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Enhanced Deep Learning Methodology for Detection and Identification of Brain Tumor using CNN

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Abstract:

Introduction: Brain tumours are a significant global public health issue that require precise and effective diagnosis techniques for well-thought-out treatment strategies. Three separate works for the automatic identification and categorization of brain tumours in magnetic resonance imaging (MR) datasets are presented in this dissertation.

Objectives: The primary objective of this work was to explore uses of the version of the discrete orthonormal S-transform (DOST) to extract texture characteristics and fuzzy C-means (FCM) for image segmentation. By using Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA) we can minimize the dimensional of the recovered features. The proposed Adaboost method is run with the reduced features, and a Random Forest (ADBRF) classifier is then employed. The proposed Adaboost method is run with the reduced features, and a Random Forest (ADBRF) classifier is then employed.

Methods: A range of machine learning algorithms Reduced Complexity Spatial Fusion CNN is applied for the brain to classify and identify the brain tumor.

Results: The results revealed significant performance enhancements, particularly for boosting algorithms. Mean, Variance, standard deviation, entropy, energy has been calculated and by using proposed design it has high accuracy rate.

Conclusions: This study highlights the potential of advanced machine learning techniques for classifying and identification of brain tumor. Accurate analysis is often hampered by the complexity and diversity of image data. To tackle this, we created the RCSF-CNN, a proposed method that combines the extraction of complexity features with CNN for brain cancer detection and classification. Notably, our methodology enhances the resilience and accuracy of detection and classification procedures by utilizing the DOST as an intermediary stage. 21% of the dataset was set aside for rigorous testing, while the remaining 79% was used for training

Keywords: Brain Tumors, Fuzzy C-means, deep learning, neural network, Discrete Orthogonal Stockwell Transform.

1. Introduction

The nervous system's core is the human brain, a marvel of biological engineering that conducts a symphony of cognitive processes that characterize the whole human experience. With an estimated 86 billion neurons, the brain is a sophisticated, networked organ [1]. These neurons, the basic elements of the nervous system, constitute a huge network that permits electrical and chemical information important for many physiological and cognitive activities to be transferred. The brain is composed of three main tissue components, each of which contributes in a unique way to the various functions that the brain performs. The first tissue component is called grey matter, and it is primarily composed of neural cell bodies. It is the computational centre where data is processed, integrated, and interpreted. The second tissue component is called white matter, and it is primarily composed of militated nerve fibres that act as communication highways between various brain regions. This complex network allows information to ow and facilitates coordinated responses. Additionally, the brain's regulatory processes heavily depend on specific brain regions including the cerebellum and brain stem. The brain stem present at the corner of brain, controls essential physiological processes like breathing, heart rate, and fundamental motor responses. The cerebellum, which is found near the rear of the brain, is crucial for balance and motor coordination. Together with specialized areas, these three main tissue components make up a dynamic and complexly structured system that controls complex information processing, communication between various body parts, and the regulation of fundamental physiological activities. These elements' intricacy and interdependence demonstrate the human brain's extraordinary capacity to inuence perception, behaviour, and thought processes. Brain tumours can arise as abnormal cell growths inside tricate system, which can be a significant hindrance to normal brain function [2]. Whether benign or malignant, these tumors have the ability to stress nearby tissues and impair cognitive abilities. Glioma is one type of brain tumor that originate from glial cells. Genetic factors, radiation exposure, and some inherited disorders are recognised as potential contributors, although the exact causes are often unclear.

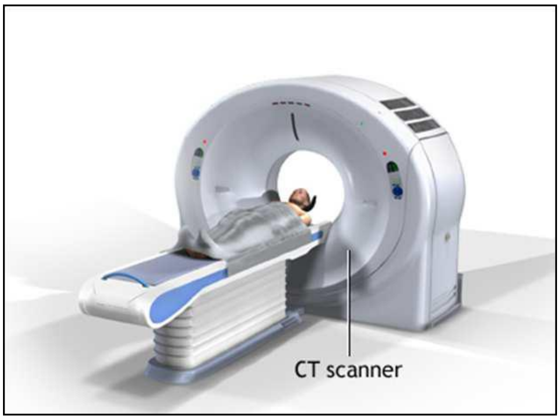

Fig.1 CT Scanner

The paper has been organized as follows: Section.2 deals with the literature survey of the brain tumor detection and classification. Proposed work has been explained in Section.3. The result analysis of the proposed work has been explained in section.4 Finally the conclusion is present in section.5.

2. Literature survey:

Understanding the intricacies of brain tumours is crucial for ensuring appropriate diagnosis and treatment, as they present a significant challenge to the medicalfield [3]. The paper[4] uses mathematical techniques to analyse normal and diseased individuals in photographs, extract traits, create models, and take measurements.

In addition to Otsu's thresholding, Sujan et al.[5] developed a method for identifying brain tumours from MRI images that includes morphological operations, namely erosion and dilation. There are several image techniques are present. They are:

a. Computed Tomography (CT): CT scans are essential diagnostic instruments that offer precise cross-sectional brain pictures that are vital for tumour diagnosis and localization and is shown in Fig.1. During a CT scan, a succession of finally detailed images from different perspectives are obtained using X-ray technology. Sophisticated computer processing then produces a comprehensive and multi-layered representation of the internal architecture of the brain[6-8].

b. **Magnetic Resonance Imaging (MRI):** It can significantly increase the contrast between soft tissues, it has become an essential technique for identifying brain tumours. Strong magnets and intense radio waves are used to create detailed, high-definition images of the brain's inside architecture, enabling a more number representation of the organ's internal structures. Because MRI offers such remarkable precision in differentiating between healthy and sick tissues, it is essential in this study[9-11].

c. Functional Magnetic Resonance Imaging (fMRI): This is an essential neuroimaging modality to evaluate brain activity, particularly in relation to brain tumours. By identifying and mapping brain areas linked to particular processes, fMRI enables medical professionals to detect variations in blood ow and oxygenation levels. Because fMRI helps identify crucial functional areas, it is possible to ensure that therapies do not impair essential abilities like motor skills, language, or sensory processing. This knowledge is helpful in surgical planning. Neurosurgeons find that fMRI's non-invasive mapping of functional connectivity helps them navigate complex brain networks while doing procedures[12-14].

d.Positron Emission Tomography (PET): PET scans that show the brain's metabolic activities. This imaging method provides a clear view of the metabolic status of the tumour by using a radioactive tracer that accumulates in areas of elevated metabolic activity. Malignant tumours are often seen on PET imaging at higher metabolic rates than the surrounding healthy tissues[15].

3. Proposed Work:

Proposed Work. As can be seen in Fig.2 of the proposed block diagram, the input image is first acquired and then pre-processed using a Weiner filter. A linear filter that is used to improve picture characteristics and reduce noise is called aWeiner filter. Once the image has been filtered, it is subjected to pixel normalisation and removal, which entails removing any pixels that are below a predetermined threshold value and normalising the image's pixel values to a standard range. The output of this step is a cleaned and normalised image. This process comprises eliminating any pixels that are below a predetermined threshold value and normalising the image's pixel values to a standard range. A cleaned and normalised image is the result of this stage. The cleaned and normalised image is then supplied to DOST. This article presents a technique aimed at improving image quality and making brain tumour identification easier. The Wiener filtering approach is used to pre-process photographs that are obtained from a medical database in the first step of the method. The process of pixel normalisation elimination is then initiated in order to normalise the pixels within the image. The image is then converted to a frequency domain representation using the Discrete Orthogonal Stockwell Transform (DOST).

Following that, features are extracted using a complexity feature approach. Finally, a subtractive spatial lightweight-based RCSF-CNN technique is applied to detect brain tumours using a trained dataset.

Pre-Processing Using Weiner Filter: Prior to further analysis, this method helps to improve the quality and dependability of brain pictures by reducing noise and artefacts using the Weiner filter. The Weiner filter, a vital part of the preprocessing pipeline, reduces noise in brain imaging data without sacrificing important information.

Pixel Normalisation and Elimination: Pixel values in an image can be changed to correct or remove certain issues that jeopardise the image's integrity. We call this procedure "pixel normalisation." Furthermore, wavelet decomposition and the fusion methods discussed in this part are to be employed for the normalization and fusing of two input photos. The function others a wide range of input and output options and streamlines picture fusion and normalisation procedures.

DOST: Following the pixel fusion and normalisation processes, the final image is subjected to the DOST. A time-frequency representation known as the DOST provides details on the frequency and time components of a signal. The signal's energy in different time and frequency domains is represented by the DOST coefficients. Subsequent analysis can utilise these coeffcients as features.

Feature extraction procedure: The photos are put through a feature extraction procedure called "Local Central Prominent," which is based on a complexity-based approach. RCSF-CNN: A novel method termed "Reduced Complexity Spatial Fusion CNN (RCSF-CNN)" may be able to accurately classify brain cancers using medical imaging. The method is based on a lightweight CNN architecture that was designed with the goal of minimising computational complexity without compromising competitive performance.

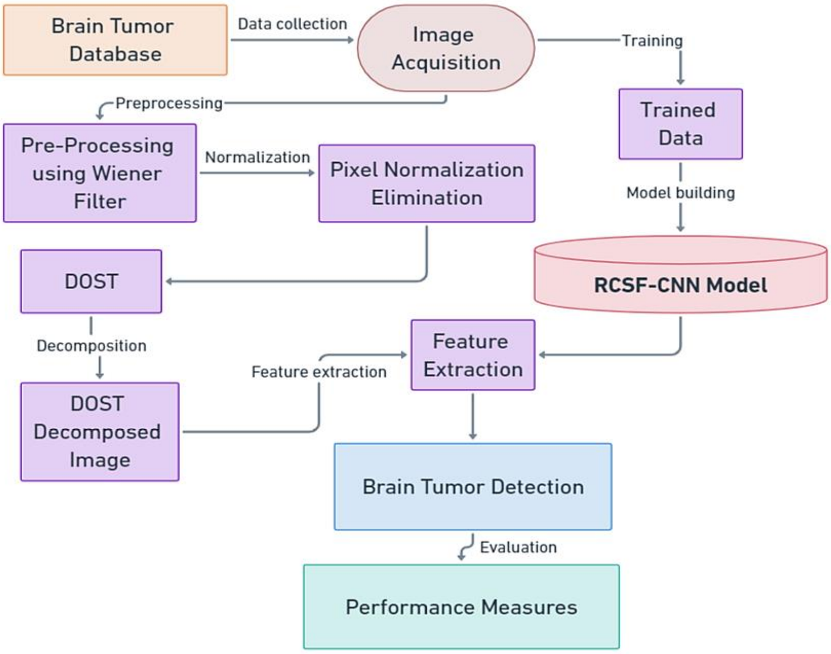

Fig.2 Proposed design

Algorithm of Reduced Complexity Spatial Fusion CNN

1. Images are obtained from medical databases and preprocessed using the Wiener filtering technique.

$$F(u,v) = \frac{G(u,v)H(u,v)}{(|H(u,v)|^2 S(u,v) + N(u,v))} \ldots\ldots..(1)$$

Where *F(u,v)*=Estimated image,

G(u,v) =Observed image,

H(u,v) = The transfer function, *H*(u,v)*

2. Initiate the Pixel Normalization Elimination process

a. The mean value is:

$$\mu = \left(\frac{1}{(M\ N)}\right) \Sigma\, P(i,j) \ldots\ldots\ldots\ldots (2)$$

standard deviation: $\sigma^2 = \frac{1}{(MN)} \sum (P(i,j) - \mu)^2 \ldots.(3)$

$$P_{norm}(i,j) = \frac{(P(i,j) - \mu)}{\sigma} \ldots\ldots\ldots(3)$$

The resulting image after pixel normalization is denoted as $P_{norm}(i,j)$where each pixel value represents the normalized value of the corresponding pixel in the pre-processed brain MRI scan. ()

3. Get the Pixel Normalization Elimination procedure started

4. Application of the RCSF-CNN method of CNN to identify brain tumours using a trained dataset.

4. **Results:**

An expanded dataset of 3000 samples, which was created from the first 300 photos in the BRATS dataset, was used to train the suggested deep learning model. Enhancing the model's capacity to identify brain tumours in medical imaging was the goal. By making many adjustments to the original photos, data augmentation techniques enhanced the dataset and boosted the model's capacity to recognise patterns associated with malignancies. Following training on 80% of the enlarged dataset (2400 samples), the model demonstrated the ability to

recognise complex features of tumours. The 600 samples from the test set that made up the remaining 20% assessed the model's performance on data that had never been seen before. The linked sub-tractive pixel extracted image is an essential part of the overall upgraded technique, and the input Brain scan is scaled for optimal processing.

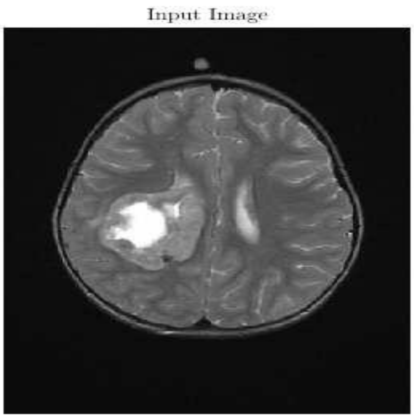

Fig.3 Original Image

Wiener filtering is the final stage in eliminating any remaining noise. At this point, the input image is examined to determine the noise's properties, including its type and noise power spectrum. The method used to determine the PSD of the input image is suitable and yields information on the frequency content of the image shown in Fig.3.

The Wiener filtering technique then applies the computed PSD to decrease noise and enhance the image. By taking into consideration signal and noise characteristics, the Wiener filter aims to lower the mean square error between the filtered and original images. After filtering, the image is post-processed to enhance its qualities and get rid of artefacts shown in Fig.4.

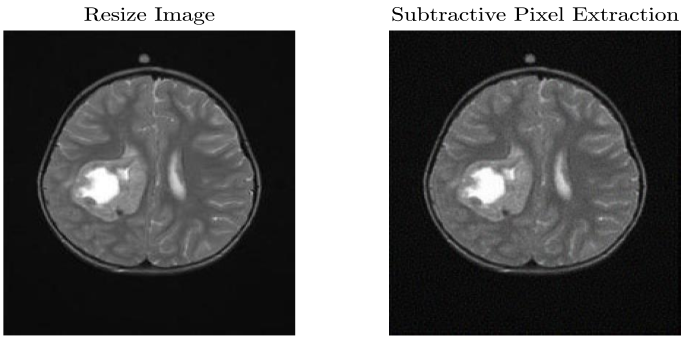

Fig.4 Resized Image and Subtractive Pixel Extracted Image

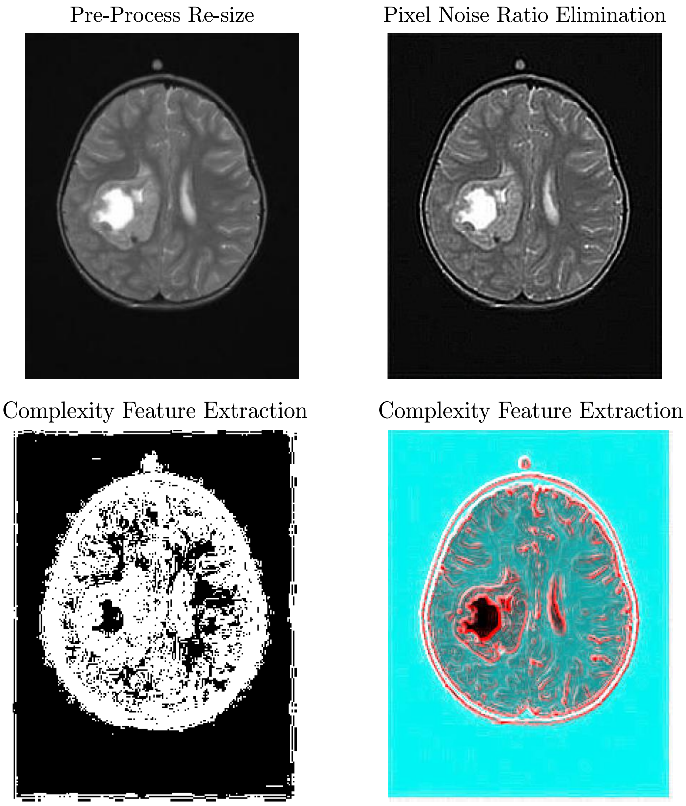

Fig.5 Steps for different images

Subtractive spatial information extraction and removal are done in the set of operations that follow. The next step is collecting the attribute called Complexity. By gathering the fundamental picture attributes|Mean, Energy, contrast, and so forth|that are critical to the detection process, this approach entails labelling the features with RCSF-CNN (Fig.5). Upon that point, the procedure of detection is finished.

Brain Tumor Detection Area

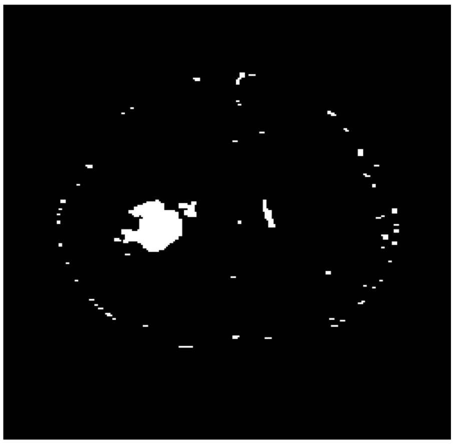

Fig. 6 Brain Tumor detection area

As shown in Fig.6, the outcome of processing these extracted features through an RCSF-NN and applying the training dataset to them is a brain tumour detection region, which indicates the presence of a brain tumour. The BRATS dataset, which had 300 original pictures, was enlarged to 3000 samples, and this larger dataset was utilised to train the deep learning model that was suggested. The main goal of this procedure was to make the model able to recognise brain cancers in medical photos with accuracy. The following equations are supplied for the features that were extracted:

Mean: An image's mean is its average pixel value

$$\mu = \left(\frac{1}{N}\right) \sum_{i=1}^{n} I(i) \qquad (4)$$

Standard Deviation: The standard deviation of an image is a measure of the amount of variation in the pixel values and is calculated as:

$$\sigma = \sqrt{\left(\left(\frac{1}{N}\right) \sum_{i=1}^{n} \left(I(i) - \mu\right)\right)^2} \ldots\ldots\ldots\ldots(5)$$

Entropy: Entropy is a measure of the randomness or uncertainty in the pixel values of an image.

Variance: Variance is a measure of how far the pixel values are from the mean.

Table.1. Samples of Brain Tumor

	Sample Brain Tumor Images				
Features Extracted	**Data-1**	**Data-2**	**Data-3**	**Data-4**	**Data-5**
Mean	0.00366	0.00461	0.003711	0.0043211	0.00334
Variance	2.53122	2.468	2.439	2.431	2.447
Smoothness	0.9342	0.941	0.929	0.928	0.931
Entropy	0.00801	0.0074	0.0069	0.0076	0.0077

Correlation	0.106722	0.1102	0.1123	0.1089	0.1094
Contrast	0.353	0.347	0.348	0.366	0.358
Energy	0.81511	0.832111	0.81872	0.816798	0.816454
Standard Deviation	0.081	0.082	0.094	0.087	0.097

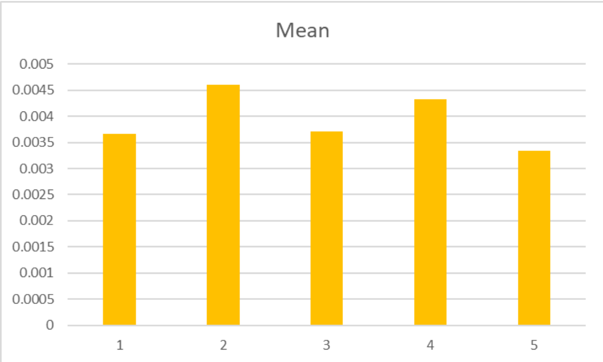

Fig.7 Mean Value

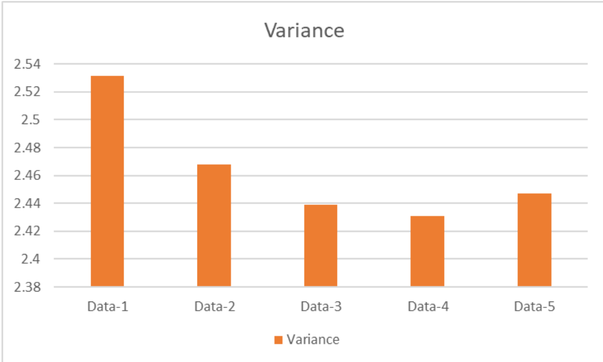

Fig.8 Variance

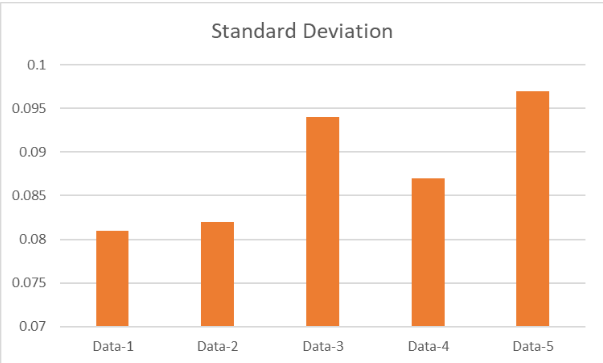

Fig.9 Standard deviation

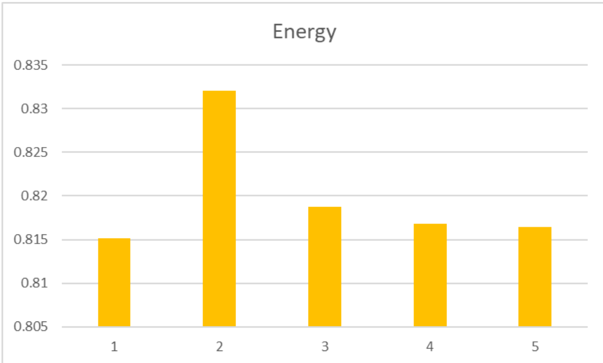

Fig.10 Energy

The Table.1 tabulated features are also displayed in corresponding graphical plots, Standard Deviation, Fig.7 deals with mean, Fig.8 explains about variance. Standard deviation was explained in Fig.9. Finally in Fig.10 was related to energy.

It is clearly visible from the comparing plot that the accuracy of the suggested method performs much better than all other ways. The graphical representation of accuracy values illustrates how the proposed methodology considerably enhanced the detection of brain tumours when compared to the state-of-the-art techniques utilized on the BRATS dataset. All of the approaches under comparison were run against the BRATS -2015 bench-mark, and for a fair comparison, the suggested method additionally made use of comparable data. The method presented in this work has demonstrated a higher degree of accuracy, which reinforces its potential for improved precision and reliability in brain tumour diagnosis. Consequently, it represents a signi_cant and auspicious contribution to the domain of medical image interpretation and brain cancer identification. The excellent performance demonstrated by the recommended strategy is visually compellingly illustrated through the deft use of a comparison plot. This demonstrates the method's value in advancing the field of research on brain tumour diagnostics and verifies its efficiency in accurately identifying brain malignancies.

5. **Conclusion**:

The paper concludes that the proposed design plays a crucial and complex endeavour to identify and categorise brain tumours within medical imaging. Accurate analysis is often hampered by the complexity and diversity of image data. To tackle this, we created the RCSF-CNN, a proposed method that combines the extraction of complexity features with CNN for brain cancer detection and classification. Notably, our methodology enhances the resilience and accuracy of detection and classification procedures by utilizing the DOST as an intermediary stage. 21% of the dataset was set aside for rigorous testing, while the remaining 79% was used for training. It is noteworthy that the suggested methodology demonstrated its practicality in real-world circumstances by achieving an impressive accuracy rate of 99.05%for brain tumour diagnosis. This approach shows promise as a robust and reliable tool for the early identification and categorization of brain tumors, leading to better treatment plans and patient outcomes.

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