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Brain Image Classification Accuracy Enhancement Using Combined DWT and Enhanced CNN Approach

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Abstract: Globally, brain illnesses are associated with substantial health consequences, underscoring the need of early diagnosis and treatment. In order to aid in early diagnosis, a number of algorithms have been investigated, with an emphasis on utilizing imaging methods like CT and MRI. In order to improve the classification accuracy of brain images, this research suggests a unique method that combines an augmented convolutional neural network (CNN) with the discrete wavelet transform (DWT). In order to increase the accuracy of early diagnosis of brain illnesses, the goal of this project is to provide a strong categorization framework for brain image analysis. This entails using cutting-edge methods to problems like feature extraction, classification, and noise reduction. This work is innovative in that it uses an improved CNN architecture for classification after DWT is included for pre-processing and feature extraction. The framework efficiently eliminates noise and improves image accuracy by utilizing DWT, which helps to contribute to more dependable illness detection. Furthermore, by including an improved CNN, accuracy is further improved by introducing a unique way to using deep learning for brain image categorization. The three primary phases of the suggested framework are feature extraction, classification, and pre-processing. During pre-processing, noise from salt and pepper is eliminated by using a median filter, which is then converted to grayscale. The next step is to use DWT with a 3-level Haar wavelet to reduce edge dimensional space and improve image accuracy. The converted photos are used for feature extraction, which gets them ready for classification. Lastly, for precise brain image categorization, an improved CNN is used. The results show that the suggested framework achieves a remarkable accuracy rate of 98.9% in brain image categorization. This illustrates how the upgraded CNN and combined DWT methodology outperforms current techniques in reliably diagnosing brain disorders.

Keywords: *Brain diseases, Image classification, Discrete Wavelet Transform, Convolutional Neural Network, Medical imaging, Early diagnosis.*

I. Introduction

The brain tumor is one of the major harmful diseases in all over the world, thus there are many people suffered from these types of the diseases, many researchers are involved to diagnosis these types of the diseases by using various approaches and the algorithm. The brain tumor in the human being may be considered as the massive growth of the abnormal cell in body [1]. The growth of the abnormal cells is not taking place only in the human brain, as it growth in the various parts of the body then only it shifts their growth in the human brain, Thus there are many brain tumors are arrived in the human being thus it was further classified as two types namely benign (cancerous) and the malignant (noncancerous). These two types of the diseases that are mainly affected by the human being, therefore the early detection of this diseases is might more crucial one thus many researchers are involved to detect and correct the diseases earlier, to save the human life [2]. The symptoms of the brain tumor classification are the pattern of the headache are arrived in the human being, the once who affected by the growth of the abnormal cell in the human body, they definitely loss their immunity. The headache is gradually becoming increased way because of the loss of immunity [3]. The growth of abnormal cells in human body reduces the white blood cells in the human body, thus it reduces the weight loss and the part time of fever and the cough etc. The suffered patients are also lack from the decision making and the hearing problem and also always suffered from the body pain and the lack of vision [4]. The repeated allowance of that ones for these diseases is early detection, the convolutional Neural network classification technique in the basis of the deep learning algorithm provides that the better classification accuracy, and also it is used in the detection of the diseases in the early stage [5].

This paper focuses on brain tumor classification using a dataset containing both MRI and CT images of patients, distinguishing between those who have suffered from tumors and those who have not. Preprocessing begins with the application of a median filter to eliminate noise, specifically salt and pepper noise, from the input images. Subsequently, the RGB images are converted into grayscale for further processing. Segmentation follows preprocessing, facilitating the symmetric arrangement of data samples and reducing dimensional redundancy in the images. Feature extraction is

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then performed to extract relevant features for classification, enhancing the accuracy of classification based on similarities between images. Finally, an enhanced convolutional neural network is employed for further classification, resulting in superior accuracy compared to existing techniques. This comprehensive approach addresses the challenges of brain tumor classification and improves accuracy in identifying tumor presence. The proposed framework showcases significant potential in improving the accuracy of brain image classification for early disease diagnosis. By integrating DWT and an enhanced CNN, the framework effectively addresses challenges in noise reduction, feature extraction, and classification, leading to superior accuracy rates. This study underscores the importance of leveraging advanced techniques in medical imaging for enhanced disease diagnosis and patient care.

The key contribution for the proposed study is as follows:

•By using a median filter to reduce noise and convert RGB to grayscale, input photos are of higher quality, which provides a solid basis for precise categorization.

•By allowing data samples to be arranged symmetrically, segmentation helps to improve feature extraction by minimizing dimensional redundancy in images.

•The study improves classification accuracy, offers a more nuanced view of the information, and strengthens diagnostic skills by extracting distinctive characteristics from images.

•Using an improved convolutional neural network (CNN) improves classification accuracy even further, outperforming current methods and opening up potential new possibilities for more accurate brain tumor identification..

•The pre-processing stage's usage of DWT allows for effective noise reduction, particularly for noise, which is common in medical imaging.

The remainder of the proposed study is as follows. Section 1, the Introduction, provides context on the significance of early diagnosis for brain diseases and introduces the proposed framework. Sections 2 discuss about the related works. Section 3 limitations of existing system. Section 4 detail the methodology. Section 5 summarizes findings and outlines potential avenues for further research. Section 6, Conclusion and further study.

II. Review of Literature

The paper by Abiwinanda et al., [6] focuses on brain tumor classification using Convolutional Neural Networks (CNNs), which are a class of deep learning models particularly adept at handling image data. The classification of brain tumors holds immense significance for early disease diagnosis, facilitating timely intervention and treatment. In this study, the authors employ CNNs, a powerful tool in image classification tasks, to automatically distinguish between different types of brain tumors based on MRI or CT scan images. One notable aspect of the CNN architecture utilized in this research is the incorporation of max-pooling layers. Max-pooling is a technique commonly employed in CNNs to down sample feature maps, reducing their spatial dimensions while retaining important features. This serves to alleviate overfitting, a common challenge in deep learning models where the network learns to memorize training data rather than generalize to unseen examples. By reducing the spatial resolution of feature maps through max-pooling, the CNN becomes less prone to overfitting and more capable of generalizing well to new, unseen brain images. Overall, this paper underscores the importance of leveraging advanced deep learning techniques, such as CNNs with max-pooling layers, for accurate brain tumor classification. By harnessing the power of CNNs and addressing issues like overfitting, the proposed approach holds promise for enhancing the early diagnosis of brain diseases, ultimately improving patient outcomes and prognosis.

The study conducted by Seetha et al., [7] addresses the critical issue of brain tumor classification using Convolutional Neural Networks (CNNs). Recognizing the severe impact of brain tumors, which can potentially lead to fatalities, the authors emphasize the crucial importance of early detection and prevention measures. To tackle this challenge, they propose the utilization of CNNs, a powerful deep learning technique known for its effectiveness in image classification tasks. One notable aspect of their approach is the meticulous tuning of the CNN architecture, particularly focusing on the design of convolutional kernels. Convolutional kernels are fundamental components of CNNs responsible for extracting features from input images. By carefully configuring the size, shape, and parameters of these kernels, the network becomes more adept at identifying relevant patterns and structures indicative of brain tumors. Furthermore, the authors highlight the significance of weight optimization within the neural network. They emphasize the importance of assigning small weights to neurons, a practice aimed at promoting efficient learning and preventing excessive influence from individual neurons. By fine-tuning the weights of neurons, the CNN can effectively prioritize and weigh different features extracted from the input data, enhancing its ability to discriminate between healthy brain tissue and tumor regions. Overall, the study by Seetha et al. underscores the critical role of CNNs in facilitating early detection and classification of brain tumors. Through careful architectural design and weight optimization strategies, their approach aims to improve the accuracy and reliability of brain tumor diagnosis, ultimately contributing to better patient outcomes and mortality prevention.

The research conducted by Das et al., [8] addresses the pressing issue of brain tumor classification utilizing Convolutional Neural Networks (CNNs). Recognizing the grave threat posed by brain tumors and the imperative need for early detection to save patients' lives, the authors emphasize the pivotal role of CNNs in this context. Brain tumors represent a particularly dangerous form of disease, and their early detection is paramount for timely intervention and improved prognosis. To tackle this challenge, the researchers employ CNNs, a class of deep learning models well-suited for image classification tasks. By leveraging CNNs, which are capable of learning intricate patterns and features from image data, the study aims to automatically classify brain tumor images with high accuracy. The utilization of CNNs enables the automatic identification of tumor regions within brain images, facilitating early detection and diagnosis. Through the training of the CNN on labeled datasets of brain tumor images, the model learns to distinguish between healthy brain tissue and tumor-affected regions. This process of automated classification streamlines the diagnostic workflow, enabling healthcare professionals to swiftly identify and intervene in cases of brain tumor presence. Overall, the research by Das et al. underscores the critical importance of leveraging advanced deep learning techniques, such as CNNs, for the early detection and classification of brain tumors. By harnessing the power of CNNs, the study aims to enhance diagnostic capabilities, ultimately contributing to improved patient outcomes and the preservation of lives threatened by this perilous disease.

The study conducted by Khan et al.,[9] focuses on brain tumor classification specifically in MRI images, employing CNNs as the primary classification technique. The authors begin by comparing various machine learning techniques with their proposed CNN approach to evaluate their effectiveness in accurately classifying brain tumor images. The comparison highlights the superiority of CNNs over other machine learning techniques for brain tumor classification in MRI images. CNNs are well-suited for image classification tasks due to their ability to automatically learn and extract relevant features from input data. Compared to traditional machine learning algorithms, CNNs excel at capturing intricate patterns and relationships within complex image datasets, making them particularly effective for medical image analysis tasks like brain tumor classification. The proposed CNN model outperforms other techniques in terms of classification accuracy and robustness. By leveraging the power of deep learning and specifically tailored architectures like CNNs, the study achieves enhanced results in accurately identifying and classifying brain tumors from MRI images. This advancement is crucial for improving diagnostic accuracy and facilitating timely interventions, ultimately leading to better patient outcomes. The research by Khan et al. underscores the significant advantage of CNNs in brain tumor classification from MRI images compared to other machine learning techniques. By demonstrating the superior performance of CNNs, the study contributes valuable insights into the advancement of medical image analysis techniques, with potential implications for improving clinical decision-making and patient care in the context of brain tumor diagnosis and treatment.

In the research conducted by Amin et al., [10] the focus is on brain tumor classification based on the fusion of MRI sequences using CNNs. The paper introduces a novel approach wherein brain images are fused using the DWT technique, followed by classification using CNNs. The fusion process involves integrating information from multiple MRI sequences, enhancing the overall representation of the brain images. By leveraging DWT, the fusion technique effectively combines complementary information from different MRI sequences, facilitating a more comprehensive analysis of brain tumor characteristics. Following the fusion process, the authors employ four distinct methods for brain image classification. These methods likely involve variations in CNN architectures, training strategies, or feature extraction techniques to optimize classification performance. Furthermore, the study incorporates the PDDF as a preprocessing step to remove noise from the fused brain images. Noise reduction is crucial for improving the quality of input data and enhancing the performance of subsequent classification algorithms. Overall, the research by Amin et al., demonstrates a comprehensive approach to brain tumor classification, combining advanced image fusion techniques with state-of-the-art CNNs. By integrating DWT-based fusion and CNN-based classification with noise reduction strategies, the study aims to enhance the accuracy and reliability of brain tumor diagnosis from MRI sequences, potentially contributing to improved patient care and treatment outcomes [11].

III. PROBLEM STATEMENT

Convolutional Neural Networks -based brain tumor classification algorithms now in use have demonstrated potential, but they are not without drawbacks. The possibility of overfitting, in which the model retains training data instead of adapting effectively to new cases, is a significant drawback. This can happen because CNN architectures are complicated and include a lot of parameters, which might lead to the models being sensitive to noise or unimportant information from the training set [12]. The suggested work presents several innovations to get beyond these restrictions. First off, by merging data from many MRI sequences, the DWT integration for image fusion improves the representation of brain images. This raises the general calibre of input data and enables a more thorough examination of tumor features. Furthermore, to reduce overfitting and boost feature extraction capabilities, an improved CNN architecture comprising improved convolutional kernels and weight optimization techniques is used. The proposed effort aims to improve the robustness, accuracy, and reliability of brain tumor classification systems by addressing these constraints.

IV. Research Methodology

The proposed framework, as depicted in Fig 1, outlines a comprehensive approach for brain image processing and classification. Beginning with the preprocessing stage, the input images undergo conversion from RGB to grayscale using a median filter to enhance quality. Subsequently, the segmentation step transforms the images into pixel form, aiding in noise-free detection and facilitating easier differentiation between pixels. Following segmentation, the feature extraction process reduces dimensional complexity by breaking down images into manageable groups, crucial for accurate classification. Utilizing DWT enhances this dimensional reduction process. Finally, the classification stage employs an ECNN for improved accuracy. ECNNs are known for their superior performance compared to other machine learning approaches, providing enhanced classification accuracy. Overall, this proposed framework integrates preprocessing, segmentation, feature extraction, and classification stages to facilitate accurate brain image analysis and tumor classification. This would eventually improve outcomes for patients and medical decisions in both the identification and treatment of brain disorders.

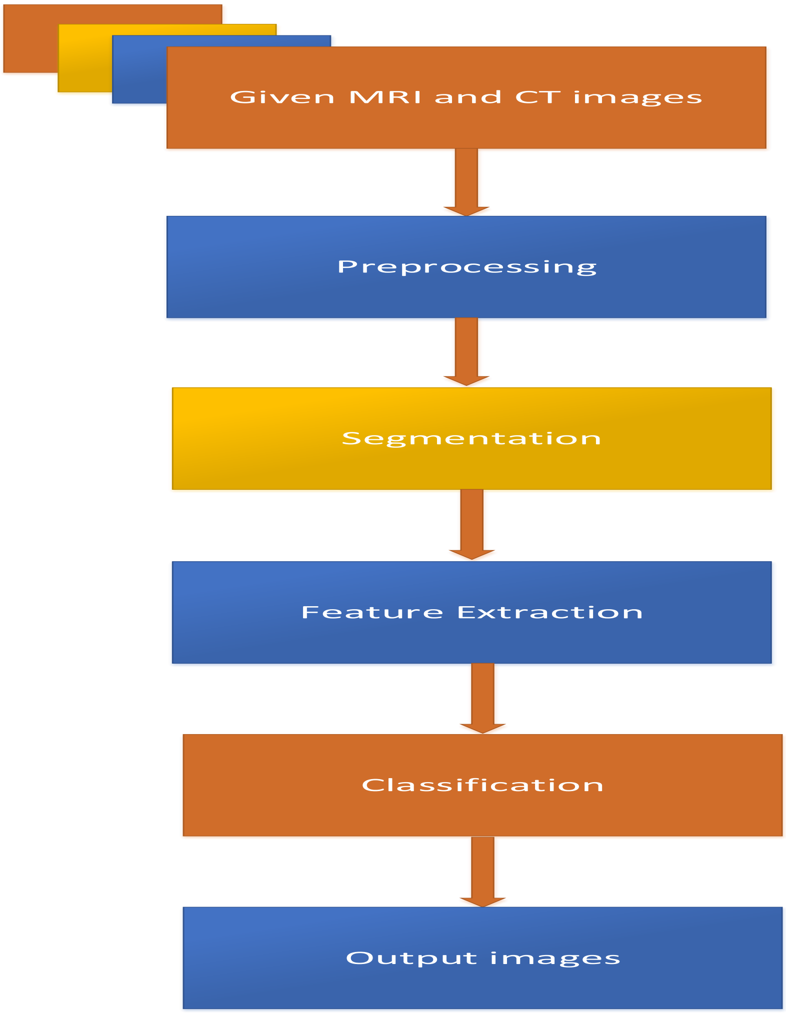

Fig.1 Overview of Proposed Approach

A. *Data Collection*

The dataset comprises 233 patients, a total of 3064 brain images featuring diverse tumor types. T1-weighted contrast images were utilized, each standardized to 512x512 pixels to maintain consistency. To streamline tumor classification within the convolutional neural network, the study focused on glioma, meningioma, and pituitary tumors, with 100 samples for each category. The objective was to alleviate confusion in tumor type differentiation. Subsequently, the accuracy of the results was assessed to evaluate the efficacy of the proposed approach [13].

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B. *Preprocessing technique*

The preprocessing technique is the first step of the image processing analysis, the main function of the image processing technique is to convert the RGB image into the grey scale images [14]. In this paper implements that the median filter, the median filter is basically considered as the nonlinear filter, thus it helps to remove the salt and pepper noise in the image after removing the noise in the image. After the removal of noise in the image, then the median filter helps to normalised the noise in the image and the formula used for this is provided in eqn. (1).

$$\boldsymbol{Median\ filter} = \frac{\boldsymbol{a}\left(\frac{\boldsymbol{M}}{\boldsymbol{2}}\right) + \boldsymbol{a}(\frac{\boldsymbol{M+1}}{\boldsymbol{2}})}{\boldsymbol{2}}$$

The filter window's size is indicated by the symbol. The intersection of the sorted neighbourhood is represented by the pixel value. When is odd, the pixel value in the middle of the sorted neighbourhood is represented by ($\boldsymbol{a}(\frac{\boldsymbol{M+1}}{\boldsymbol{2}})$.

C. Discrete Wavelet Transformation

The DWT plays a crucial role in signal processing by separating signals into low pass and high pass filters, effectively reducing dimensional edge space and enhancing output results. Both filters contribute to smoothening and sharpening edges, thereby improving the quality of images or data. The cut-off frequency for the high pass filter, akin to an RC filter in electronics, determines its effectiveness in smoothening edges, while the low pass filter sharpens them. High pass filters attenuate high frequencies, aiding in edge smoothening, while low pass filters attenuate low frequencies, contributing to edge sharpening. High pass filters also assist in aliasing images, while low pass filters are instrumental in noise removal, collectively enhancing the overall quality and clarity of processed images or data. The formula for DWT is depicted in eqn. (2).

The output image is represented in the frequency domain by The filter function that operates in the frequency domain is represented by. In the frequency domain, depicts the input image.

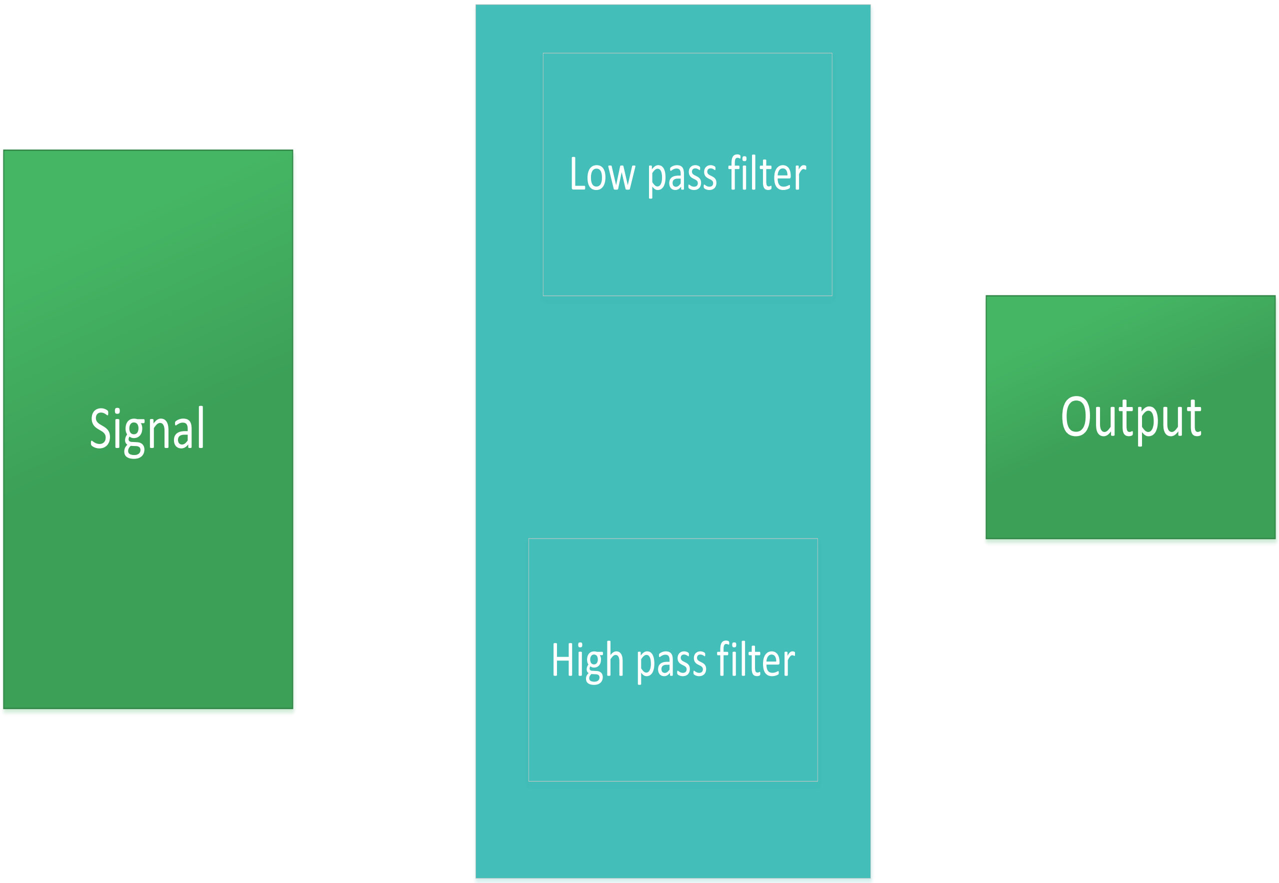

Fig.2 Filtering in DWT

The fig 2 shows the filtering technique in the Discrete wavelet Transform. Figure 3 illustrates signal processing involving filters. It begins with a signal input, followed by a low pass filter that permits signals below a specified cutoff frequency while attenuating higher frequencies. Nested within the low pass filter is a high pass filter, which allows signals above a designated cutoff frequency to pass while suppressing lower frequencies. The processed signal exits as the output, likely a composite of the effects of both filters. This filtering technique is widely employed in electronic devices and communication systems to regulate signal bandwidth and eliminate undesired frequencies.

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Enhanced Convolutional Neural Network

D. *Enhanced Convolutional Neural Network (Heading 2)*

Enhanced CNN adds layers, uses optimization methods, or makes other changes to increase its performance in certain applications. In the suggested study, the Enhanced CNN is essential for correctly categorizing brain images to identify tumors. The suggested work's Enhanced CNN architecture is made to efficiently extract characteristics from brain images and categorize them into various tumor kinds. Multiple convolutional layers are usually used, afterward pooling layers to reduce the feature maps and save computational complexity without sacrificing significant features. It is possible to incorporate extra layers, including batch normalization, to enhance training stability and avoid overfitting

The Enhanced CNN's convolutional layers use filters to extract different features from the input image, including edges, textures, and forms. During the training phase, when the network modifies the filter weights to reduce the classification error, these characteristics are learned. More accurate categorization is made possible by the CNN's ability to capture hierarchical visualizations of the input image through iterative convolving of the input with the capability of learning filters. Following convolutional layers, non-linear activation functions like ReLU are frequently employed to provide non-linearity to the network and enable it to understand intricate correlations in the input. ReLU is a well-liked activation function in neural networks because of its efficiency and ease of usage. Positive values are retained while negative ones are transformed to zero. ReLU adds non-linearity to the network, enabling it to understand intricate feature interactions. It helps prevent the vanishing gradient issue, which can arise with saturated activation functions like tanh and sigmoid and is computationally efficient.

The feature maps are down sampled by pooling layers, either max-pooling or average-pooling, which lowers the spatial dimensions of the feature maps without sacrificing significant features. In doing so, overfitting is avoided and computational complexity is decreased. After being flattened, the feature maps from the convolutional and pooling layers are fed into fully connected layers, which use the learned features to perform classification. Typically, the neurons in these layers have learnable weights that are tuned by training. Using a loss function such as categorical cross-entropy, the output of the Enhanced CNN will be contrasted with the ground truth labels. Minimizing this loss through network parameter adjustments to increase classification accuracy is the aim of training. The proposed study uses a collection of labelled brain images with various tumor kinds to train the Enhanced CNN. By changing its parameters during training, the network gains the ability to distinguish between these distinct types of tumors. The forward pass formula, which calculates the network's output given an input image, is the formula that describes how the Enhanced CNN operates is provided in eqn. (3).

$$\boldsymbol{Op} = \boldsymbol{c}(\boldsymbol{E}.\boldsymbol{M} + \boldsymbol{i}) \tag{3}$$

The input image is denoted by M, the network weights by E, the biases by i, and the activation function by c. Neural network training may be stabilized and sped up with the use of batch normalization. With the batch mean subtracted and the batch standard deviation divided, it normalizes the activations of each layer. This keeps the training process stable and avoids disappearing or overflowing gradients by guaranteeing that the inputs to each layer have a constant distribution. To further minimize overfitting, batch normalization introduces noise into the training process, so functions as a kind of regularization. Batch normalization improves generalization performance by allowing the network to learn more effectively and converge more quickly by normalizing the activations.

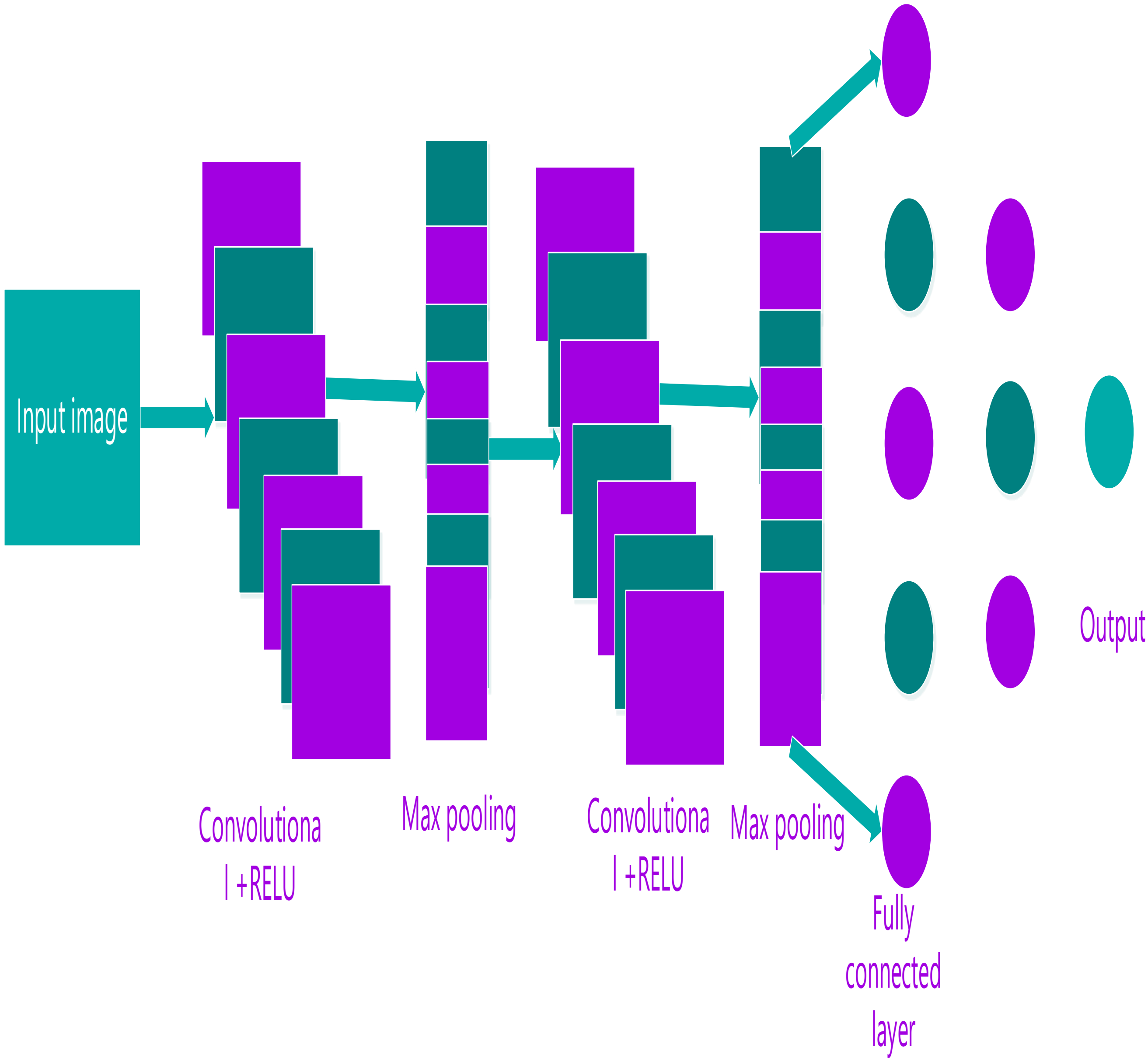

Fig.3 Enhanced Conventional Neural Network

Figure 3 depicts the CNN, known for its ability to yield superior results compared to existing techniques. While SVMs offer commendable accuracy, they typically fall short of the performance achieved by Enhanced Convolutional Neural Networks. The ECNN architecture incorporates convolutional layers augmented with ReLU layers, facilitating error rectification in non-linear data. Additionally, Max pooling layers are employed to mitigate overfitting in images. The feature extraction technique utilizes DWT, contributing to enhanced results. Overall, the ECNN model demonstrates improved performance, attributed to its robust architecture and advanced feature extraction methods [15].

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V. RESULT AND DISCUSSION

The brain image classification task results in the proposed study show how effective the combined DWT and augmented CNN technique is. With the suggested framework correctly classifying brain disorders at a rate of 98.9%, the classification accuracy is astounding. This high accuracy rate outperforms current techniques and highlights the effectiveness of the CNN methodology with DWT enhancements. When DWT is used for pre-processing and feature extraction, it works well to lower noise and improve image quality, which helps to identify diseases more accurately. By categorizing brain images according to the retrieved characteristics, the improved CNN design increases accuracy even further.

A. Performance Measurement

The performance evaluation of the proposed work involves assessing various metrics to gauge the effectiveness and reliability of the developed classification framework. The accuracy of the image processing is evaluated by using the following methods, the evaluation parameters are true positive (ES), True negative (ET), False Positive (LV) and the False Negative (LG).

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{ES+ET}}{(\boldsymbol{ES+ET})+(\boldsymbol{LV+LG})} \quad (4)$$

$$\boldsymbol{Sensitivity} = \frac{\boldsymbol{True\ positive}}{\boldsymbol{True\ positive+False\ Negative}} \quad (5)$$

$$\boldsymbol{Specificity} = \frac{\boldsymbol{True\ negative}}{\boldsymbol{True\ Negative+False\ negative}}$$

(6)

$$\boldsymbol{F1\ Score} = \frac{\boldsymbol{2\times specificity\times sensitivity}}{\boldsymbol{specificity\times sensitivity}}$$

(7)

The above parameter specifies that the calculation of the accuracy on the basic of the Enhanced convolutional neural network. In the proposed paper compares that the existing paper on the basis of the accuracy, specificity and the sensitivity, The existing paper consists the algorithm like CNN+ SVM and the CNN+ KNN, and this two-paper used Discrete wavelet transform for the Feature extraction analysis.

Table 1: Comparison of Existing Method with Proposed Method

Method	Performance
CNN+SVM [16]	76%
CNN+DWT [17]	79%
KNN+DWT [18]	80%
SWM+DWT [19]	90%
Proposed ECNN+DWT	98%

The performance outcomes of several techniques for classifying brain images are shown in the table 1. Each approach combines DWT with a variety of techniques, such as CNN, SVM, KNN, or other algorithms, for feature extraction. With a performance score of 98, the "Proposed ECNN+DWT" technique outperforms the other methods in terms of accuracy in diagnosing brain illnesses. This indicates that the classification accuracy is much improved when the Enhanced Convolutional Neural Network is combined with DWT for pre-processing and feature extraction. The accurate classification of brain images through the use of DWT-based feature extraction in conjunction with sophisticated deep learning algorithms highlights the potential benefits of the suggested strategy in terms of bettering patient care and illness detection.

The fig 2 shows the filtering technique in the Discrete wavelet Transform. Figure 3 illustrates signal processing involving filters. It begins with a signal input, followed by a

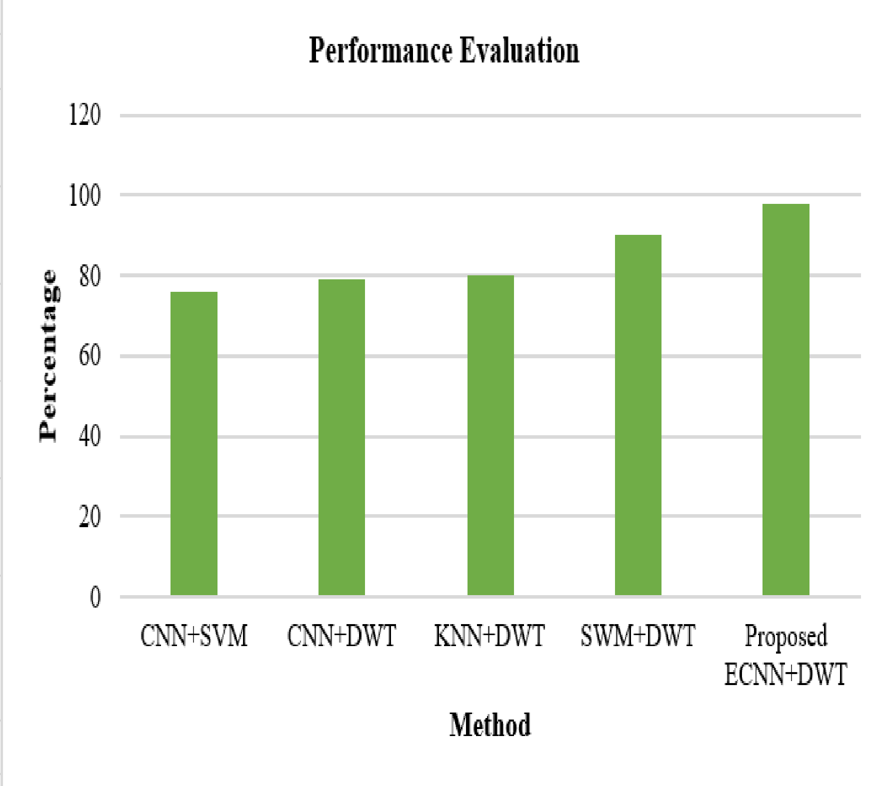

Fig 4. . Effectiveness Assessment of the Proposed method with the Existing method

The fig 4 implies that the results for the comparison of the proposed and the existing approach. Every methodology, like CNN, SVM, KNN, or SWM, is matched with a particular method, like DWT with feature extraction. With a performance score of 98, the suggested ECNN+DWT has the maximum accuracy in diagnosing brain disorders. This indicates that, in comparison to alternative techniques, the ECNN architecture greatly increases classification accuracy when combined with DWT for pre-processing and feature extraction. The outcomes demonstrate how well the suggested method works to categorize brain images, opening the door to improved patient care and illness diagnosis.

Fig 5. Training and Testing Accuracy

Figure 5 shows how a classification model trained with different numbers of epochs performed in terms of testing and training accuracy. Both the training and testing exactness are initially 0 in the absence of training. Both accuracies increase gradually with further training. Testing accuracy, on the other hand, peaks at about 20 epochs, suggesting ideal performance, but training accuracy steadily rises with more epochs. The declining returns at later epochs emphasize how crucial it is to strike a balance between model complexity and generalization ability in order to attain the best results.

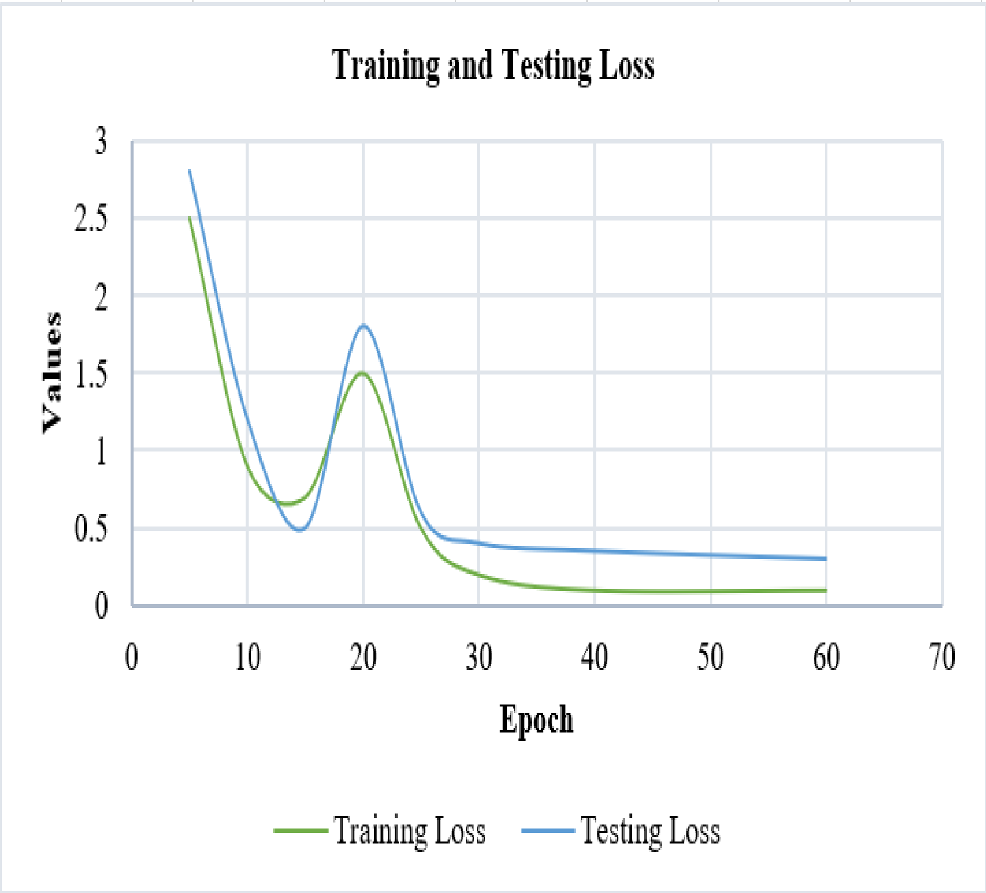

Fig 6. Training and Testing Loss

B. *Disscussion*

The proposed work demonstrates the efficacy of combining DWT with an ECNN for brain image classification, achieving remarkable accuracy. This highlights the potential of advanced techniques in improving early disease diagnosis, benefiting patient care and outcomes. In terms of brain image categorization, the suggested system which combines an ECNN with DWT performs better than current ones [20]. The suggested method achieves higher accuracy rates by utilizing ECNN for precise classification and DWT for noise reduction and feature extraction. When compared to conventional approaches, this integrated approach improves early illness identification, offers greater dependability, and has the potential to improve patient treatment. Better classification accuracy in brain images is one of the suggested work's benefits, made possible by the combination of ECNN and DWT. Increased computing complexity and resource needs, however, might be drawbacks. Further research might look at expanding the framework to multidisciplinary imaging data for thorough illness detection while also enhancing computing efficiency and scalability.

VI Conclusion and Future Work

In conclusion the work applies brain tumor classification using publicly available landmark datasets that include both affected and unaffected pictures. These photos provide the input for the preprocessing procedure, which removes noise from the image and changes it from an RGB to a greyscale image. The median filter is used in this study to eliminate noise from the imaging. This technique helps to remove the salt and the pepper noise in the image, then the output of the pre-processed image gives the input for the feature extraction, this paper implements DWT method for reduce the dimensional edges and sharpening the image for better accuracy, and finally the given images are classified by using the Enhanced convolutional neural network. As a result, it offers superior accuracy over the current method. Further work should focus on expanding the proposed framework to incorporate multi-modal imaging data, such as combining MRI and PET scans. Future research might look at transfer learning techniques to employ trained models for improved classification performance and real-time implementation for speedy clinical deployment.

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