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Enhanced Identification of Brain Tumors Based on 3-Dimensional Hybridseqnet-CNN with RNN

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Abstract: Brain tumors pose a significant threat to human health, necessitating accurate and timely diagnosis for effective treatment. The identification technique is difficult since brain tissues in both healthy and pathological states resemble one another. It is particularly challenging to automatically identify medical images when conducting clinical examinations of brain tumors and earlier patient care. Rapid decision-making is made possible by computerized medical imaging, which also helps doctors provide patients with necessary care. Brain tumors can take diverse shapes and arise in various regions across the brain. Machine learning models face a huge hurdle in effectively identifying and classifying these various tumor types and locations. The data samples used to train our suggested 3DHybridseqnet-CNNRNN approach are gathered from the BraTS2021 database. Blur reduction is first performed in raw data using a standardized median filter (SMF) for picture de-noise and quality enhancement. The modified 3D adaptable threshold (M3DT) approach is subsequently employed to segment the data. The features retrieved using the wavelet-based Local Binary Pattern (W-LBP) technique are further processed using the whale optimization algorithm (WOA) to yield optimized feature subsets. Their importance, however, has to be determined and validated, as the abstract of this study does not provide definitive data. The developed 3DHybridseqnet-CNNRNN model is then employed for improved brain tumor identification. The simulated results (using the Python tool) established that the recommended techniques improved identification consequences, as measured by precision, accuracy, recall, and f-measure metrics, are greater than the existing methods. With a combination of improved identification accuracy (98%), medical professionals may be able to make more precise diagnoses and save lives. Therefore, our results on improved tumor detection show very good efficiency when compared with comparable methods.

Keywords- Brain tumor, enhanced identification, standardized median filter (SMF), modified 3D adaptable threshold (M3DT), whale optimization algorithm (WOA), 3DHybridseqnet-CNNRNN

1. Introduction

The essential nervous organization is controlled by the brain, the bone marrow is linked to the human brain, which completes the Central Nervous System (CNS). They can either be cancerous (malignant) or benign (not cancerous). Brain tumors can develop directly in the brain, or they can advance from another region of the body to the brain. After making judgments, it gives the body instructions using the information it has received from various senses. Both malignant and benign forms of large brain tumors are quite widespread in today's medical world. Brain tumors are suspected to be a cause of death in both adults and children. When the brain's

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tissues grow unnaturally, the result might be a brain tumor. The mass of cells that eventually give rise to tumors is created when aberrant tissues outgrow a healthy cell (Khan et al. (1)). Medical imaging technology is now playing a bigger part in everyday medical diagnostics and research as current medical standards continue to advance. As a result, it is crucial to research medical imaging data for diagnostic purposes. Brain tumors have grown to be a major area of study in the medical industry as a tumor condition with high frequency and complexity. Typically, image processing of brain tumor information is used to make a diagnosis of brain tumors. To accurately assess brain tumor photos, there are many important steps that must be taken. However, the proper processing of picture data can be impacted by disparities in experience levels, visual tiredness, and the accumulation of doctors' medical expertise. Thus, it is critical to comprehend how to identify brain cancers in photographs (Mzoughi et al. (2)). MRI allows for imaging of human materials and structures without exposing patients to significant stages of ionizing radioactivity. The subsequent images are characterized by their remarkable precision and clarity. MRI significantly increases the effectiveness of diagnosis, prevents the essential for exploratory procedures such as thoracotomies or laparotomies, and serves as a reliable tool for locating lesions and planning surgical procedures. The MRI of a brain tumor employs technology for 3D multi-band imaging and chest X-ray scanning. A 3D multi-band MRI may allow doctors to pinpoint a lesion's location exactly and coordinate its position. Also, by utilizing an underutilized development process, MRI imaging may also get various tissue structures that are an MRI multi-modal picture. Various modes can reveal various characteristics of brain tumors (Aygün et al. (3)).

Brain tumor detection is a major medical challenge with far-reaching implications for patient treatment. While such as MRI and computed tomography (CT) are valued, they fall short of providing the precision and early diagnosis required for excellent treatment. Brain tumors, which are frequently aggressive and rapidly developing, require quick diagnosis and treatment. The existing reliance on manual interpretation of imaging images, on the other hand, introduces subjectivity and interobserver variability, impeding consistent and reliable diagnosis (Ker et al. (4)).

Furthermore, the resource-intensive nature of these old procedures, such as the requirement for expensive equipment and trained radiologists, leads to rising healthcare costs and significant diagnostic delays. Brain tumors are highly heterogeneous, changing in size, location, and histological features, making correct detection and classification critical for tailored treatment regimens (Shrestha et al. (5)). The aim of the study is to illustrate the difficulties in both diagnosing and treating brain tumors while highlighting the demand for cutting-edge, precise medical imaging methods. Using cutting-edge data processing methods, the proposed 3DHybridseqnet-CNNRNN model seeks to better the detection of brain tumors, potentially leading to more accurate diagnoses and improved patient care. Therefore, this work attempts to solve the issue of brain tumor detection via the following:

- The research introduces a novel deep learning architecture, the 3DHybridseqnet-CNNRNN, specifically designed for brain tumor identification in MRI images.
- To improve the quality of raw data samples, the research incorporates blur removal through a standardized median filter (SMF)
- The research utilizes the Whale Optimization Algorithm (WOA) to select and optimize feature subsets from the extracted features.

This article follows a structured approach: Section II outlines related work, Section III explains our methodology, Section IV presents results and discussion, and Section V concludes with future research directions.

2. Related Work

(Mostafa et al. (6)) proposed feature segmentation and fusion, a unique and effective automated brain tumor detector. They preprocessed an image utilizing the tool SynthStrip for brain skull stripping and Gaussian Filter (GF) to enhance localization outcomes. (Wu et al. (7)) developed an automated system for detecting brain tumors focused on optimization and deep learning (DL). The CNN is arranged in the best possible way using an approach that makes use of an upgraded version of a political optimizer. (Patil et al. (8)) examined numerous brain tumor segmentations of active tumorous tissue, sedated tissue, and other markers of tumor development utilized in approaches to pinpoint the location and progression of tumor leakage of serous fluid into cell gaps within tissues or into body cavities. Three performance metrics that are frequently employed for the segmentation of brain tumors are dice score, sensitivity, and specificity. (Haq et al. (9)) provided two efficient methods for the rapid utilization of deep CNN and MRI data. (Solanki et al. (10)) Provided a thorough review of the overview of brain cancer detection using Magnetic Resonance imaging (MR). To identify brain tumors and cancer using computational intelligence and statistical image processing methods. (Ghanshala et al. (11)) Presented a unique design that combines a 3D CNN with a U-Net for the detection of brain tumors. According to comparative analysis, it outperforms comparable existing methodologies regarding results. (Deeksha et al. (12)) suggested a model that uses CNN based on DL methods to categorize all major forms of benign tumors to increase the effectiveness and precision of radiologists' and neurologists' diagnoses. (Ghassemi et al. (13)) presented the use of DL to categorize cancer in MRI images. A DNN is originally pre-trained as a discriminator in order to retrieve optimal characteristics and comprehend the size of MR images in its convolutional layers using diverse datasets of MR images. (Samhithaet al. (14)) Created a CNN technique of segmentation procedure to solve issues with manual segmentation, and it works well when accuracy, recall, and precision are considered. One of the conservative methods for using MRI as a previous brain tumor diagnosis tool. (Shah et al. (15)) investigated the acceleration and compression of 3D CNNs by identifying duplicate parameters in pre-trained networks, a variety of approaches to lower the memory need, and processing the complexity of deep neural networks. Traditional Deep Neural Networks (DNNs)(Sahaai et al. (16)), including specific architectures like AlexNet(Rajagopal et al . (17)) and ResNet (Hashmi et al. (18)), have experienced various constraints, including the demand for huge datasets, a lack of interpretability, and the risk. Acquiring a sufficient number of high-quality, annotated MRI scans for training can be both challenging and expensive, and the "black box" nature of these models makes clinical decision-making difficult due to poor interpretability. Compromises their effectiveness, as models trained too well on limited data can perform poorly on new, unseen cases. The proposed method effectively addresses these challenges. (Hossain et al.(19)) introduced a multiobjective evolutionary technique that was used to create a Radial Basis Function (RBF) network using Multiobjective Particle Swarm Optimization (MPSO) and local search features. The approach combined MPSON with local search features. The results demonstrated that MPSON was more accurate and simpler than other algorithms. Limitations included the algorithm's dependency on certain datasets as well as its performance on more complicated issues. (Hossain et al. (20)) Considered DL approaches that enhanced MRI brain image segmentation for the diagnosis of brain cancers. It investigated traditional MRI brain tumor segmentation approaches based on DL. It enhanced diagnostic accuracy; DL has the ability to segment tumors properly and efficiently. MRI scan variability, multi-modal image integration challenges, and the need for clinical consistency are the key restrictions. (Hossain et al.21))enhanced brain tumor identification by using an efficient Fuzzy C-Means Adaptive Convolutional Long Short-Term Memory (FCM-CLSTM) methodology and a variety of preprocessing approaches to improve MRI image quality. The results demonstrated higher accuracy, precision, recall, and F1-score. Limitations include the method's reliance on high-quality preprocessing and the need for additional validation on varied datasets.

2.1. Problem Statement

In the context of brain tumor identification, traditional Deep Neural Networks (DNNs) (Sahaai et al. 16), including particular architectures like AlexNet (Rajagopal et al. 17) and ResNet (Hashmi et al. 18), have encountered several issues, require large datasets, a lack of interpretability, and the possibility of overfitting. Recently, DNNs have become more and more popular, particularly voice recognition. To achieve high accuracy, DNNs need enormous amounts of labeled training data. AlexNet and ResNet can be difficult and costly to get enough high-quality annotated MRI images for training, and the black-box nature of these models makes clinical decision-making hard to comprehend. Their efficacy is further undermined by overfitting, as models that are overfitting on sparse data can underperform on novel, unobserved instances. To identify these challenges and overcome the issue through the process of the proposed 3DHybridseqnet-CNNRNN method. The other advantages of the proposed 3DHybridseqnet-CNNRNN method identified by the problem of data scarcity addressed using transfer learning and data augmentation approaches, allowing training of the models on comparatively smaller scale data without compromising their generalization capacity. This increases clinical confidence by offering human-understandable explanations for the model's predictions. As a result, the suggested approach provides enhanced interpretability, resilience, and high accuracy, making it ideal for use in clinical settings.

3. Methodology

Both diagnosis and treatment plan depend on accurate segmentation and classification of malignancies. Hence, we developed a 3DHybridseqnet-CNNRNN method for improved brain tumor identification. The flow of this research is depicted in Figure 1. There are many uses for the 3-dimensional Hybridseqnet-CNN with RNN, including video analysis, where it can efficiently record spatiotemporal information for action detection and gesture analysis. It is also helpful in medical imaging for the recognition and segmentation of intricate 3D structures, assisting with operations like tumor detection and categorization. Furthermore, it can help with 3D environment perception and navigation in robots for better object recognition and scene comprehension. I describe the process since it has advantages.

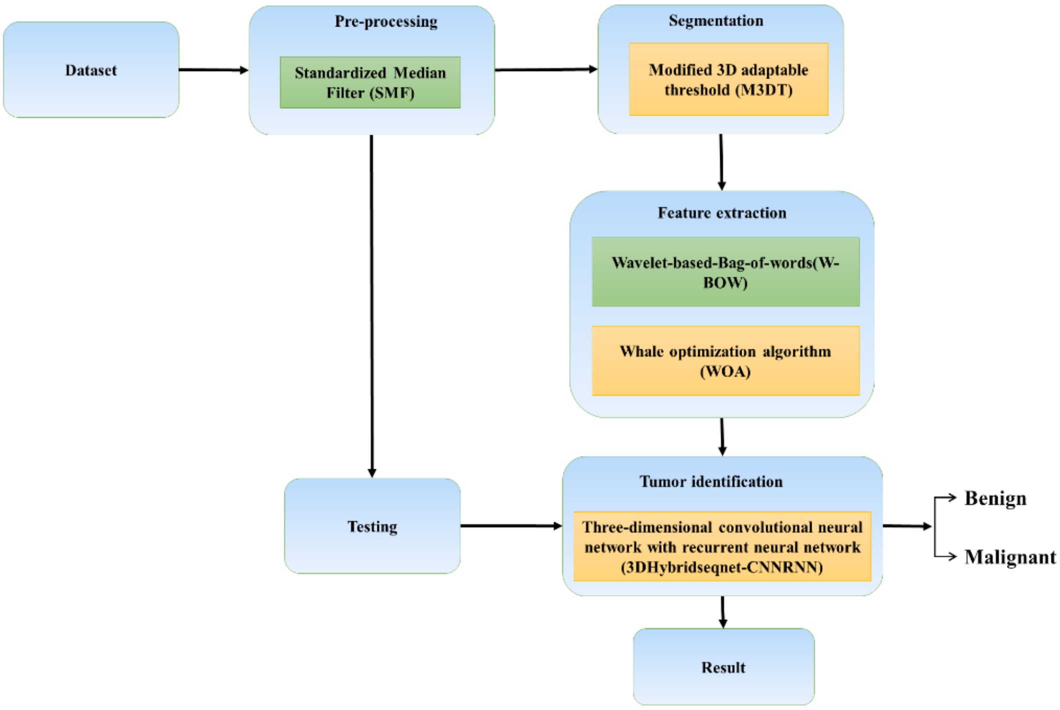

Figure 1: The proposed methodology

3.1 Dataset

The research makes use of the “Brats 2021 Brain MRI for brain tumor” Identification database, which has approximately 3000 files with tumor and non-tumor brain imaging and is shown as "yes" and "no" folders. The Visual test may be classified with greater accuracy using the labeled data. The data is typically split into two distinct subsets, training (2400) and testing (600), and there are two classes Benign and malignant. The MRI structures that are extracted from the labeled data are then utilized to forecast the production of the current images. The amount of noise in the captured image lowers the precision with which brain tumors may be identified. As a result, image noise should be reduced in order to increase overall prediction efficiency (Kurdi et al. (22)).

3.2 Preprocessing of Standardized Median Filter (SMF)

The ability of the SMF to successfully decrease noise without compromising edges or features is useful for image processing and computer vision. Such techniques were adopted extensively for improving image quality and analysis, like in medical imaging, satellite photography, and many real-time video processing operations. The SMF is among the methods that are highly favored for image quality enhancement and noise suppression. SMF is a nonlinear filtering algorithm that replaces a pixel's value with the median value of the neighboring pixels. This method works successfully to remove random noise from the image while retaining its features and crisp edges. Other applications of SMF involve the removal of blur from images. Blurs appear for a multitude of reasons, including shaking on the part of the camera, motion blur, and focal problems. SMF assists in removing the blur by sharpening the edges and features in the image. SMFs are commonly employed as preprocessing steps in additional complex image-processing techniques, including image segmentation, object recognition, and tracking.

The median filter, which is also an easier method, eliminates pulse or spike noise and speckle noise from an image. By measuring the magnitude of each vector included within a mask and sorting magnitudes, the Median Filter is applied. The investigated pixel is then swapped out with one median magnitude. The median filter's operation may be stated in Equation 1.

$$e(q, z) = median\ (t, s) \in Twz\{\mathrm{h(t, s)}\} \tag{1}$$

The rectangular sub-image window's middle, or median, and the set of coordinates within that window, Twz, have their origin at the coordinates (s, t). The median represents the midpoint of a rectangular sub-image window centered at (q, z), and $e(q, z)$ represents a collection of coordinates inside that window.

3.3 Segmentation of Modified 3D Adaptable Threshold (M3DT)

It is used in various places, such as medical imaging and segmentation. Utilizing Modified 3D Adaptable Threshold (M3DT) has benefits, particularly in recognizing and outlining specific structures in complicated 3D pictures. It benefits activities like organ segmentation, tumor identification, and precise measurements for medical diagnosis and therapy planning. M3DT segmentation is also used in material research, geological surveys, and industrial imaging to precisely identify and analyze complex 3D structures. I introduce the method because of its benefits. M3DT, an automated brain tumor segmentation technique, employs a 3DHybridseqnet-CNNRNN in the context of medical imaging to segment and eliminate tumors from MRI data. Its primary use is in medical diagnostics. The 2-dimensional representation is often distorted and loses depth awareness, making it difficult to effectively transmit complicated spatial information. This might make it difficult to comprehend complicated relationships and structures in spatially complex systems or things. Thus, I implement the 3D. The 3DHybridseqnet-CNNRNN is a form of neural network that was developed expressly for the purpose of analyzing data in three dimensions. It takes MRI scans as its source and performs a number of layers of convolution, pooling, and fully connected stages on them to generate a segmented masking that pinpoints the location of the tumor. The M3DT technique employs an adaptive thresholding mechanism to get better separation findings. The thresholding method is utilized to differentiate between tumor-free brain tissue and normal brain tissue in the affected region. This approach is based on a histogram of MRI data. As a consequence, there is a lower chance of incorrect positives and erroneous negatives during categorization. The threshold values are modified dynamically using MRI image properties.

The M3DT approach has been investigated utilizing a large number of cerebral MRI images, and it has been demonstrated to give consistent and precise tumor categories. For individuals with brain tumors, the M3DT technique could offer divisions that can improve accuracy allowing clinicians to make the optimal decision. These segmentations are produced through the utilization of 3DHybridseqnet-CNNRNN and adjustable thresholding approaches. Segmentation of a wide variety of brain tumors, such as glioblastomas, meningiomas, and metastatic brain tumors, has been accomplished using M3DT. Even in situations in which more conventional thresholding approaches are unsuccessful, it has been demonstrated to be useful in precisely segmenting tumors. M3DT has also been demonstrated to be resistant to differences in the protocols used for MRI and the types of scanners used.

3.4 Features extraction using the wavelet-based Local Binary Pattern (W-LBP)

Feature extraction is the procedure of eliminating a large collection of features into a manageable number that captures the essential information for a certain work or study. In the instance of images, it involves transforming raw image data into an assortment of sample characteristics that capture visual data. Based on their visual qualities, photos will be analyzed, categorized, and recognized using this procedure.

A quantitative method utilized in image processing called wavelet-based local binary patterns (W-LBP) enables us to retrieve important features from images. In the world of computer vision usage, it is frequently employed. Every pixel is given a binary value $s(f_P - f_C)$by the W-LBP operator after being compared to the center pixel f_C and pixels around (f_P =0, 1,…,7).

$$LBP_{P,R}(x_c) = \sum_{p=0}^{P-1} \mu(x_p - x_c)2^p, \mu(y) = \begin{cases} 1, y \geq 0 \\ 0, z < 0 \end{cases} \tag{2}$$

The radius and length between neighboring pixels and the center pixel are specified by R in the W-LBP, R equation, while the number of neighbor pixels involved in the process is indicated by P. The neighbor number P is assumed to be eight (8), and radius R is considered to be one (1). The majority of the locations in the images are made up of predictable patterns, as shown by proposals. Identical arrangements are ones with a minimum of two transitions and a binary W-LBP code of 0-1 or 1-0. For instance, the patterns 01100000 and 11000011 and 00000000 and 11111111 are identical arrangements since they contain 0 and 2 changes, accordingly. Additionally, similar arrangements may describe simple surfaces like spots, edges, and corners. There is a total of (P-1) P + 2 identical arrangements.

3.5 Whale Optimization Algorithm (WOA)

The WOA is a revolutionary metaheuristic optimization process that mimics bubble net feeding and attack mechanisms used by humpback whales as a hunting strategy. This allows WOA to accurately model the behavior of humpback whales during hunting. The WOA algorithm is primarily made up of three distinct phases: the roundup phase, net bubble assault phase, and prey-seeking phase. By adjusting the position vector it occupies, a whale may hunt either in a two-dimensional or three-dimensional space using this approach. The whale itself is a metaphor for a potential solution, and the location or value of the potential answer serves as a metaphor for requirements that must be satisfied to solve a problem. Because of its practical search mechanism, it is possible to strike an appropriate balance between phases of exploration and development. The following is a full explanation of the algorithm's operation:

(1) Searching and surrounding prey:

$$\vec{C} = |\vec{D}.\vec{W} * (s) - \vec{W}\,(s) \quad (3)$$

$$\vec{W}(s+1) = \vec{W}_{mind} - \vec{B}.\vec{C} \quad (4)$$

The coefficient vectors $\vec{B}$ and $\vec{D}$ are used in the formula above to indicate the current iteration number, $\vec{W}$ *best individual position of the whale currently attained, and the most variable.

$$\vec{B} = 2\vec{b}.\vec{q} - \vec{b} \quad (5)$$

$$\vec{d} = 2\vec{q} \quad (6)$$

In the range$[0, 2]$, the value $\vec{q}$ declines linearly with several repetitions, while a value of $\vec{q}$ is created at random in the range$[0, 1]$. As a result, the value of $\vec{B}$obtains is an arbitrary value in the range$[1, 1]$.

(2) Spiral updating position: Using the circular update position strategy described in Formula 7, a new position consistent with spiral motion is the whale's initial location and the prey's current location. This new position is then shown to be between the whale's original location and the prey's current location, which is shown in Equation 7.

$$\vec{W}^{(s+1)} = \vec{C'} f^{ak}.\cos(2\pi k) + \vec{W} * (s) \quad (7)$$

Where $\vec{C'}$ stands for separation between the ith whale and intended prey, is an internal parameter, and k is a random value generated between$[1, 1]$. To simulate events that are going on simultaneously, an arbitrary method is used to determine whether the whale will take a circular or spiral path to its destination. Equation 8 can be used to represent the procedure for creating a new position for a whale:

$$\vec{W}(s+1) = \begin{cases} \vec{W} * (s) - \vec{B}.\vec{C}, & if\ 0 < 0.5, \\ \vec{C}'.f^{ak}.\cos(2\pi k) + \vec{W}.(s), if & 0 \geq 0.5. \end{cases} \quad (8)$$

O is produced at random between [0, 1].

(3) Find potential prey: The present population of whales will be selected at random to serve as a present optimum solution for the population as a whole, while the other whales will shift about their optimal individual places to achieve balance. The mathematical expressions for equations 9 and 10 are as follows:

(4) $\vec{C} = |\vec{D}.\vec{W}_{rand} - \vec{W}$ (9)

$$\vec{W}(s+1) = \vec{W}_{rand} - \vec{B}\vec{D} \quad (10)$$

In the WOA method, each whale starts at a random place and subsequently changes its position based on the best individual whale position found after each repetition or a particular whale that was picked randomly.

3.6 Three-dimensional convolutional neural network (3DHybridseqnet-CNNRNN)

3.6.1 Convolutional Neural Network (CNN)

CNN for efficient identification and classification of tumor scan imaging from MRI analysis. It is capable of realizing hierarchically organized spatial features to enhance diagnostic accuracy, lower false positive decisions, and assist in clinical decision-making.

Convolutional Layer: This layer is used to apply filters to the input image to extract edges, textures, shapes, etc. The convolution operation is utilized to maintain the spatial relationship between the pixels.

Activation Function (ReLU): The ReLU function is an example of a nonlinear activation function that helps learn complicated patterns by letting positive values pass through and making all the negative values equal to zero.

Through the establishment of local receptive fields, CKs can extract numerous properties. The way a CL works is described by Equation (11),

$$a_v^u = \varphi\left(\sum_o a_o^{u-1} * j_v^u + c_v^u\right) \tag{11}$$

Feature map attained through the vth filter jth layer is signified by a ll in this context. a_o^{u-1} explains map of the $u-1$ layer mentioned j_v^u. c_v^u denotes bias φ (.) value denotes the beginning purpose.

Pooling layer (PL): PLs are often referred to as feature mapping layers or sample layers. Its primary aim is to extract secondary properties. The pooling operation intends to reduce the network by reducing the convolutional feature map. Max pooling is a prominent pooling technique. Equation (12),

$$D_v^u = \max_{(s-1)Y<s<qY}\{a_v^{u-1}(s)\}\; q = 1,2,\ldots \tag{12}$$

D_v^u represents a variable that depends on v and u. S is a variable that meets the requirement $Y < s < qY$. Y denotes pooling window scale, q is the number of steps moved, $a_v^{u-1}(s)$ (s) r represent the value feature map attained from lth layer, Q is an infinitely long growing sequence of integers starting at 1.

Fully Connected Layer: Following the convolutional and pooling layers, the recovered features are flattened and passed through fully connected layers to get final predictions. This layer integrates previously learned characteristics to identify or recognize items in an image using Equation(13).

$$gr^{u+1} = \delta\left(F_{gr}^u gr^u + c_{gr}^u\right) \tag{13}$$

The loss function is then computed using the cross-entropy function. An effective error metric function for pattern recognition is the cross-entropy function is described in Equation (14). Where, C is the total number of classes, $I^y 1x(e)$similarly is an indicator function for a different condition. Cross-entropy loss is $Q(F,c)$ formula calculates the difference between anticipated probability and true labels.

$$Q(F,c) = -\frac{1}{C}\sum_{y=1}^{C}[I^y 1x(e) + (1-I^Y)\, 1x(1-e)] \tag{14}$$

Where the total amount of samples is, I^Y denotes the Softmax classifier.

3.6.2 Recurrent neural network (RNN)

Consider the sequence$\{l_1, l_2, \ldots, l_u\}$, where the kind of variable l_u (scalar or vector) depends on the situation. A recurrent function in a recurrent neural network determines hidden states y_u, as described in Equation (15),

$$y_u = RNN(y_{u-1}, l_u) \tag{15}$$

Hidden states encode the data in transmitted input entries that are most important for producing the intended outputs. Because the variables of the recurrent function remain constant during the sequence indicated by s, it may be trained by backpropagation. However, due to gradient disappearance, typical RNN cells cannot create particularly long-term interdependence. Therefore, recurrent skipping is employed to exploit the recurring structure in the input information.

$$y_u = RNN(y_{u-z}, l_u) \tag{16}$$

In Equation (16), the provided data is used as the source of the period value z.

3.6.3 3DHybridseqnet-CNNRNN

The detection of brain tumors is an important healthcare application that requires great accuracy and efficiency. Traditional methods, such as MRI, are frequently followed by manual interpretation by radiologists, which is prone to human error. A unique option for automating this procedure with improved accuracy is a Hybrid CNN-RNN (3DHybridseqnet-CNNRNN) technique. The CNN component in this hybrid design extracts spatial characteristics from MRI data, detecting locations that may contain malignancies. The CNN functions as a feature selector inside the brain images, isolating crucial properties like edges, textures, and forms. Following that, the retrieved characteristics are sent into the RNN component.

The RNN specializes in interpreting data's temporal or sequential characteristics. In the case of brain tumors, this might indicate examining a series of MRI slices to determine how tumor features grow spatially over the brain's depth. This sequential approach is more effective than single CNN techniques at capturing tumor development patterns and abnormalities. This method, which combines the strengths of both CNN and RNN, provides a powerful tool for detecting brain cancers. It combines spatial feature identification with sequential pattern interpretation to provide a more complete and accurate diagnosis, allowing for more early and successful treatment.

4. Result and discussion

The proposed methodology has been implemented in Python. The suggested optimization techniques were simulated using a Windows 10 laptop equipped with an Intel i7 CPU and 8 GB of RAM. The 3DHybridseqnet-CNNRNN method and its effects on quality and output are extensively studied through comparison and evaluation. To demonstrate that a proposed methodology is successful, its effectiveness is measured against those of modern approaches like Deep Neural Networks (DNN)(Sahaai et al. (16)), AlexNet (Rajagopal et al. (17)), and ResNet (Hashmi et al. (18)). The simulated findings using a Python tool showed that the recommended strategy produces improved identification outcomes over current methods compare with of accuracy, precision, recall, and F1-score metrics.

Accuracy is the metric for accurately predicting something by a technique or system. The effectiveness of a technique is frequently assessed in machine learning and data science. The technique's accuracy predictions are made by the number of forecasts it gets right. Below, equation 15 provides an accurate mathematical expression.

$$Accuracy = \frac{Numberofcorrectpredications}{Totalnumberofpredictions} \tag{17}$$

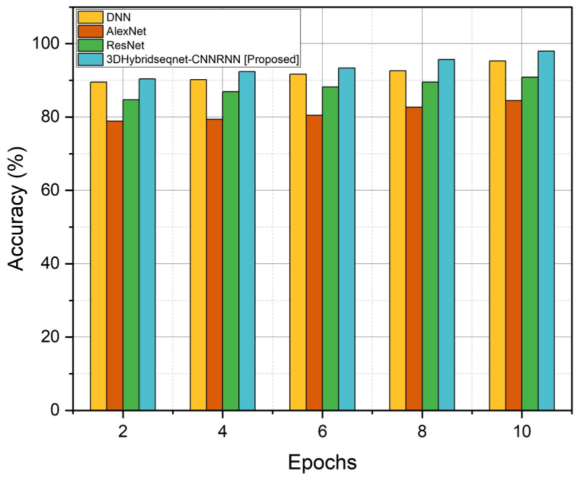

Figure 2: Accuracy

This comparison of accuracy is depicted in Figure 2 and Table 1. Both the effectiveness of the existing system and the proposed approach for predicting future consumption are highlighted. While the advanced system achieves the proposed **3DHybridseqnet-CNNRNN** with 98% accuracy, DNN has obtained 95.3%, Alexnethas gained 84.5%, and Resnethas attained 90.9%. It shows that the proposed method is more effective than the existing one.

Table 1: Accuracy

Epochs	DNN	AlexNet	ResNet	3DHybridseqnet-CNNRNN [Proposed]
2	89.5	78.9	84.7	90.4
4	90.2	79.4	86.9	92.4
6	91.7	80.5	88.2	93.4
8	92.6	82.7	89.5	95.7
10	95.3	84.5	90.9	98

Precision is the amount of detail and exactness in anything or the correctness of a measurement or computation. Precision may signify different things in various industries. The proportion of genuine positives (positives that were correctly detected) among all positive identifications (including true positives and false positives), for instance, is referred to as precision in statistics. Below, equation 16 provides the precision mathematical expression.

$$Precision = \frac{R_o}{R_o + D_o} \tag{18}$$

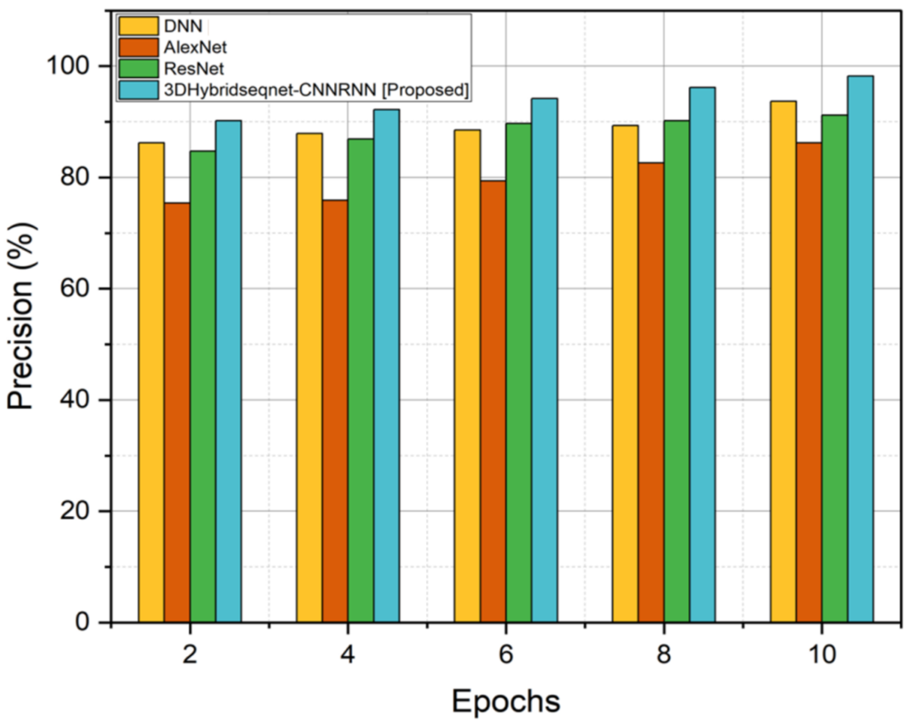

Figure 3: Precision

The contrast of precision is shown in Figure 3. Where $R_o$and D_o stands for a true positive and a false positive, respectively. Predictions of precision utilization for the proposed system and existing systems are explored. ResNet has a precision of 91.2%, DNN has 93.7%, Alexnet has 86.2%, and the recommended approach has 98% accuracy. It demonstrates that the suggested approach is more efficient than the current one.

Table 2: Precision

Epochs	DNN	AlexNet	ResNet	3DHybridseqnet-CNNRNN [Proposed]
2	86.2	75.4	84.7	90
4	87.9	75.9	86.9	92
6	88.5	79.4	89.7	94
8	89.3	82.6	90.2	96
10	93.7	86.2	91.2	98

The capacity to recall knowledge that has already been taught or experienced is referred to as recall and is a phrase that is frequently used in cognitive psychology. It is a process of getting knowledge out of long-term memory and accessing it. The capacity to identify or recognize previously learned material when given again is recognition, which is distinct from recall. Below, equation 17 provides the recall mathematical expression.

$$Recall = \frac{R_o}{R_o + D_s} \quad (19)$$

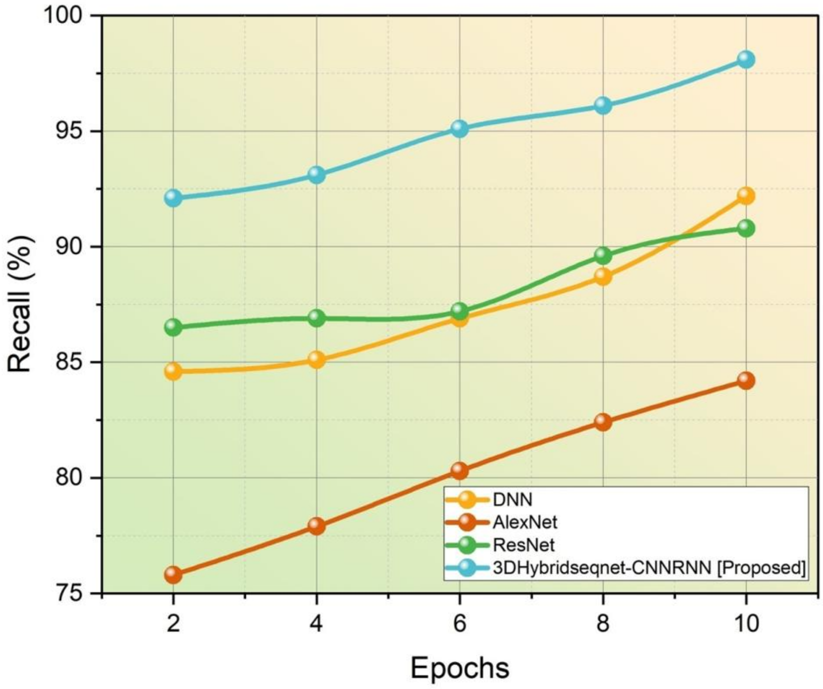

Figure 4: Recall

The recall contrast is shown in Figure 4. Where R_o stands for genuinely positive and D_s stands for false negative. Where $R_o$and D_s stand for a true positive and a false positive, respectively. Forecasts of recall consumption are shown for the proposed system as well as the existing system. Compared to 84.2% for Alexnet, 92.2% for DNN, and 90.8% for Resnet, the recommended approach yields 98% recall. Table 3 illustrates the degree to which the present recommended technique is effective.

Table 3: Recall

Epochs	DNN	AlexNet	ResNet	3DHybridseqnet-CNNRNN [Proposed]
2	84.6	75.8	86.5	92.1
4	85.1	77.9	86.9	93.5
6	86.9	80.3	87.2	95
8	88.7	82.4	89.6	96.8
10	92.2	84.2	90.8	98

The score is a statistical metric utilized to assess the effectiveness of a binary categorization method by combining precision and recall. Another term for it is the harmonic mean of accuracy and recall. Recall evaluates how successfully every technique recognizes all positive instances out of all real positive occurrences, whereas precision measures how correctly a technique predicts positive samples out of all instances when it shows a beneficial result. The F1-score is determined by taking the harmonic mean of accuracy and recall, which can be found using formula 18:

$$F1 = \frac{2 * (precision * recall)}{(precision + recall)} \quad (20)$$

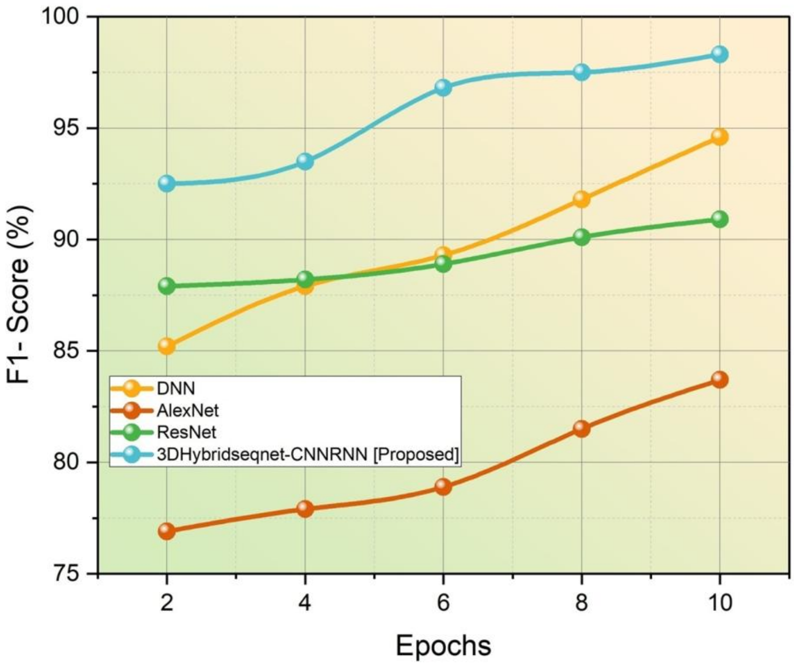

Figure 5: F1-score

Figure 5 shows the F1-score comparison, which varies between 0 and 1, with 1 signifying flawless recall and precision and 0 signifying subpar performance. Forecasts of recall consumption are shown for both the recommended system and the actual system. Compared to 94.6% for DNN, 83.7% for Alexnet, and 90.9% for Resnet, the suggested technique obtains 98% F1-source. Table 4 illustrates the degree to which the present advised technique is effective.

Table 4: F1-score

Epochs	DNN	AlexNet	ResNet	3DHybridseqnet-CNNRNN [Proposed]
2	85.2	76.9	87.9	92
4	87.9	77.9	88.2	93.5
6	89.3	78.9	88.9	96
8	91.8	81.5	90.1	97.5
10	94.6	83.7	90.9	98

Discussion

Traditional Deep Neural Networks (DNNs) (Sahaai et al. (16)), including specific architectures like AlexNet (Rajagopal et al. (17)) and ResNet (Hashmi et al. (18)), have experienced various constraints of brain tumor identification, including the demand for huge datasets, a lack of interpretability, and the risk of overfitting. Acquiring a sufficient number of high-quality, annotated MRI scans for training can be both challenging and expensive, and the "black box" nature of these models makes clinical decision-making difficult due to poor interpretability. Overfitting further compromises their effectiveness, as models trained too well on limited data can perform poorly on new, unseen cases. Our method efficiently addresses these issues. By employing transfer learning, the data scarcity issue is mitigated, allowing the model to be trained robustly on a relatively smaller dataset without compromising its ability to generalize. Integrate it into the model to enhance interpretability, providing human-understandable rationales for its predictions and thereby enhancing clinical trust. Regularization methods and cross-validation are also applied to minimize the risk of overfitting, leading to consistent performance on new data. Consequently, proposed robustness, making it well-suited for deployment in clinical settings.

5. Conclusion

The brain controls all physical actions in the human body. It is commonly recognized that a brain disorder may have a detrimental impact on a person's life. One of the worst illnesses caused by aberrant brain cell proliferation is the brain tumor. Automated brain tumor categorization is crucial for the early stages of tumor discovery and improves individual survival chances by enabling prompt diagnosis. In this article, using a three-dimensional convolutional neural network (3DHybridseqnet-CNNRNN), a method for identifying MRI brain tumors is suggested. The Brats 2021 database is where the data samples are taken from. SMF is used for image de-noising and quality enhancement. The data is segmented using the M3DT technique. While the input feature subsets are ideally created using WOA, the relevant features are retrieved using the W-LBP approach. The suggested strategy successfully outperforms more recent methodologies like DNN, Alexnet, and Resnet in efficacy. In terms of accuracy (97.5%), recall (98%), precision (97%), and F1-score (98%) metrics, the simulated results using a Python tool demonstrated that the proposed technique generates better identification outcomes than the existing methods. A significant improvement has occurred in the identification of brain tumors. Various types of images can be incorporated in future work, and utilizing modern technology in the proposed system will enhance the detection results.

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