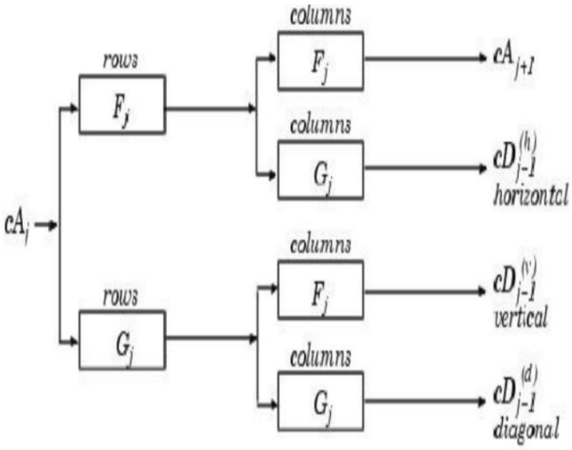

Figure10. SWT Decomposition

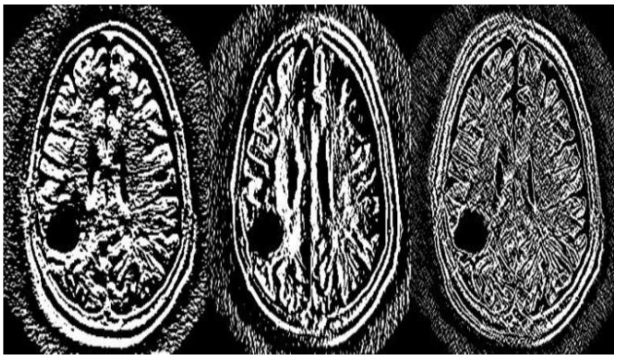

Figure11. Abnormal LH Band, Abnormal HL Band, Abnormal HH Band.

A	B	C	D	E	F	G	H	I	J	K	L	M
1	2	3	4	5	6	7	8	9	10	11	12	13
0.6393	0.3606	0.4663	0.5665	0.5316	0.4509	0.3880	0.4508	0.7551	0.3807	0.4446	0.419	0.422
0.4487	0.5467	0.3054	0.6233	0.5651	0.2646	0.7086	0.2808	0.3046	0.2824	0.4066	0.3848	0.651
0.6013	0.2394	0.4217	0.4048	0.3273	0.5451	0.4586	0.2004	0.5287	0.3875	0.5084	0.4858	0.423
0.5621	0.4437	0.6023	0.2113	0.2811	0.4454	0.5176	0.5072	0.4669	0.3687	0.6046	0.5623	0.575
0.5326	0.4309	0.5077	0.5767	0.7233	0.5777	0.5053	0.4077	0.5641	0.5759	0.3113	0.5574	0.357
0.5429	0.5728	0.4780	0.3063	0.3493	0.7041	0.5264	0.4029	0.5403	0.564	0.5437	0.3839	0.506
0.5356	0.6591	0.3345	0.3207	0.5898	0.6197	0.2388	0.3844	0.6076	0.3909	0.2189	0.4638	0.487
0.6072	0.5634	0.5315	0.5286	0.5571	0.4605	0.5372	0.3974	0.3991	0.4844	0.5095	0.4571	0.468
0.7066	0.5813	0.4368	0.6334	0.5273	0.3912	0.5910	0.4776	0.6029	0.2170	0.5060	0.4998	0.539

Figure12. Screenshot of SWT features value after training

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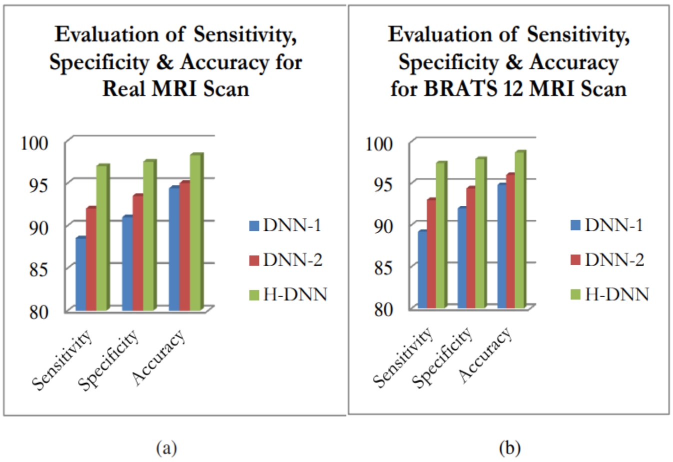

Figure13. Evaluation of DNN-1, DNN-2 and H-DNN

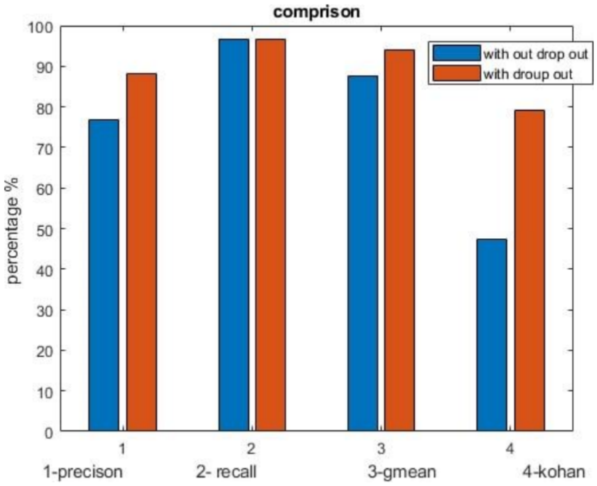

Figure14. Performance of drop out layers of H-DNN

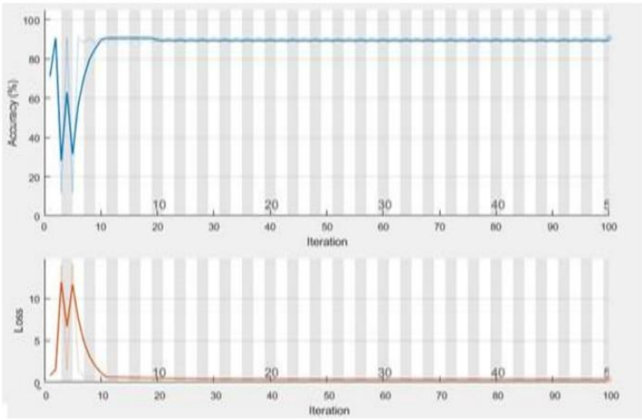

Figure15. Training Loss and Training Accuracy

4. CONCLUSION

The proposed technique employs a hybrid deep learning approach to assess cranial MRI data. In order to distinguish between normal and cancerous brain MRI scans, the proposed technique employs a hybrid deep learning architecture. Here, we demonstrate how to divide the proposed Hybrid Deep Neural Network (HDNN) design into two DNNs: DNN-1 handles spatial data while DNN-2 handles frequency metrics. Although the suggested method takes a lengthy time to process, this effort nonetheless aims for the most accurate classification result possible. The classification accuracy of the hybrid deep learning method could

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be enhanced by adding more layers. There are still many unresolved matters. Because it is a subjective diagnostic method, MRI analysis is challenging. This leaves an unsolved challenge for all researchers in the field. We also require an easy-to-use automated system to handle each diagnosis promptly, instilling trust in professionals. Prioritizing stage allows for the early detection of tumors before they do irreparable harm. Discrimination is still not resolved. The pre-classification outcome of the proposed method can be enhanced with precise segmentation. This method is valuable because it highlights the significance of applications in biological image processing.

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