Advances in Public Healthcare: Computational Model for Brain Tumour

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KEYWORDS

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ABSTRACT

Accurately assessing the size of brain tumours and scheduling for their treatment both heavily depend on determining the overall size of the tumour. For brain tumour, MRI (magnetic resonance imaging) has become the gold standard for diagnosis. Classifying a brain tumour physically takes a lot of time and is mostly dependent on the operator's experience. This work advances public health by presenting a computer approach for brain tumour detection. For the efficient diagnosis of brain tumours, a novel puzzle optimization-driven kernel optimised resnet (PO-KOResnet) technique is put forth. The PO approach is used to maximise the performance of the KOResnet technique. This study used a publicly available data set that was taken from the Kaggle website. It contained 1,500 [256 x 256] MRI pictures, both with and without brain tumours, to evaluate the detection performance of the suggested method. Median filter (MF) is used to enhance the image processing by eliminating noises from the collected raw images. Also, the purpose of this study is to evaluate the suggested method's performance using a variety of measures using the Python platform. The PO-KOResnet technique outperformed other approaches in terms of accuracy value when it came to improving public health consequences globally.

1. Introduction

The development of computer simulations aimed at brain tumour detection to enhance the accuracy and efficiency of artificial intelligence (AI) and machine learning (ML) models of brain tumour detection has dramatically changed public health in recent years [1].These computer models can now analyse complex medical images faster and more accurately than ever before. When a brain tumour is first being started, careful analysis of scan data from CT and MRI scans will reveal abnormalities and subtle features [2]. Early detection can prevent tumour development and incurability, reduce patient morbidity through less invasive treatments, and improve early medical intervention and treatment planning. Overall, the prediction output grows smaller [3].AI driven medical imaging automation promises to streamline strategies and standardize research within the clinical subject. Physician workloads can be reduced and the chance of diagnostic mistakes can be reduced via automating imaging information and facilitating quick interpretation [10]. Enhanced clinical workflow optimization through imaging interpretation automation affected person care by means of supplying materials with a whole lot of fitness care perspectives [17]. The use of computer simulations in public health has greatly improved the diagnosis and treatment of brain tumours [14]. With faster diagnosis, better treatments, and improved patient outcomes, these models will pave the way for targeted medicine and precise healthcare delivery during development [5].To improve global public health outcomes, the goal is to revolutionize brain tumour identification utilizing MRI with better accuracy and efficiency with the novel PO-KOResnet technology.

Related works

Choudhury et al. [6] categorized an MRI as "tumour detected" or "tumour not detected," by using a deep neural network (DNN) approach with convolutional neural network(CNN)-based model [4]. Arunkumar et al. [15] presented a novel MR image-based brain tissue segmentation method in that study. Three computer vision fiction methodologies made up the technique: image segmentation, texture and histograms-oriented gradient (HOG) characteristics-based non-region of interest(ROI) filtering, and picture enhancement [7]. To detect and categorize brain tumour, Khan et al. [8] employed CNN in their optional hierarchical deep learning-based brain tumour (HDL2BT) classification method. That technique classified tumours into four categories: pituitary, meningioma, glioma, and no tumour. Two deep learning models were developed by Khan et al. [9] to identify brain tumour that are multiclass (meningioma, glioma, and pituitary) or binary (normal and abnormal). Brain tumourwere distinguished from 2D MRIby utilizing a CNN, conventional classifiers, and deep learning algorithms, as proposed by Chattopadhyay and Maitra [16].

2. Methodology

Dataset

The dataset utilized in this investigation were gathered from a Kaggle project (Br35H) and was made publicly available [11]. The dataset allows for thorough analysis and comparison since it includes 1500 MRI images with brain tumours and an equivalent number without tumours. Every picture was two-dimensional, with width and height measured in 256 × 256 pixels. The craniums of each image had been peeled off, and the labels indicated whether or not the object was a tumour. The example images with and without tumours are displayed in Figure 1.

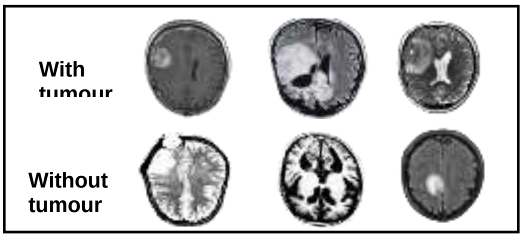

Figure 1 Sample dataset

Pre-processing using median filtering

In brain detection, the median filter (MF) is used to remove noise from the acquired raw pictures, improving image processing.

Median Filtering

The median filter is the most frequently employed order-statistics filter. It substitutes the neighborhood median of the gray level for the value of a pixel.

$$\hat{g}(a,b) = \underset{(p,q)\,\in\, P_{ab}}{median}\{i(p,q)\} \quad (1)$$

When calculating the median, the pixel's beginning value is taken into account. More specifically, compared to linear smoothing filters of comparable size, median filters significantly reduce blurring, which makes them very useful for attenuating noise in various forms of random noise.

Puzzle Optimization-driven Kernel Optimized Resnet50

Puzzle-based kernel optimization is integrated into ResNet50 to enhance the accuracy of brain tumour detection with medical imaging data.

Puzzle Optimization: The POA, a population-based approach, uses puzzle game simulation to model problems using assessment and objective function value. It focuses on fitting members into a jigsaw puzzle, utilizing advice from knowledgeable individuals.

In POA, each member of the population selects the values of the issue variables as a feasible solution. Consequently, the algorithm population in POA may be mathematically modeled using a matrix provided in Equation (2).

$$W = \begin{bmatrix} W_1 \\ \vdots \\ W_j \\ \vdots \\ W_M \end{bmatrix}_{M\times n} = \begin{bmatrix} w_{1,1} & \cdots & w_{1,c} & \cdots & w_{1,n} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ w_{j,1} & \cdots & w_{j,c} & \cdots & w_{j,n} \\ \vdots & \iddots & \vdots & \cdots \ddots & \vdots \\ w_{M,1} & \cdots & w_{M,c} & \cdots & w_{M\times n} \end{bmatrix}_{M\times n} \quad (2)$$

W represents the population of puzzles, W_j the $j\,'th$ puzzle, N the total number of problems in the population, n the number of problem variables, and$w_{j,c}$ the value of the $c'th$ variables given by the $i'th$ puzzle.The value of the objective function may be ascertained by comparing the number of population members to the optimization problem; the values so obtained are then simulated using a vector in Equation (3).

$$E = \begin{bmatrix} e_1 \\ \vdots \\ e_j \\ \vdots \\ e_M \end{bmatrix}_{M\times 1} = \begin{bmatrix} E(W_1) \\ \vdots \\ E(W_j) \\ \vdots \\ E(W_M) \end{bmatrix}_{M\times 1} \tag{3}$$

The objective function of the$j\,'th$issue is represented by the value e_j, and the vector of obtained values for the objective function is indicated by E. Equation (4) is used to compute the acquired values for the objective function, which are then compared to identify the best member of the population.

$$A = W_l, e_l = \min\,(E) \tag{4}$$

In this case, the l'th problem with a minimal objective function equal toe_l is represented by W_l, and B is the best member.The POA suggests updating population members in two phases: first, following the advice of other members, and then, to ensure a cooperative and successful approach, trying to finish their jigsaw with parts recommended by other members.Equations are employed to mathematically model the concept presented in the first phase.Equation from (5) to (9)

$$HN_j = W_h, \quad h \in \{1, 2, 3, \dots, M\}(5)$$

$$dx_{j,c} = \begin{cases} \left(HN_{j,c} - J \times w_{j,c}\right), & E_h < E_j \\ \left(w_{j,c} - J \times HN_{j,c}\right), & else \end{cases} \tag{6}$$

$$J = round(1 + rand) \tag{7}$$

$$W_j^{new} = W_j + q \times dX_j \tag{8}$$

$$W_j = \begin{cases} W_j^{new}, E_j^{new} < E_j \\ W_j, \qquad else \end{cases} \tag{9}$$

In this instance,HN_j is the guiding member of the $j\,'th$puzzle, HN_j,c is $c'th$ dimension, and E_j is its value of the objective function.J is a random number that can be either 1 or 2, $dx_{j,c}$ is the changes of the c'th dimension of the $j'th$ puzzle, q is a random number in the [0 1] interval, W_j^{new} is the new status of the$j\,'th$ puzzle, and E_j^{new} is its value of the objective function.

The second step involves each member of the population updating their status using mathematically modeled puzzle pieces (Equation (10) to (12) that have been offered by others.

$$M_o = round\left(0.5 \times \left(1 - \frac{s}{S}\right) \times M\right) \tag{10}$$

$$w_{j,c_i}^{new} = w_{g,c_i}, \quad \begin{cases} g \in \{1,2,3, \dots., M\} \\ i \in \{1,2,3, \dots., M_o\} \\ c_i \in \{1,2,3, \dots., n\} \end{cases} \tag{11}$$

$$W_j = \begin{cases} W_j^{new}, E_j^{new} < E_j \\ W_j, \qquad else \end{cases} \tag{12}$$

In this case,S is the highest possible iteration count,M_o is the number of optional puzzle pieces, s is the iteration counter, $w_{j,c_i}^{new}$is the new value for $c_i\ th$ dimension of $i'th$ puzzle and $w_{g,c_i}$is the selected optional puzzle piece from $g'th$ puzzle which g is selected randomly.

The POA algorithm updates all population members in iterations, determining their new status based on Equation (4) to (12). After all iterations are finished, POA offers the best quasi-optimal solution to the optimization problem. Up to the most recent iteration, the procedure is updated.

Kernel Optimized Resnet50

The research optimizes the Kernel ResNet-50 network structure by including an Optimized ResNet-50 module, fifty convolutional layers, and a global mean pooling layer, and a layer with full connectivity in the final network.

- **Optimized Resnet50 block**: This study adds a 1x1 size to the convolution kernel in the residual block, improving its size and improving operation performance while lowering parameters.

Considering that the leftover block's output, $E(w)$, for input network w, is the best solution mapping, $E(w) = G(w) - lw$is created, resulting in $G(w)$being represented as $E(w) + lw$. The precise expression for $G(w)$ is

$$E(w) = X_3\sigma(W_3\sigma(W_1w)) \tag{13}$$

The residual block's ultimate result is:

$$G(w) = X_3\sigma(W_3\sigma(W_1w)) + lw \tag{14}$$

where σ is the linear activation function Relu, W_1, W_2, and W_3 stand for the first, second, and third-layer weights, and the output of the residual block that occurs before the third layer's activation function is represented by the notation E(w).

Assuming the weight $W_j \approx 0$, Equation (14) demonstrates that the ultimate output $G(w)$will notequal 0. By using a convolution procedure, the parameter k modifies the dimension of w.

- **Include a layer of batch normalization:** The BN layer is added before activation function to reduce data edge noise, improve accuracy, and speed up training, while removing the dropout layer enhances network generalization.
- **Model of movable jump link coefficients:** This study discusses network training issues, dealing with undesired network layers, and inadequate training levels. It suggests gradient increases for layer parameters and an efficient coefficient for modifiable jump connections in upgraded ResNet blocks to improve recognition performance.
- **Fully linked layer with global mean pooling layer:** The global average pooling layer prevents overfitting, improves feature map consistency, and stabilizes data by adding spatial information. It applies global average pooling to the entire picture, enabling each feature map production. The classifier can receive input from two connected layers.

Combining puzzle optimization with kernel optimization approaches, the Puzzle Optimization-Driven Kernel Optimized ResNet50 (PO-KOResNet) hybrid methodology improves brain tumour identification. By dividing MRI pictures into smaller patches and concentrating on local characteristics, puzzle optimization helps to simplify the tumour identification effort. Kernel optimization refines the convolutional kernels of the ResNet50 network to more effectively gather detailed brain scan information. This dual optimization improves accuracy and dependability by strengthening the model's capacity to discriminate between healthy and tumourous tissues. A major development in medical imaging, PO-KOResNet facilitates accurate and timely identification of brain tumours.

3. Results and discussion

We compare the performance of the suggested method (PO-KOResnet) with the current approaches (f1 score, accuracy, recall, and precision) and with CNN-LSTM [12] and DL-TL [13].

Accuracy: The exactness and correctness of identifying tumour tissue in a medical imaging are referred to as brain tumour detection accuracy. Table 1 and Figure 2 display the accuracy results. Our proposed method PO-KOResnet (99.4%) achieve higher than existing methods (CNN-LSTM (99.1%)and hybrid DL-TL (99.1%)).

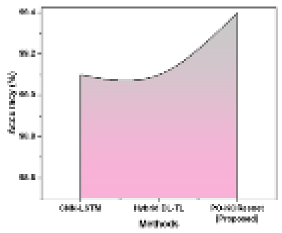

Figure 2 Outcome of Accuracy

Precision: The precision of brain tumour detection is determined by dividing all positive predictions by the proportion of accurately diagnosed tumourous tissues. Figure 3 show the precision results. The results of our suggested method, PO-KOResnet (99.1%) outperform those of the existing approaches (CNN-LSTM (98.8%) and hybrid DL-TL (98.9%))

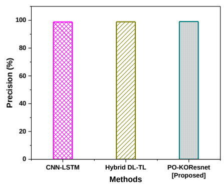

Figure 3 Outcome of Precision

Recall: The ratio of accurately diagnosed tumourous tissues to all real tumourous tissues present is known as recall for brain tumour detection. Table 1 and Figure 4 display the recall results. Our proposed method PO-KOResnet (99.2%) achieve higher than existing methods ((CNN-LSTM (98.9%) and hybrid DL-TL (98.6%)).

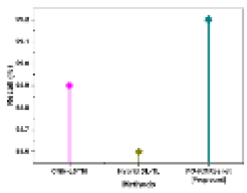

Figure 4 Outcome of Recall

F1 Score: By striking a balance between recall and precision, the F1 score is a metric for identifying brain tumours that offers a single assessment of overall classification performance. Table 1 and Figure 5 show the f1 score results. The results of our suggested method PO-KOResnet (99.2%), outperform those of the existing approaches, ((CNN-LSTM (99%) and hybrid DL-TL (98%)).

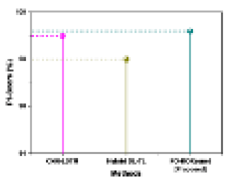

Figure 5 Outcome of F1-score

Table 1 Outcomes of accuracy, precision, recall, and f1-score

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN-LSTM	99.1	98.8	98.9	99.0
Hybrid DL-TL	99.1	98.9	98.6	98
PO-KOResnet [Proposed]	99.4	99.1	99.2	99.2

4. Conclusion and future scope

The study presented PO-KOResnet, a novel method for effective MRI-based brain tumour identification. The strategy improved tumour classification accuracy by using puzzle optimization (PO) to optimize a kernel-optimized ResNet model. Making use of a median filter for noise reduction, the strategy outperformed previous approaches using a dataset of 1,500 MRI scans from Kaggle. The performance of the proposed technique was simulated using a Python and compared with other existing methods. As a result it shows that recall (99.2%), precision (99.1%), F1-score (99.2%), and accuracy (99.4%). Comparing our recommended approach to other conventional method, it worked more effectively. This development has the potential to have a major worldwide impact on public health outcomes through enhanced diagnosis accuracy and management of brain tumours.

Limitation and Future scope

Limitation: The PO-KOResnet technique's dependence on high-quality MRI images is one of its drawbacks. Accurate detection may be impacted by variations in picture quality or artifacts because the technique mainly depends on certain image attributes. Furthermore, there can be difficulties with generalizability across various MRI machines or imaging protocols, which might affect its use in various clinical contexts. The resolution of these variability concerns is crucial for increased utilisation and dependability in actual clinical settings.

Future scope: In the future, the PO-KOResnet method creates opportunities for more developments in brain tumour identification. To improve accuracy even further, future studies may investigate using other sophisticated image processing methods. Furthermore, expanding the real-time diagnosis methodology and incorporating it with telemedicine platforms may transform global access to prompt and precise brain tumour detection. These advancements have the potential to improve results and shorten treatment times, which will benefit worldwide public health.

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