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Research Article

Advanced Brain Tumor Classification Using DeepBeleif-CNN Method

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ABSTRACT

Computer-aided research to improve image decoding is a long-standing theme in medical imaging. A variety of imaging techniques, including ultrasound imaging, The Magnetic Resonance Imaging (MRI), and Computed Tomography (CT), are generally depleted to estimate tumors in the prostate, lung, brain, breast, and liver. The study used MRI images of the brain to identify the tumors. Brain tumors are an almost common and cruel disease that can significantly shorten life expectancy. It is important to use MRI images to locate and classify contaminating tumors. There are many tumors including gliomas, meningiomas, pituitary tumors, and no tumors. One of the most difficult aspects of brain tumor assortment is the diagnosis and prevention of tumor type. Accurate tumor classification helps to assess disease progression and select therapeutic strategies. To resolve the issue, a Deep Belief Neural- Convolutional Neural Network (DeepBeliefCNN) method was proposed. At first phase, we preprocess the brain tumor MRI dataset by using 2D Wavelet Filter method. This method allows for the analysis of images at multiple resolutions, thus enabling detection of features at different scales. This effectively reduces noise in medical images while preserving important details. This improves the definition of tumor boundaries and other important features, helping in accurate diagnosis and analysis. Then preprocessing the dataset segment the preprocessed images based on Watershed method. It is a powerful image segmentation technique used to outline objects in images. When used for image segmentation of a brain tumor, it can help identify tumor boundaries within the brain. Markers are assigned to areas of interest in the image. These markers can be manually set by experts or generated automatically using techniques such as distance transforms and morphological functions. At last, the dataset is classify by using the DeepBeleifCNN method. The DeepBeleifCNN approach combines the hierarchical feature extraction capabilities of DBN with the spatial feature extraction capabilities of CNN. This allows a detailed understanding of brain tumor images and improves classification performance. This method successfully generalizes to new and unrecognized brain tumor images because of its capability to study healthy and biased features in together pre-training and fine-tuning stages. The investigational outcomes illustrate that our deployed methodology beats the existing method in accuracy, sensitivity, F1 score, specificity, and error rate.

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1. INTRODUCTION

The brain is an important organ in charge of the central nervous system. The human brain supplies the central nervous system via connections to the bone marrow. Also controlling human body functions is the brain. It receives information from other senses, makes decisions and issues commands to the body. The brain is the central part of the human body's management department, controlling all functions of the human body with the help of nerve cells. Malignant and benign brain tumors are by far the most common types of brain tumors. Brain tumors are considered the most dangerous cancer in both adults and children. Brain tumors occur when brain tissue develops in an abnormal manner. Abnormal tissue overgrows compared to normal cells, causing the cells to form in large numbers and eventually become tumors. Benign tumors are tumors with minimal damage and no tumor cells. Malignant tumors are the most dangerous and intentionally lethal tumor cells. Malignant tumors can affect the whole brain. The most common primary tumors in adults include gliomas, meningiomas, and pituitary gland tumors. Gliomas arise from glial cells in the brain's supporting tissues. Meningiomas are usually slow-growing, benign tumors that begin in the outer casing of the brain just below the skull. Meningiomas usually occur in one hemisphere of the brain and can take several years to diagnose. The pituitary gland is at the base of the brain. Its primary function is to produce hormones that regulate various glands in the body, such as the thyroid gland [1]. Currently, the imaging method is becoming increasingly popular among radiologists because it is extra precise and poses fewer hazard to patients. There are many methodologies of obtaining clinical image data including radiography, MRI, tomography and echocardiography. In between them, MRI has attracted a lot of attention because it can obtain high-resolution images deprived of using somewhat radiation. The MRI is a non-invasive test that affords radiologists through beneficial information on clinical imaging data to diagnose brain abnormalities. Computer-Assisted Diagnosis (CAD) methods, on the other hand, aim to detect brain tumors early without human intervention. CAD architectures can create diagnostic chronicles on the basis of MRI images and provide leadership to radiologists [2].

There are several categories of tumors, including gliomas, meningiomas and pituitary tumors, but no tumors. Doctors and radiologists spend a lot of time analyzing test results and scans, which can be extremely time-consuming. Interpretation of these images depends on the individual clinician's judgment and experience. In recent years, MRI has received much attention from medical researchers. One of the most difficult aspects of brain tumor classification is identifying and preventing tumor types. Accurate tumor classification helps to assess disease progression and select therapeutic strategies [3]. To attain the objective, a DeepBeleif CNN method was proposed. DeepBeliefCNN collates the advantages of Deep Belief Networks (DBN) and Convolutional Neural Networks (CNN). DBN is known for its ability to learn hierarchical representations and serve as a pre-training step to initialize the network with meaningful features. Then refine these features by using multiple convolutional layers of CNN, known for their powerful capabilities in image processing tasks. The DeepBeleifCNN method enables the model to capture complex patterns and subtle differences in brain tumor images, thus improving classification performance.

This approach combines the unsupervised learning capabilities of DBNs to model complex data distributions and the supervised learning capabilities of CNNs to achieve high accuracy in classification tasks. This method has shown promising results in differentiating different categories of brain tumors such as gliomas, meningiomas, and pituitary tumors as of clinical imaging data. DeepBeleifCNN has great potential to advance clinical diagnosis and improve patient outcomes by providing a powerful and useful brain tumor classification framework.

The main contributions of DeepBeleifCNN method:

- By initializing the network with meaningful features using the proposed method, the model can learn a robust representation of brain tumor images and capture complex details and patterns that differentiate different tumor types.
- The DeepBeleifCNN method takes advantage of the deep hierarchical feature learning capabilities of DBN and the powerful pattern recognition capabilities of CNN, so it can achieve higher classification accuracy and robustness than conventional methods.
- This method is suitable for clinical image analysis, especially brain tumor classification, as it can handle the complexity and variability of clinical image data, resulting in better diagnostic results.

2. LITERATURE SURVEY

S. Gopalakrishnan [4], carried out Advanced Attention Capsule Network (AACNet) methodology to examine the difficulty of miscellaneous medical images. The innovative integration of dynamic channel attention and capsule networks makes AACNet a pivotal solution for medical image analysis. They also suffer from disadvantages of long training times, large data requirements, slow inference times, dynamic environments and hardware dependencies.

Soheila Saeedi [5], carried out 2D CNN methodology to distinguish with large level of accurateness tumors in initial stages. The network is not very complex and can be used in clinical settings by radiologists and doctors to diagnose brain tumors. Associating the execution of different CNN and Machine Learning (ML) methodologies in detecting three categories of brain tumors, the author found that the 2D CNN accomplished archetypal execution and the best processing time with no latency. Hamza Rafiq Almadhoun [6], carried out Deep learning (DL) is a technology that uses MRI images to quickly and easily distinguish and categorize brain tumors and identify brain tumors. The goal was to find a better, more effective MRI-based brain tumor detection method that would allow neurologists to formulate verdicts easier, more accurately, and faster. However, it requires high computing power and specialized hardware (such as GPUs), which are expensive and require technical expertise.

Sarmad Maqsood [7], carried out Multiclass Support Vector Machine (M-SVM) method to attained large level of process basically of together visually and enhanced quantitative assessment through enhanced accuracy. This approach involves many layers of interconnected nodes, which makes it difficult to understand how the model arrives at predictions and conclusions. Ayesha Younis [8], carried out VGG 16 method to produce convolutional feature maps, at that time classified these to grant tumor region recommendations. However, the network is huge, training the parameters takes more time. Muhammad Aamir [9], carried out an automated methodology for perceiving brain tumors via MRI. This is scaled to an encoded size and imparted to the apex network for sorting. However, exaggeration ensues when a methodology is trained too fine on training data, causing it to perform poorly on novel, unnoticed data. Fatma Taher [10], carried out Transfer Learning (TL) based protocols additionally to a CNN termed BRAIN-TUMOR-net trained as of scratch are acquaint with to categorize brain MRI images into tumor or non-tumor. However, TL has potential disadvantages. If a proposed methodology is not done properly, it can result in negative transfer, where learning performance decreases rather than improves.

Asaf Raza [11], carried out a hybrid DeepTumorNet methodology for classify the three categories of brain tumors. In the proposed method, the expressive power of the model was improved by using the Leaky ReLU activation methodology in the feature map. However, they suffer from computational complexity, need for large amounts of labeled data, susceptibility to overfitting, lack of interpretability, and resource requirements. D. Rammurthy [12], carried out Whale Harris Hawks optimization (WHHO) methodology for brain tumor discovery via MR images. The foremost disadvantage of the deployed methodology is that it is susceptible to local optimization. To solve this issue, a new mutation strategy based on Brownian motion is proposed in combination with the original HHO. Hanaa ZainEldin [13], carried out an Adaptive Dynamic Sine-Cosine Fitness Grey Wolf Optimizer (ADSCFGWO) for utilizes both the sine-cosine and gray wolf mechanisms in an adaptable framework that leverages the strengths of both methodologies. Although these GWO variants improve the convergence speed and accuracy of homogeneous functions and have the ability to exit local optima for multimodal functions and complex problems, they still have problems such as slow convergence speed and low accuracy, and they can easily get into the problem.

Naeem Ullah [14], carried out a deep TL methodology for perceive and categorize the three furthermost projecting categories of brain tumors, for instance glioma, meningioma and pituitary. However, the deployed methodology has potential disadvantages. If a transfer learning algorithm malfunctions, it can result in negative transfer, which degrades rather than improves learning performance. Saif Ahmad [15] discussed that to detect brain tumors, several TL-based deep learning methods were analyzed via numerous outdated classifiers. The discoveries are based on a labeled dataset of normal and abnormal brain images. However, the refinement of the method may be limited by the large amount of categorized data available for the objective mission and the resemblance among the cause and objective missions. Shahzad Ahmad Qureshi [16], carried out an Ultra-Light Brain Tumor Detection (UL-BTD) methodology for widely obtainable MRI brain tumor datasets can be classified into multiple classes in minimal time, allowing real-time tumor detection without sacrificing accuracy. This method has drawbacks such as extensive training period, huge data necessities, deliberate inference period, large level environment, and hardware craving.

Subburayalu Gopalakrishnan [17], discussed that in previous research, various image processing techniques such as segmentation, optimization and classification have been introduced in gesture recognition. Nevertheless, major problems of inefficiency in processing large-dimensional datasets are still limited, requiring high time consumption, increase in false positives, error rates, and misclassified outputs. To resolve the issue, a Heuristic Manta-ray Foraging Optimization (HMFO) methodology was deployed. Additionally, the number of feature dimensions is reduced, which reduces error rates and improves classification accuracy.

3. MATERIALS AND METHODS

This portion presents the detailed mechanisms of the deployed research. Figure 1 shows the details of the introduced methodology. In this novel, we gather the brain tumor MRI dataset at IEEE data port website https://ieee-dataport.org/documents/brain-tumor-mri-dataset.

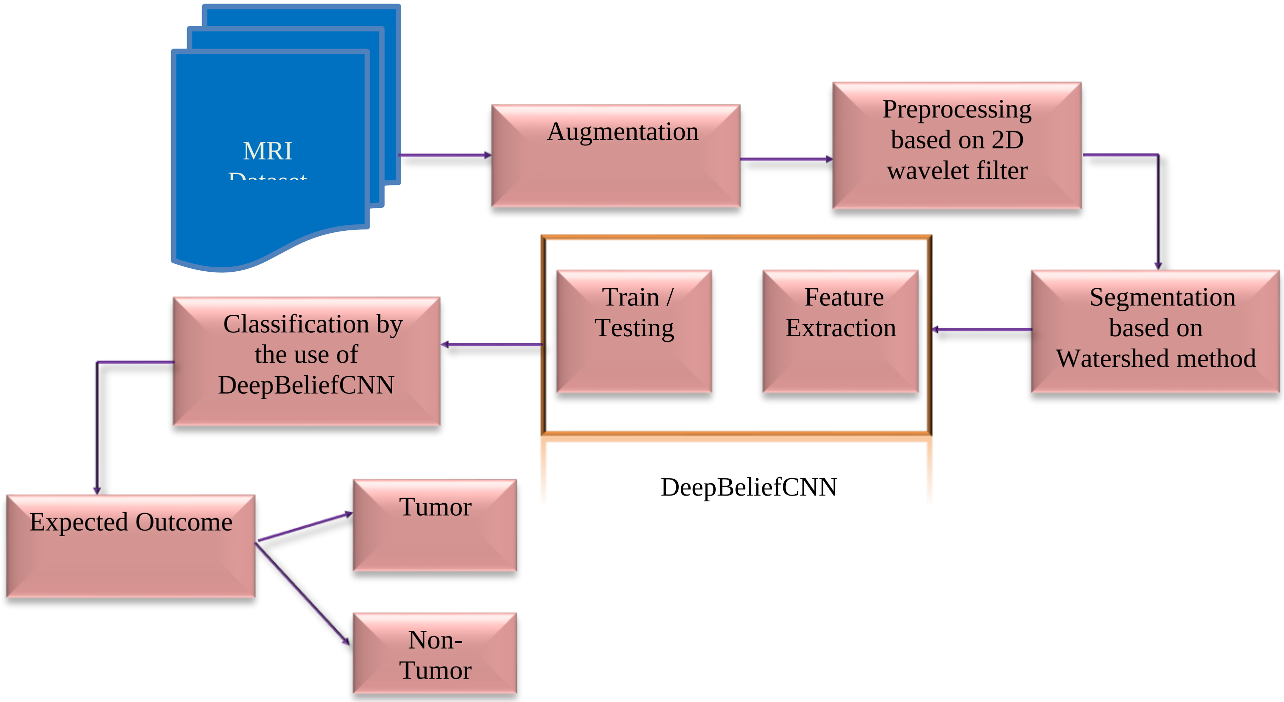

Fig. 1. The architecture diagram of the DeepBeliefCNN method

The dataset was collected and preprocessed by using 2D Wavelet Filter method. This method can effectively detect the edges and increase the contrast between the tumor area and the background. It helps to distinguish the tumor from the surrounding healthy tissue. After preprocessing, segment the preprocessed images by the use of Watershed method. A watershed approach can provide precise boundaries, which are critical for diagnosis and treatment planning. It can be collective with further segmentation protocols, such as region growing and DL-based methods, to improve robustness and accuracy. Finally, classify the dataset images by the use of DeepBeleifCNN method. DeepBeleifCNN has great potential to advance clinical diagnosis and improve patient outcomes by providing a powerful and useful brain tumor classification framework.

3.1 Data Augmentation

The dataset is collected at the IEEE data port website and it was known as Brain Tumor MRI dataset. It is publicly available dataset and it contains MRI images brain tumors. This dataset is obtaining the three combination of datasets by following figshare, SARTAJ, and Br35H datasets. This dataset encompasses 7023 images of human brain MRI images those are categorized into 4 classes: glioma - meningioma - no tumor and pituitary. The no tumor class images stood occupied as of the Br35H dataset. The SARTAJ dataset has an issue where images in the glioma category are misclassified. So, we observed this problem from the results of other people's work and the various models trained on. So, delete the images in that folder and browse the images on Figshare website instead.

3.2 2D Wavelet Filter method

In this section the brain tumor MRI images are preprocess by the use of 2D Wavelet Filter method to detect edges and reduce noise. Wavelet transforms allow you to analyze images at multiple resolutions, making it easier to identify features at different scales. It is particularly useful for images of brain tumors, which can have complex structures of varying sizes. Wavelet filtering reduces noise in medical images while retaining important details. It improves the clarity of tumor boundaries and other important features, enabling accurate diagnosis and analysis. This method can effectively detect the edges and increase the contrast between the tumor area and the background. It helps to distinguish the tumor from the surrounding healthy tissue. This approach allows compressing images without significant loss of important information, thus facilitating efficient storage and processing, especially when processing large medical image datasets. Numerical methods for estimating frequencies, their application to synthetic patterns, and detection methods basically a normalized resemblance measure M are correspondingly obtainable here.

The space $s^2\ \left(V_{L_1} x V_{L_2}\right)$is definite as an expansion of the vector space $s^2(V_L)$. Here, the components of V_L are well thought-out as complex vectors through components of L.

$$s^2\left(V_{L_1}xV_{L_2}\right) = \{v = [v(l_1, l_2)]: v(l_1, l_2) \in C, 0 \le l_1 \le L_1 - 1, 0 \le l_2 \le L_2 - 1\} \qquad (1)$$

The dimensions of the vector space are $L_1 . L_2$, and the addition and multiplication of complex scalars is the same as in the one-dimensional case. The complex dot product of s^2 is $\left(V_{L_1}xV_{L_2}\right)$:

$$\langle v, q\rangle = \sum_{l_1=0}^{L_1-1} \sum_{l_2=0}^{L_2-1} v(l_1, l_2). \overline{q(l_1, l_2),} \forall v, q \in s^2(V_{L_1}xV_{L_2}) \qquad (2)$$

In 2D cases the rotation operator is correspondingly beneficial.

Hence, $v \in s^2(V_1 x V_{L_2})$, prolonged by periodicity, and $p_1, p_2 \in V$. The rotation operator on $s^2\left(V_{L_1}xV_{L_2}\right)$ is defined by,

$$B_{p_1,p_2}: s^2\left(V_{L_1}xV_{L_2}\right) \to \left(V_{L_1}xV_{L_2}\right) v \to B_{p_1,p_2}v \qquad (3)$$

$$\left(B_{p_1,p_2}v\right)(l_1, l_2) = v(l_1 - p_1, l_2 - p_2) \qquad (4)$$

Let $D_1, D_2 \in V, L_1 = 2D_1, L_2 = 2D_2$. Let $\left\{B_{2p}t_1\right\}_{p=0}^{L_1-1} \cup \left\{B_{2p}r_1\right\}_{p=0}^{L_1-1}$ be a beginning-phase wavelet source for $l^2\left(V_{L_1}\right)$ and let $\left\{B_{2p}t_2\right\}_{p=0}^{L_2-1} \cup \left\{B_{2p}r_2\right\}_{p=0}^{L_2-1}$ be a beginning-phase wavelet source for $l^2\left(V_{L_2}\right)$. If we define,

$$q_0(l_1, l_2) = t_1(l_1). t_2(l_2) \qquad (5)$$

$$q_1(l_1, l_2) = r_1(l_1). t_2(l_2) \qquad (6)$$

$$q_2(l_1, l_2) = t_1(l_1). t_2(l_2) \qquad (7)$$

$$q_3(l_1, l_2) = r_1(l_1). t_2(l_2) \qquad (8)$$

then,

$$\bigcup_{x=0}^{3}\left\{B_{2p_1,2p_2}q_x\right\}_{p_1 \in V_{L_1}}^{p_2 \in V_{L_2}} \qquad (9)$$

is an orthonormal basis for $s^2\left(V_{L_1}xV_{L_2}\right)$, where t_1, r_1 and t_2, r_2 are termed producers of the wavelet source for $s^2(V_{L_1})$ and $s^2(V_{L_2})$, respectively

We propose a strategy to implement 2D wavelet filters on the basis of the tensor product of one-dimensional vectors, but with a different approach based on the detection conditions. In Equation (8), we see that the oblique aspect coefficient of the 2D bandpass filter depends on two aspects: the image is distorted and the 1D high-pass filter t depleted in the de-decomposition. Subsequently, to acquire a 1D filter that can detect patterns considered in the oblique aspect coefficients of 2D wavelet filter when applied to 2D discrete wavelet transform, e (1D) and filter coefficients at specified positions, positional samples of 2D pattern at subsequent positions, samples of 2D pattern at vertically consecutive positions;

Let $d[.,.]$ be a two-dimensional array with l_1 rows and l_2 columns. As in DST-II, the dimensions L_1 and L_2 are preferred via captivating even numbers beneath the real dimensions, since these dimensions must be equal to achieve a perfect reconstruction. Hence, the supported size of a one-dimensional filter e is $= max\{L_1, L_2\}, L \ge 8$, which must be an even number.

The NLES $F(e_0, e_1, \dots, e_{L-1}) = 0$ of L equ and L nonentities, belonging result is the high-pass filter of the 2D wavelet, is the subsequent:

Unit energy to certify that shapelets conserve the energy of a signal:

$$\left(\sum_{p=0}^{L-1} e_p^2\right) - 1 = 0 \qquad (10)$$

$\frac{L}{2} - 4$ disappeared instants for a tolerable uniformity of the shapelet: $\sum_{p=0}^{L-1} ep \,.\, p^b = 0$, where $b = 0,1, \dots, \frac{L}{2} - 5$.

$\frac{L}{2} - 1$ orthogonality conditions: $\sum_{p=0}^{L-1} ep \,.\, ep + 2s = \delta_{0,1}$, somewhere direct delta is represented as δ and $l \in L$

Four circumstances for pattern recognition,

$$\sum_{x=1}^{L_1}\sum_{y=1}^{L_2} e_x. e_y. d_{x,y} = 0 \qquad \sum_{x=1}^{L_1}\sum_{y=1}^{L_2} e_x. e_y. d_{x,y-1} = 0$$

$$\sum_{x=1}^{L_1}\sum_{y=1}^{L_2} e_x. e_y. d_{x-1,y} = 0 \qquad \sum_{x=1}^{L_1}\sum_{y=1}^{L_2} e_x. e_y. d_{x-1,y-1} = 0$$

NLES uses a strategy for numerical solution somewhere a preliminary approximation attained by an iterative mechanism is depleted to initiate a Newton iteration protocol. Then, in the 1D case, a complete regenerative filter bank is obtained.

$$Rp = (-1)^p . e_{L-p-1};\ \overline{R_p} = R_{L-p-1};\ \overline{e_p} = (-1)^{p+1} . Rp, p = 0,1, \ldots, L-1 \tag{11}$$

To obtain the 2D wavelet $g([.,.])$, using a tensor product-based methodology, the signal $g\ [.,.]$ discovery is on the basis of a normalized resemblance amount H, which ever accentuates the occurrence of zeros in the shapelet coefficients. In certain, this measure applies individual to the oblique detail coefficients of 2D wavelet, as 2D pattern patterns are designed to detect patterns within these coefficients.

The analysis is performed using the $g\ [\cdot,\cdot]$ 2D wavelets of $J_1 x J_2$ dimension and the corresponding diagonal coefficient mZ matrix of $D_1 x D_2$ dimension. Let us assume that the pixel position is (x, y) and the units are mA. Let the normalized unity $K = o^{-(|2D\ wavelet(g[.]|)^{\alpha}}\alpha, 0 < \alpha \leq 1$. If $K(\alpha = 0.1)\left[mZ_{x,y}\right] > 0.7$, a 2D pattern occurs. Inside a rectangle, the coordinates of its upper right corner are:

$$a = (2. D_2 - L_2 + J_2)\ mod\ (J_2)$$

$$b = (2. D_1 - L_1 + J_1)\ mod\ (J_1)$$

through a width of L_2 pixels and a length of L_1 pixels. Uncertainty around are no coefficients that satisfy this circumstance, the pattern will not be initiate in the image. This method efficiently captures spatial and frequency information by decomposing the image into different frequency subsets, thereby achieving accurate noise reduction while preserving the salient features of the tumor. Thresholding and reconstruction processes improve image clarity, making tumor detection and analysis easier. This preprocessing technique improves image quality and increases the accuracy and reliability of the subsequent feature extraction, classification, and detection processes. Ultimately, the 2D wavelet filter protocol has been established to be an influential and effective method for enhancing brain tumor images, facilitating better clinical analysis, and aiding early and accurate diagnosis of brain tumors.

3.3 Watershed Method

In this section, we segment the preprocessed images by using Watershed method. Watershed method is a powerful image segmentation technique commonly used for outlining objects in images. When used for image segmentation of a brain tumor, it can help identify tumor boundaries within the brain. Image gradients are calculated highlighting areas of varying intensity that may be the boundaries of various structures, including tumors. Markers are assigned to areas of interest in the image. These markers can be manually set by experts or generated automatically using techniques such as distance transforms and morphological functions. The watershed algorithm treats the gradient image as a topographic surface and "floods" from the markers. The algorithm segments the image by searching for different labeled water-intersecting lines. It corresponds to the boundaries of different areas. Unlike traditional hydrographic algorithms, we reduce the gradient scale image to diminish the amount of false edges. We deploy an automatic thresholding method based on normalized gradient size histograms. Entire edge image pixels through standards better than the threshold retain their real standard, while edge image pixels through standard beneath the threshold have their standards set to 0.

The purpose of this spatial criterion-based post-segmentation merging step is to significantly reduce the number of partitions without affecting the accuracy of the segmentation map. To add this section, follow these steps:

$X(a, b)$ consider as the original image

The preliminary sections attained as of the watershed segmentation as $S = \{S_1, S_2, S_3 \ldots S_M\}$, where S_x designates the x th partitions and M represents as the total number of sections.

The S_x size of every section be designated by M_x, compute the mean concentration of every section S_x is designates by this,

$$P_x = \frac{1}{M_x} \sum_{(a,b) \in S_x} X(a, b) \tag{12}$$

Express two measures among somewhat two neighboring sections $a\ and\ b$. The initial is the variance in P indicate intensity among section x and section y. It is distinct as below,

$$P_{xy} = |P_x - P_y| \tag{13}$$

The second measure Q is the modification in asset among section x and section y.

$$Q_{xy} = \frac{1}{M_{xy}} \sum_{(a_x,b_x),(a_y,b_y)} |X(a_x, b_x) - X\left(a_y, b_y\right)| \tag{14}$$

where $(a_x, b_x) \in S_x$ and $(a_y, b_y) \in S_y$ are the 8 pixels attached to the boundary between the sections S_x and S_y , and M_{xy} is the number of pixels on the boundary between the sections x and y.

Describe a criterion D_{xy}, which is an amount of the resemblance of intensity standards among two sections x and y, and is distinct as:

$$D_{xy} = \frac{1}{2}(P_{xy} + Q_{xy}) \tag{15}$$

After determining D_{xy} for all the x and y distributions, determine the threshold V_d that D_{xy} must meet before the x and y distributions merge. If D_{xy} is less than V_d, it means that section x and section y are the same in terms of spatial scales, so they must be merged. Determine V_d using the automatic thresholding technique described previously in this section. This method, which can accurately depict complex structures in clinical images, is an effective and widely used technique for image segmentation of brain tumors. This method uses the concept of landscape representation and considers the image intensity values as the landscape of flooded areas to identify boundaries.

3.4 DeepBeleif CNN Method

In this section we classify the brain tumor images by the use of brain tumor MRI dataset based on DeepBeleifCNN method. DBN is acknowledged meant for the aforementioned capability to study hierarchical representations and serve as a pre-training step to initialize the network with meaningful features. We refine these features by using multiple convolutional layers of CNNs, known for their powerful capabilities in image processing tasks. The integration of DBN and CNN in the DeepBeleifCNN method permits the method to acquire the complex patterns and subtle differences in brain tumor images, thereby improving the classification performance. This approach combines the unsupervised learning capabilities of DBNs to model complex data distributions and the supervised learning capabilities of CNNs to achieve high accuracy in classification tasks. This approach has exposed auspicious outcomes in characteristic numerous categories of brain tumors, for instance gliomas, meningiomas, and pituitary tumors, as of medical imaging data. DBN contain of numerous layers of Restricted Boltzmann Machines (RBMs).

DBN is useful for unsupervised learning of hierarchical feature representations from the input data. It can capture complex shapes and structures in brain tumor images, which are critical for accurate classification. CNN is very useful for extracting spatial features from images through convolutional layers. They preserve the spatial hierarchy of features, which is important for understanding the intricate details of brain tumors. The DBN involves of numerous layers of the RBM overlaid to extract deep features of the real data.

The RBM is a random continuous neural network with random binary units and undirected edges between them. RBM consists of a hidden unit layer where connections between hidden units are constrained, resulting in a highly efficient learning algorithm. The probability distribution U of the hidden units and the visible units is defined using power functions.

$$U(g, p) = \frac{1}{Q}\exp(-D(g, p)) \tag{16}$$

where,

$$Q = \sum_{g,p} \exp(-D(g, p)) \tag{17}$$

g and p represent visible and hidden units, respectively, and Q is the partition function. D is a power-based model that can be learned by running a power function (a random gradient based on the empirical negative log-likelihood of the training data). In this case, the DBN can perform unsupervised training first and then apply the model to a deep neural network on a set of image data.

The proposed method requires a careful setting of the parameters. A DL DeepBeleifCNN includes a stack of RBMs that collectively perform the tasks of a DeepBeleif. Algorithm 1 shows the RBM process for the sigmoid unit, and algorithm 2 shows the DeepBeleifCNN learning process.

Algorithm 1

Begin: RBM $(w, \varepsilon, e, f, k)$;

where, w is meant for training distribution sample, ε is meant for learning rate, e is meant for (lxm) weight matrix, f is meant for hidden units of bias vector, k is meant for inputs units of bias vector.

For whole hidden layers x:

```
Estimate $S\left(l[0][x] = {}^{1}/_{(1 + \exp\,(w[0]))}\right)$
# for Gaussian layers, Sigmoid $\left(f[x] + sum_{y}(e[x][y]\ x\ w[0][y])\right)$
Sample $l[0][x]$ as of $S\left(l[0][x] = {}^{1}/_{(1 + \exp\,(w[0]))}\right)$
End for
For whole visible layers $y$:
Estimate $R\left(g[0][y] = {}^{1}/_{(1 + \exp\,(l[0]))}\right)$
# for Gaussian layers, Sigmoid $\left(k[y] + sum_{x}(e[x][y]\ x\ l[0][y])\right)$
Sample $g[1][y]$ as of $S\left(g[1][y] = {}^{1}/_{(1 + \exp\,(l[0]))}\right)$
End for
For whole hidden layers $x$:
Estimate $S\left(l[1][x] = {}^{1}/_{(1 + \exp\,(w[1]))}\right)$
# for binomial layers, Sigmoid $\left(f[x] + sum_{y}(e[x][y]\ x\ w[1][y])\right)$
End for
```

$$E{+}{=}\ \varepsilon\ x\ \left(l[0]\ x\ w[0]^{H} - S(l[1][.] = 1|(v[1]))\right)\ x\ w[1]^{H}$$

$$f{+}{=}\ \varepsilon\ x\ (l[0] - S(l[1][.] = 1|w[1]))$$

$$k{+}{=}\ \varepsilon\ x\ (w[0] - w[1]\$$$

Algorithm 2:

Phase 1: DeepBeleifCNN $(V, K, epsilon\_K, m, N, E, f, P, k)$

where, V is represented as DeepBeleifCNN supervised training distribution of input samples $(a, b), K$ is represented as training criterion purpose that catches a network output $f(a)$ and target b and proceeds a scalar distinguishable in $f(a)$, epsilon_K is represented as learning rate for the stochastic gradient decent on supervised cost K, N is represented as number of layers $1, 2, \dots, N$, $f[x]$ is represented as bias attributes for level x where $X = 1, 2, \dots, N$, P is represented as weight matrix for the supervised output layer, and k is represented as bias vector for supervised I/O layer.

Phase 2: Recursively express mean-field propagation:

$op[x](a) = \text{Expecting}(z[x]z[x-1] = op[x-1](a))$

where,

$op[x](a) = a$ and

$\text{Expecting}(z[x]z[x-1] = op[x-1](a))$ is the expected assess of $z[x]$ under the RBN conditional distribution $S(z[x]z[x-1])$

Phase 3: when the assess of $z[x-1]$ are replaced by mean field assess $op[x-1](a)$

in case, if $z[x]$ has Gaussian Units:

$\text{Expecting}(z[x]z[x-1] = Sigmoid(f[x][y] + sum_{c}E[x][y][c]op[x-1][c](a))$

Phase 4: Express the network I/O function

$f(a) = P\ x\ op[N](a)' + k$

Phase 5: Iteratively diminish the expected assess of $K(f(a), b)$.

Training is performed using uniform gradient descent, learning rate epsilon_K (values 0 to 1), and appropriate stopping criteria based on the validation set.

The DeepBeliefCNN method has shown higher accuracy than traditional methods in classifying brain tumor images. It demonstrates that the combination of DBN and CNN can effectively capture complex shapes and features of brain tumor images. The hierarchical structure of DBN captures the low-amount and high-amount features required for accurate classification and enables detailed feature extraction. Integration with CNNs further improves this by using topological hierarchy of data.

4. RESULT and DISCUSSION

The execution of the deployed methodology was estimated via accuracy, sensitivity, specificity, error rate, and F1 score for the analysis. This evaluation uses the proposed methods of TL, M-SVM, and WHHO to determine the enhanced images. New simulations and parameters are shown in Table 1. Image classification using brain tumor MRI dataset of 7023 images. This article was conducted using Python and Anaconda Navigator.

TABLE I. SIMULATIONS PARAMETERS

Parameters	Values
Name of the Dataset	Brain Tumor MRI dataset
Containing the No. of Images	7023
Used Language	Python
Used Tool	Anaconda

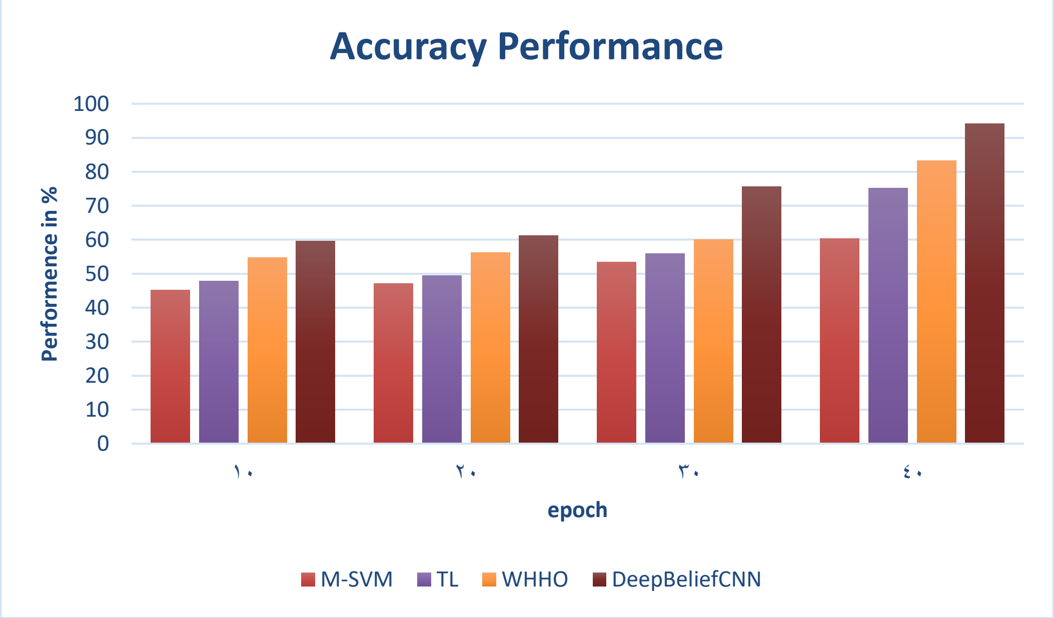

Fig. 2. Performance analysis of DeepBeliefCNN accuracy

It can be perceived as of Figure 2 that the analysis accuracy of M-SVM method is 60.4%, TL is 75.2%, WHHO is 83.2% and DeepBeleifCNN method is 94.2%. This method has higher accuracy than traditional methods. DBN provides layer-by-layer pre-training technology for deep networks. This helps to initialize CNN weights, avoid undesirable local minima and improve convergence during training.

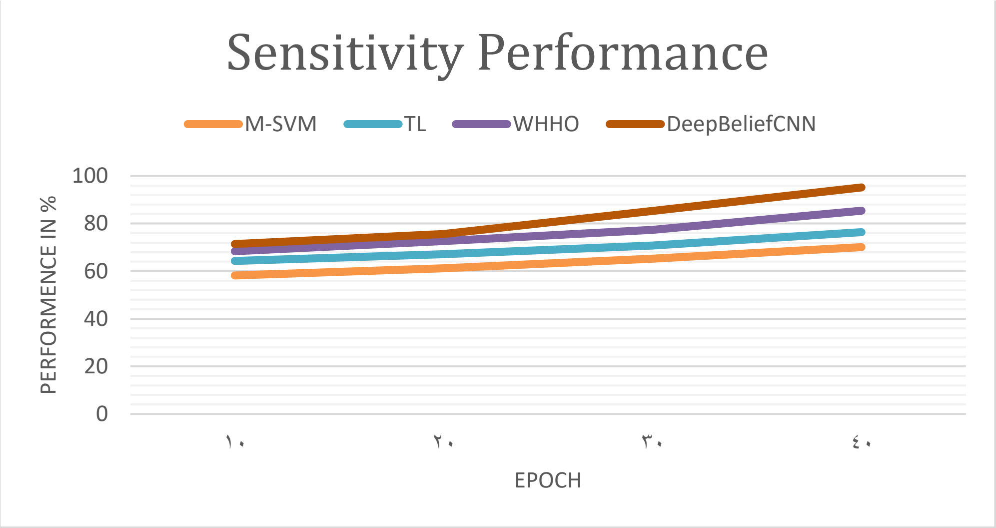

Fig. 3. Performance analysis of DeepBeleifCNN sensitivity

It can be seen from Figure 3 that the analysis sensitivity of M-SVM method is 70.1%, TL is 76.4%, WHHO is 85.4% and DeepBeleifCNN method is 95.2%. This method has higher sensitivity than traditional methods. This method effectively captures complex patterns and details in the data, improves initialization and reduces overfitting, and improves both generative and discriminative learning methods. This combination creates models that are better at detecting true positives and less likely to miss important features or anomalies in the data.

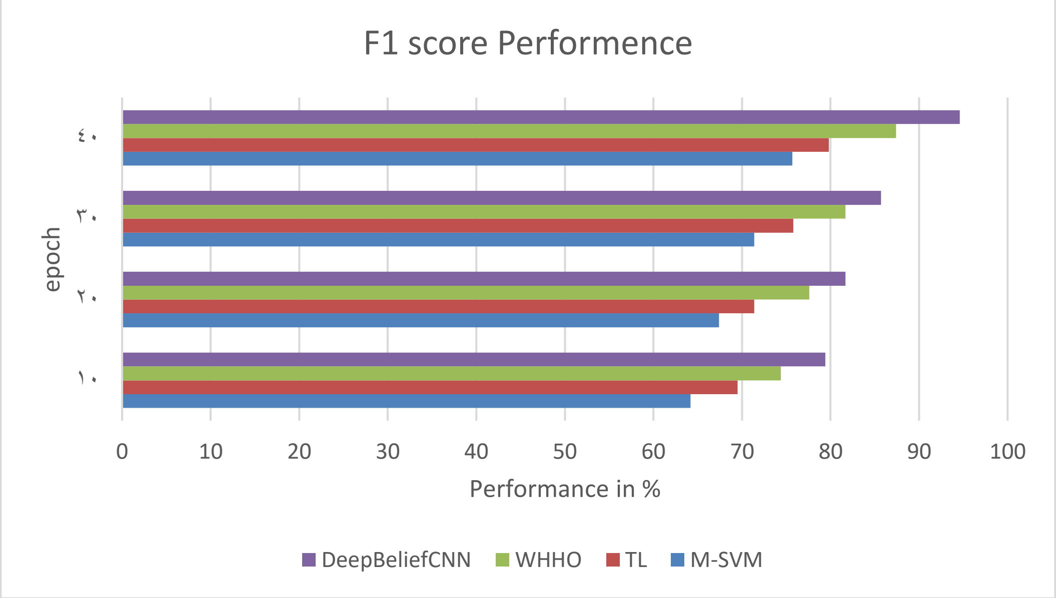

Fig. 4. Performance analysis of DeepBeleifCNN F1 score

It can be seen from Figure 4 that the analysis sensitivity of M-SVM method is 75.7%, TL is 79.8%, WHHO is 87.4% and DeepBeleifCNN method is 94.6%. This method has higher F1 score than traditional methods. The F1 score is an amount of a method accurateness that deliberates together accuracy and sensitivity, and is particularly useful when evaluating classifier performance on unbalanced datasets.

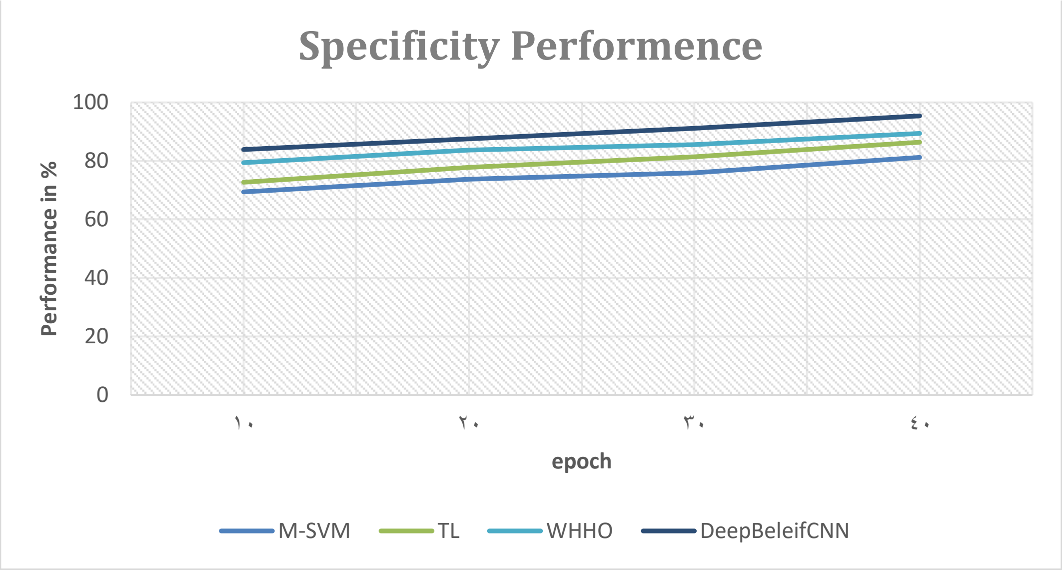

Fig. 5. Performance analysis of DeepBeleifCNN specificity

It can be seen from Figure 5 that the analysis sensitivity of M-SVM method is 81.2%, TL is 86.4%, WHHO is 89.4% and DeepBeleifCNN method is 95.4%. This method has higher specificity than traditional methods. The DeepBeliefCNN method improves the specificity of image classification through a combination of robust feature extraction, improved generalization, noise immunity, and generative and discriminative learning methods. Taken together, these advantages make the classification model more accurate and reliable, capable of accurately identifying negative events and achieving high specificity.

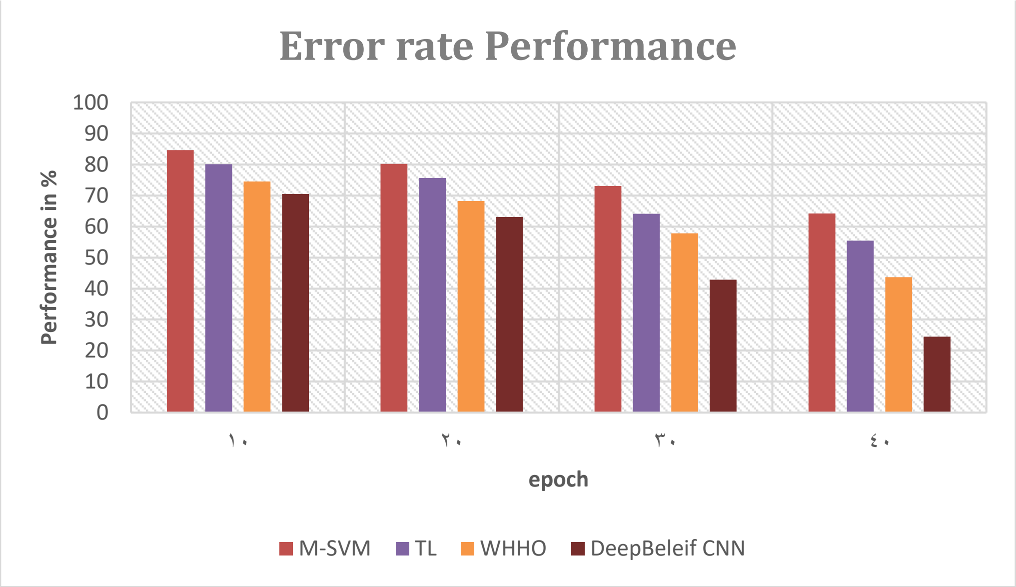

Fig. 6. Performance analysis of DeepBeleifCNN error rate

It can be seen from Figure 6 that the analysis of M-SVM method is 64.2%, TL is 55.4%, WHHO is 43.7% and Deep Beleif CNN method is 24.5%. This method has lower error than traditional methods. Sampling is used to generalize unobserved data and minimize overfitting. A model that generalizes well is less likely to make mistakes on new data, thus lowering the error rate.

5. CONCLUSION

Our research paper deployed the DeepBeleifCNN method for classifying the brain tumor images. Similarly, this novel study the brain tumor MRI dataset to evaluate the narrative nature and comprehensiveness of the 2D Wavelet Filter method. We used 2D wavelet filter method to effectively reduces noise in medical images while preserving important details. Then identify tumor boundaries within the brain and image gradients are calculated highlighting areas of varying intensity by the use of Watershed method. The DeepBeliefCNN method has shown higher accuracy than traditional methods in classifying brain tumor images. It demonstrates that the combination of DBN and CNN can effectively capture complex shapes and features of brain tumor images. The hierarchical structure of DBN captures the low-amount and high-amount features required for accurate classification and enables detailed feature extraction. Also, the DeepBeleifCNN method showed good performance, with 94.2% accuracy, 95.4% specificity, 94.6 F1 score, 95.2% sensitivity, and 24.5% low error rate on brain tumor MRI dataset. The DeepBeliefCNN approach combines the hierarchical feature extraction capabilities of DBN with the spatial feature extraction capabilities of CNN. This allows a detailed understanding of brain tumor images and improves classification performance. This method successfully generalizes to new and unrecognized brain tumor images because of its capability to study vigorous and biased features in together pre-training and fine-tuning stages.

Conflicts Of Interest

The paper explicitly states that there are no conflicts of interest to disclose.

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