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Enhancing Brain Tumour Detection using an Ensemble approach of Particle Swarm Optimization and Convolution Neural Network

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ABSTRACT

Detecting brain tumor is vital in medical imaging research and computer-aided diagnosis to improve timely diagnosis and treatment outcomes. The diagnostic accuracy depends on the subjective analysis of radiologists applying conventional methods for brain tumor identification, which include MRI scans and biopsies. Innovations in machine and deep learning provide promising automation to improve the precision of tumor diagnosis as compared to the current methods. In this paper, image augmentation, feature extraction, and optimization methods are used to enhance the diagnosis of brain tumors. The proposed approach employs rotation augmentation, median filtering, Grey-Level Co-occurrence Matrix (GLCM) feature extraction, Particle Swarm Optimization (PSO), and a Convolutional Neural Network (CNN) to boost the accuracy and pliability of brain tumor classification. The Harvard repository dataset was used. It has a wide range of brain images for training and validation. The convolutional neural network combines particle swarm optimization techniques to detect brain tumors in MRI images. An accuracy rate of 96.71% is obtained with this integrated approach, which surpasses the present system. An effective solution for automated tumor detection in MRI images is achieved by integrating cutting-edge image processing methods such as rotation augmentation, median filtering, and GLCM feature extraction with the optimization strengths of PSO and the effective learning capabilities of CNNs.

Keywords: *Brain tumor, Median Filtering, Feature optimization, Particle Swarm algorithm, Ensemble approach*

1. INTRODUCTION

The number of fatalities from brain tumors has increased by 300% in recent decades, indicating the need for better detection techniques. The primary approach is Magnetic Resonance Imaging (MRI) for brain tumor detection. However, because brain tumors are complicated, there are still difficulties. Owing in particular to Convolutional Neural Networks and autoencoders, medical imaging has found great use in machine learning and deep learning. The drawbacks of human-based diagnosis are overcome by improving tumor detection and classification accuracy. The rapid expansion of computer devices has spurred additional progress in diagnostic methods, highlighting the critical function of medical imaging in effectively identifying a range of illnesses [1]. Based on their level of aggression, brain tumors are categorized by the World Health Organization (WHO) into categories I through IV. Grade I and II brain tumors are often benign (low grade), but Grade III and IV brain tumors are considered high grade [2]. Early identification is necessary for both benign and malignant forms, which are differentiated by their capacity to spread. Based on their origin and severity, meningiomas, pituitary tumors, and gliomas belong to different classifications. The depth of neural networks during model training presents questions regarding possible information loss, notwithstanding the advantages [3].

Identifying brain tumors in MRI scans manually is challenging and susceptible to errors, necessitating a highly accurate automatic detection system [4]. Despite several notable efforts and promising results, effective classification and segmentation remain challenging in this field. The variations in tumor size, shape, and location pose a significant challenge to brain tumor detection [5]. Deep learning techniques enhance the understanding of what defines a healthy brain and what does not. The application of these approaches enables radiologists to make prompt and well-informed decisions, a crucial aspect given the elevated incidence of brain tumors, particularly in children [6]. Through segmentation, distinct characteristics in spatially continuous regions of the brain image are expressed, which enhances interpretation. The use of UNet in medical image processing, particularly brain tumor segmentation, demonstrates developments in this area [7].

Machine learning and deep learning are integrated into Computer-Aided Diagnosis (CAD) systems to improve premature tumor diagnosis. Overall diagnostic precision is increased by transfer learning, which reduces data restrictions, and data augmentation, which solves CNN's problems with slanted or rotated pictures [8-10]. Important datasets for the development of classification algorithms are made available via competitions such as the Multimodal Brain Tumor Segmentation Challenge (BRATS) [11]. Clinical acceptability is impacted by things like the degree of human supervision and simplicity [12]. Convolutional Neural Networks such as U-Net, SegNet, and Res-Net18 provide quick and precise segmentation [13, 32]. Super pixels and Principal Component Analysis (PCA) are also used to improve feature extraction, lower picture complexity, and enable precise brain tumor segmentation and identification in MRI images [14].

Following image improvement and noise reduction, morphological procedures are performed on MRI images to detect tumors based on presumptions about their size and shape [15]. Planning radiation therapy and receiving medical care depends on accurately classifying tumors and their locations within the brain [16]. Although MRI is a commonly used imaging modality for brain tumor detection, precise segmentation is still complicated since tumor forms, intensities, and locations can vary [17]. The complexity, number of parameters, long execution times, and strict system requirements plague CNN solutions [18]. MRI, with and without gadolinium contrast, is the gold standard for glioma imaging; diagnosis and therapy depend on precise segmentation [19].

MRI is a crucial technique, but issues with inadequate picture resolution and equipment quality can pose challenges. Super-resolution (SR) methods are employed to enhance features in low-resolution (LR) photos, creating high-resolution (HR) photographs [20]. Due to advancements in processing medical images, MRI device soft-ware has integrated several algorithms [21]. Automatic diagnosis using MRI images is essential for rapid and reliable evaluation, eliminating the need for labour-intensive human interpretation of large amounts of data [22-24]. Artificial intelligence, particularly deep learning, offers a viable alternative to conventional machine learning approaches by combining high-level and low-level information without manual extraction for automated brain tumor identification [25-29]. The complexity of brain function and the severe implications of anomalies emphasize the crucial need to address brain illnesses, especially those classified as "untreatable" [30]. Further testing on a variety of datasets is essential for broader applicability in medical diagnostics [31].

The primary goal is to develop a robust brain tumor detection model capable of accurately classifying medical images. The well-known dataset is employed to classify brain cancers, concentrating on tumor uniqueness, location, growth, and automated diagnostic process. This research study models brain tumors using a neural network and the Particle Swarm Optimization Algorithm [34] to enhance sensitivity and specificity. This study evaluates the correctness of an improved PSO algorithm for feature classification in combination with CNN. Furthermore, the relevant parameters [34] to update features during the blended approach of CNN and PSO have been carefully selected for experimentation. Identification of the most revealing features from varied types of tumor datasets is achieved through feature selection. An improved method for phase-wise accuracy detection and feature optimization using a PSO-based CNN model is employed in this study. The remaining paper is structured as follows: Part 2 studies the literature on brain tumor recognition, Part 3 outlines the proposed methodologies, Part 4 investigates results and interpretations, and Part 5 summarizes the research and its potential implications.

2. LITERATURE REVIEW

In order to classify brain tumors using MRI data, S. Saeedi et.al describes a study on two deep learning networks: a convolutional auto-encoder and a 2D CNN with an accuracy rate of 96.47% and 95.63% [1]. R. Chawla et al. highlight the use of MRI images to identify and classify brain cancers using an integrated bat algorithm and convolutional neural network technique with 99.5% accuracy [2]. A shallow convolutional neural network (SCNN) and a VGG16 network are the two models that S. Patil and D. Kirange. used to create the ensemble model, providing a 97.77% classification accuracy [3]. A 9-layer Convolutional Neural Network (CNN) algorithm is used in the proposed method of A. Chattopadhyay and M. Maitra for brain tumor identification in MRI images (99.74% accuracy) [4]. P. Gokila Brindha et al. discussed several deep learning methods, including voxel-wise classification, CNN, and CNN with Hough voting, to detect brain tumors from MRI data, achieving an overall accuracy of 91.3% [6].

S. Sangui et al. describe an automatic medical image segmentation method using the U-Net architecture to identify brain tumors, achieving a 99% validation accuracy [7]. M. S. I. Khan et al. present two deep learning models that utilize a 23-layer CNN architecture and Fine-tuned CNN with VGG16 to detect brain anomalies and categorize tumor grades with prediction accuracy of 97.8% and 100% using two datasets [8]. In the study by O. Turk et al., four ensemble deep learning architectures-ResNet50, InceptionV3, VGG19, and Mobile Net-are employed. Based on the Res-Net50, InceptionV3, and Mobile Net designs, the accuracy of ResNet50 was 100%, while on VGG19, it was 99.71% [9]. M. A. Salam et al. employ transfer learning methods like Mobile Net, VGG19, InceptionResNetV2, Inception, and DenseNet201 with high accuracy rates ranging from 84.19% to 99% for various approaches [10].

The design of the convolutional neural network and performance evaluation using four different methods (two 10-fold cross-validation and two datasets) is one of the main results of M. M. Badža and M. C. Barjaktarović's studies with 97.28% accuracy [11]. M. Lather and P. Singh combined the Modified Fuzzy K-means (MFKM) and Bacteria Foraging Optimization (BFO) algorithms [12]. D. Daimary et al. proposed three hybrid CNN models for brain tumor segmentation from MRI images: Seg-UNet, Res-SegNet, and U-SegNet. The Seg-UNet model achieved a global accuracy of 99.11% [13]. M. K.

Islam et al. introduced a K-means clustering approach based on templates, principal component analysis, and super pixels for brain tumor diagnosis, obtaining an accuracy of 95.0% [14]. M. Jian et al. approach is based on saliency computational modelling and a principal local contrast saliency-detection frame-work, which predicts a precision of 0.8255 [15]. R. Vankdothu and M. A. Hameed used recurrent convolutional neural networks (RCNN), GLCM, and improved K-means clustering (IKMC) with an accuracy of 95.17% [16].

The Harris Hawks Optimization (HHO) and Whale Optimization (WOA) algorithms are integrated for the training of a deep convolutional neural network (DeepCNN) in D. Rammurthy and P. K. Mahesh's studies, achieving an accuracy of 81.60% [17]. N. Kesav and M. G. Jibukumar's architecture integrates an RCNN for object identification with a two-channel CNN for feature extraction, achieving an accuracy of 98.21% [18]. R. M. Kronberg, et al. method used in this work combines the variational auto encoder with the efficiency of a U-Net (ResNet) architecture [19]. Three AI methods are combined by A. Deshpande et al. architecture. Res-Net50, CNN with super-resolution, and discrete cosine transform (DCT) based framework achieves an 89% accuracy for brain cancers [20].

G. Saad et al. proposed a hybrid approach that blends principal component analysis (PCA), local binary features (LBP), k-nearest neighbor (KNN), and GLCM with support vector machines (SVM). The medium Gaussian SVM (MG-SVM) model produced a testing accuracy of 93.3% [21]. S. Solanki et al. proposed a 5-layer CNN architecture with traditional machine learning classifiers (97.86% accuracy) [22]. D. K. Sahoo et al. proposed a solution utilizing the MobileNetV2 architecture, achieving a test accuracy of 89% [23]. H. Mohsen et al. used discrete wavelet transform (DWT) to train a deep neural network (DNN) for brain tumor classification, accomplishing a classification percentage of 96.97% [24].

M. Alnowami et al. provided a DenseNet framework that unites deep-learning systems without region-based pre-processing steps. It obtains an average accuracy of 96.52% [25]. S. Tankala et al. developed LWCAR-Net, for brain tumor segmentation using MRI images. A Depth Search Block (DSB) is applied, and a CAR block produces an F1 score of 96% [26]. K. Dang et al. employed GoogleNet, VGG, and UNet to classify brain tumors. The pipeline of UNet with VGG achieved an accuracy of 97.44% [27]. A lightweight U-Net architecture is proposed by J. Walsh et al. for brain tumor segmentation with an average mean Intersection over Union (IoU) of 84% [28]. H. M. Rai and K. Chatterjee developed the LU-Net model that combines Le-Net and U-Net, accomplishing an overall accuracy of 98% [29].

A. S. M. Shafi et al. achieved an accuracy of 97.95% with the integration of the weighted kernel width SVM (WSVM), the histogram intersection kernel SVM (HIK-SVM), and KNN [30]. F. M. Refaat et al. used KNN, SVM, and GRNN methodologies for the automated classification of brain tumors with an accuracy of 97%, 96.24%, and 94.7%, respectively [31]. Y. Peng and J. Sun introduced the automated weighted dilated convolutional network (AD-Net) method for multimodal MRI brain tumor segmentation. AD-Net employs Jensen-Shannon divergence, dual-scale convolutional feature maps, and automatic weighted dilated convolutional units to address the challenge of recovering multimodal input. The proposed AD-Net achieved dice scores of 0.90 for the overall tumor (WT) [32].

3. METHODOLOGY

The proposed methodology integrates the PSO Algorithm and Convolutional Neural Network (CNN) to enhance the segmentation of brain images from tumor containing ones, ensuring faster and less complex processing. This approach involves three key steps: Pre-processing, Feature Removal, and Feature Selection through PSO-CNN Classification, as depicted in Fig. 1.

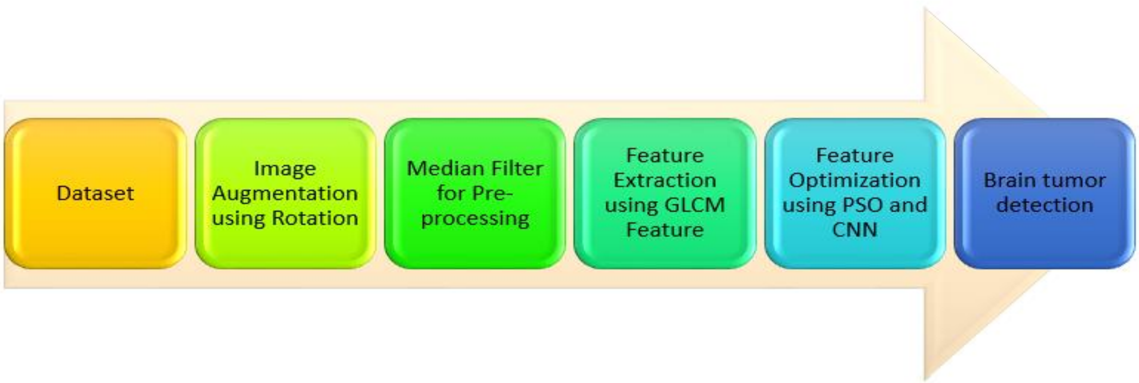

Fig. 1. Proposed Method

By leveraging the GLCM, distinctive characteristics are extracted from MRI brain images. The CNN algorithm, in tandem with PSO, strategically selects relevant features, improving the precision of tumour image separation. The systematic workflow underscores the efficiency and accuracy of this innovative method in medical image analysis.

3.1 Dataset loading and pre-processing

3.1.1 Dataset

The dataset, sourced from the Harvard repository, comprises a collection of 152 MRI slices, encompassing both T1 and T2-weighted contrast images [33]. Within this dataset, 71 slices represent healthy brain images devoid of tumors, while 81 slices show-case abnormalities, featuring five distinct tumor types: Glioma, Metastatic adenocarcinoma, Meningioma, Metastatic bronchogenic carcinoma, and Sarcoma. This diverse dataset provides a comprehensive foundation for training and evaluating brain tumor detection models.

3.1.2 Image Augmentation

Random rotation angles ranging from -15 to 15 degrees are implemented to enhance dataset diversity. A rotation transformation is expressed with a rotation matrix. The matrix obtained is applied to every image pixel to complete the rotation. The array of rotated images with all images is the output of this step.

3.1.3 Image Pre-processing

Median filtering is a nonlinear method utilized to eliminate noise from an image while conserving edges with minuscule particulars. The median filter substitutes each pixel's value with the median of its adjacent pixels. The kernel size is set to 3x3. It means that the median value is found using the intensity values of the centre pixel and eight adjoining pixels inside a 3x3 frame. The median value is then dispensed to the suitable pixel in the filtered image. Median filtering substantially diminishes noise while conserving key outlines in the image, resulting in a popular choice for image pre-processing in different computer vision applications.

3.1.4 GLCM Feature Extraction

The pre-processed image texture features are mined using the GLCM. GLCM provides noteworthy data on the spatial correlations between pixel intensities. The pre-processed brain images are provided as input to GLCM to extract features. The statistical approach of GLCM finds the spatial correlations among an image's pixel brightness. Information about the image insights pattern, texture analysis, and structures inside the images is provided. Each of the GLCM's essentials (i, j) specifies how often pixel pairs with intensity values i and j occur inside a certain spatial relationship (such as at a particular distance and angle) inside the image.

The GLCM is calculated by considering all pairs of pixels separated by the specified distance d and occurring at the specified angle θ. The formula for computing the GLCM element (i,j) is as follows:

$$P(i,j,d,\theta) = \frac{Number\ of\ occurences\ of\ pixel\ pair\ (i,j)\ at\ distance\ d\ and\ angle\ \theta}{Total\ number\ of\ pixel\ pairs\ at\ distance\ d\ and\ angle\ \theta} \tag{i}$$

The GLCM is recurrently normalized to produce probabilities, and the matrix's whole components add up to 1. Normalized GLCM (Pnorm) can be calculated as:

$$Pnorm(i,j,d,\theta) = \frac{P(i,j,d,\theta)}{\sum_{i,j} P\ (i,j,d,\theta)} \tag{ii}$$

The GLCM is a valuable means for texture analysis and feature extraction in image processing and computer vision applications since it provides information on the spatial patterns and relationships of pixel intensities in the image.

3.2 Feature optimization and using classification (PSO+CNN)

The PSO method purposes to optimize a neural network's GLCM feature selection. The objective function is employed to assess the model's performance in accordance to specific attributes. The PSO method looks over the feature space to identify the best subset that reduces classification error, drawing inspiration from social behavior in nature. A simple CNN is employed, consisting of a dense hidden layer with ReLU activation and an output layer with a sigmoid activation for binary classification. The neural network is trained on the selected GLCM features using the Adam optimizer and binary cross-entropy loss. The trained model is evaluated on a test set to assess its accuracy. Metrics such as test accuracy, confusion matrix, and classification report are utilized for evaluation.

A CNN is a specialized artificial neural network for image recognition and feature extraction. Its strength lies in capturing intricate patterns within images. In CNN, neurons undergo evaluation for biases and weights, and the activated function selects the one with the highest value. Through convolutional layers and Rectified Linear Unit (ReLU) functions, CNN efficiently extracts essential features, and the maximum pooling layer aids in downsizing feature maps. Neurons in each layer are interconnected, promoting comprehensive information processing. During training, techniques like backpropagation and gradient descent are employed. The Softmax function ensures the output probabilities sum to 1. CNN generates feature maps at hidden layers, facilitating the learning of intricate image details.

In PSO, the optimal solution is found by a population of possible solutions, referred to as particles, moving around the search space. Based on its own experiences as well as the swarm's collective knowledge, each particle modifies its position. A particle moves according to its current speed, its unique best location, and the global best position that all the particles in the swarm have found. Until the algorithm converges to an ideal solution, the particle placements are refined iteratively in this process.

The velocity update equation in PSO is given by:

$$Velocity\ (i,j) = w\ X\ Velocity\ (i,j) + c1\ X\ r1\ X\ (PersonalBest\ (i,j) - Position\ (i,j) + C2\ X\ r2\ X\ (GlobalBest(j) - Position\ (i,j) \quad \text{(iii)}$$

Algorithm: Brain Tumour Detection with PSO-CNN

1. Input: dataset of brain images with tumour and non-tumour classes.
2. Output: detection of brain tumour based on various features.
3. Apply rotation augmentation to diversify the dataset.
4. Apply noise reduction and contrast enhancement techniques to improve image quality using median filtering.
5. Extract relevant features from enhanced images using GLCM.
6. Initialize PSO parameters and bounds.
7. Use PSO to select features with values above a threshold. selected_features=where(best_features>threshold)
8. Build and train the CNN model on the selected features.
9. Evaluate the trained model on the test set.
10. Adjust hyperparameters and thresholds based on characteristics.

The CNN and PSO parameter values from a brain tumour data set are used to train the model. A median filter is employed throughout the algorithmic development process. The most crucial characteristics are then found through feature selection. After reading input brain data, test/validate the training at an 80:20 ratio, defining the labels for each brain picture throughout the training stage. The suggested technique trains the CNN model for certain brain imaging features by applying the activation function to the model. The PSO–CNN algorithm for the suggested system is provided in Fig. 2, which pre-processes pictures using a median filter. The GLCM Filter improves the resilience and efficiency of the model. The next step is feature selection, which uses the data to determine which characteristics are most significant (PSO–CNN).

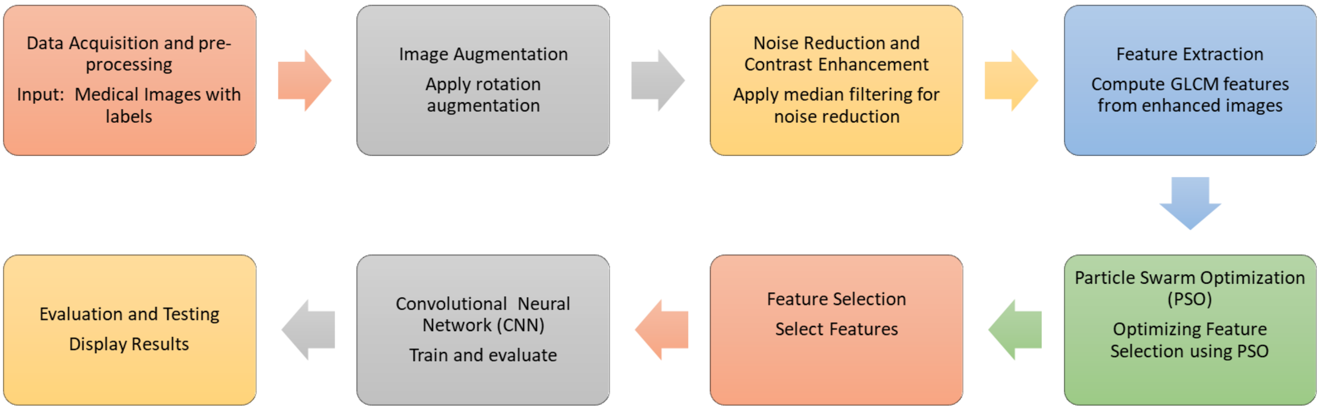

Fig. 2. Architecture PSO-CNN Model

4. RESULTS AND DISCUSSION

The PSO algorithm identifies a subset of GLCM features that significantly contribute to the model's performance. The CNN, trained on the selected features, demonstrates improved accuracy and robustness compared to traditional methods. The Harvard dataset is used for brain tumour detection, consisting of 152 MRI slices. Among these, 81 slices contain abnormal images with tumours, while 71 slices have healthy images. Each image was resized to 128 by 128 pixels. The accuracy of separation models is often assessed, and this is seen as one of the most crucial factors, in providing an accurate approximation of the overall value of the forecast. Every test scenario is unique, with a significant condition separator that upholds the correctness of half of the most prevalent labels in the test set given the primary category. Accuracy is now quantified using a scale. Three metrics are used to assess the performance of the proposed system: accuracy, precision, and recall. Here's how these metrics are computed:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$\mathrm{F1-score} = 2\mathrm{X}\frac{\mathrm{Precision} * \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}}$$

Table 1 presents the performance metrics for different types of brain tumours. The proposed methodology incorporates mathematical metrics, focusing on accuracy, recall, and specificity, to evaluate the classification of brain tumours. The suggested method, utilizing a Deep Neural Network (DNN) and the Particle Swarm Optimization Algorithm (PSO + CNN), demonstrates high specificity values for each type of brain tumour depicted in MRI samples. It underscores the effectiveness of the proposed approach in directly classifying MRI brain imaging samples. The proposed method without PSO obtained an accuracy of 90.28%, a precision, and F1- score of 91%, and a Recall of 90%. If the PSO feature optimization method is integrated with CNN then the model accuracy is increased up to 96.71%. The model obtains a precision and an F1-score of 97%, and a recall of 96%. The results are improved after applying the ensemble approach of PSO-CNN proposed architecture.

Table 1. Proposed System Result

Proposed Method	CNN	PSO + CNN
Accuracy	90.38	96.71
Precision	91	97
Recall	90	96
F1-Score	91	97

Impressive performance metrics set apart the proposed solution, which integrates a CNN with PSO. It outperforms the majority of the other models with an accuracy of 96.71%, closely matching the 96.52% accuracy of DenseNet model [25]. But the suggested approach excels with 97%, 96%, and 97% for precision, recall, and F1-score, respectively. Compared to the SCNN + VGG16 model [3], which reports a high accuracy of 96.49%, precision of 96.66%, recall of 98.30%, and F1-score of 97.47%, these numbers are slightly more balanced.

While the accuracy rates of other models, such as PCA + TK-means [14], RCNN [16] and WHHO + CNN [17], are comparatively lower at about 95%, 95.17%, and 81.6%, respectively, direct comparisons are challenging due to the absence of precise, recall, and F1-score data. CNN models [11, 6] perform noticeably inferior, with accuracies of 95.40% and 65.21%, respectively. The GRNN model [31] displays an accuracy of 94.7% with balanced but poorer precision and recall. Notably, the overall performance of the proposed algorithm outperformed other tested approaches, yielding superior outcomes in the conducted tests.

Table 2. Comparison of PSO-CNN approach with existing methods

Author	Modality	Accuracy (%)	Precision	Recall	F1-Score
Suraj Patil et al. [3]	SCNN + VGG16	96.49	96.66	98.30	97.47
P Gokila Brindha et al. [6]	CNN	65.21	65	65	68.69
MilicaM. Badža et al. [11]	CNN	95.40	94.81	95.07	94.93
Md Khairul Islam et al. [14]	PCA + TK-means	95	X	X	X

Ramdas Vankdothu et.al. [16]	RCNN	95.17	X	X	X
D. Rammurthy et.al. [17]	WHHO + CNN	81.6	X	X	X
Majdi Alnowami et.al. [25]	DenseNet	96.52	X	X	X
Fatma M. Refaat et.al. [31]	GRNN	94.7	94	93	94
Proposed Method	**PSO+CNN**	**96.71**	**97**	**96**	**97**

The performance of methods in terms accuracy, precision and recall are also shown in Fig. 3. The confusion matrix shown in Fig. 4 shows the classification report of the proposed method. Fig.4 shows that a total of 66 and 81 MRI slices are accurately categorized as having no tumour and tumours. While the proposed architecture only misclassifies five MRI slices.

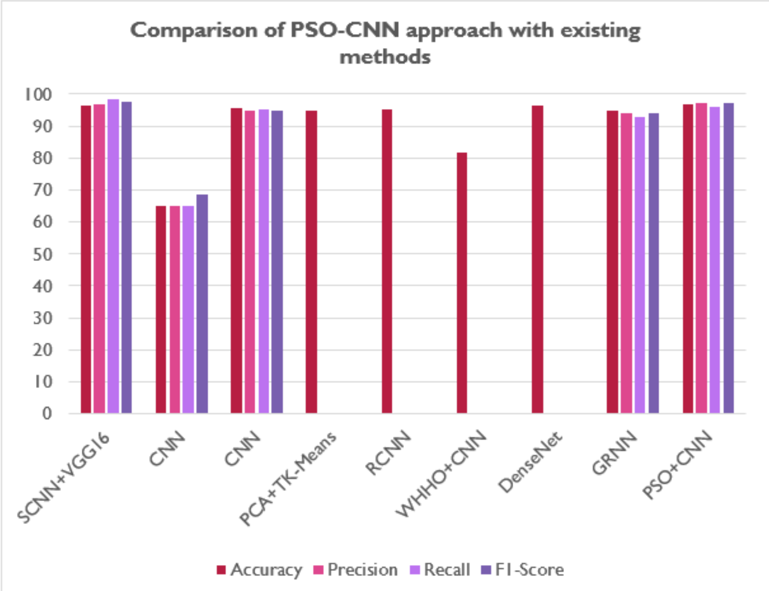

Fig. 3. Comparison of PSO-CNN approach with existing methods

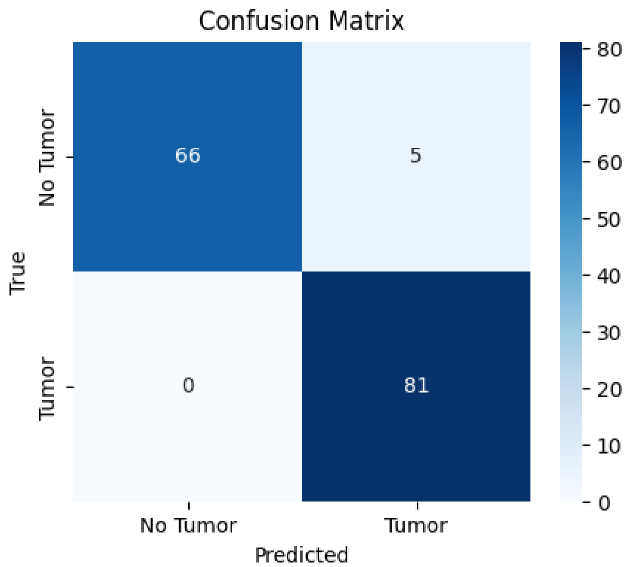

Fig. 4. Confusion Matrix PSO-CNN Model

5. CONCLUSION AND FUTURE WORK

The combination of rotation augmentation, median filtering, GLCM feature extraction, PSO for feature selection, and a simple CNN demonstrates a holistic approach to brain tumour classification. This methodology aims to enhance the model's robustness and performance by incorporating diverse image transformations and extracting meaningful texture features. The use of PSO ensures the selection of a subset of features that optimally contributes to the classification task. The presented pipeline provides a comprehensive framework for brain tumour detection in medical imaging. The proposed methodologies involve extracting specific brain features from MRI images for permanent waveform manipulation. The integration of a Convolutional Neural Network (CNN) with the PSO Algorithm enhances the capabilities of the system. In comparison to related methods, the proposed system exhibited outstanding precision in categorization. The accuracy of the Convolutional Neural Network Algorithm with PSO reached 96.71%. Future advancements may explore alternative forms of artificial intelligence to further enhance performance speed and accuracy. It may involve further optimization of hyperparameters, exploration of additional image augmentation techniques, and testing the model on diverse datasets for generalization.

REFERENCES

[1] S. Saeedi, S. Rezayi, H. Keshavarz, and S. R. Niakan Kalhori, "MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques," BMC Med. Inform. Decis. Mak., vol. 23, no. 1, pp. 1–17, 2023, doi: 10.1186/s12911-023-02114-6.

[2] R. Chawla et al., "Brain tumor recognition using an integrated bat algorithm with a convolutional neural network approach," Meas. Sensors, vol. 24, no. July, p. 100426, 2022, doi: 10.1016/j.measen.2022.100426.

[3] S. Patil and D. Kirange, "Ensemble of Deep Learning Models for Brain Tumor Detection," Procedia Comput. Sci., vol. 218, no. 2022, pp. 2468–2479, 2022, doi: 10.1016/j.procs.2023.01.222.

[4] A. Chattopadhyay and M. Maitra, "MRI-based brain tumour image detection using CNN based deep learning method," Smart Agric. Technol., vol. 2, no. 4, p. 100060, 2022, doi: 10.1016/j.neuri.2022.100060.

[5] J. Amin, M. Sharif, A. Haldorai, M. Yasmin, and R. S. Nayak, "Brain tumor detection and classification using machine learning: a comprehensive survey," Complex Intell. Syst., vol. 8, no. 4, pp. 3161–3183, 2022, doi: 10.1007/s40747-021-00563-y.

[6] P. Gokila Brindha, M. Kavinraj, P. Manivasakam, and P. Prasanth, "Brain tumor detection from MRI images using deep learning techniques," IOP Conf. Ser. Mater. Sci. Eng., vol. 1055, no. 1, p. 012115, 2021, doi: 10.1088/1757-899x/1055/1/012115.

[7] S. Sangui, T. Iqbal, P. C. Chandra, S. K. Ghosh, and A. Ghosh, "3D MRI Segmentation using U-Net Architecture for the detection of Brain Tumor," Procedia Comput. Sci., vol. 218, pp. 542–553, 2022, doi: 10.1016/j.procs.2023.01.036.

[8] M. S. I. Khan et al., "Accurate brain tumor detection using deep convolutional neural network," Comput. Struct. Biotechnol. J., vol. 20, pp. 4733–4745, 2022, doi: 10.1016/j.csbj.2022.08.039.

[9] O. Turk, D. Ozhan, E. Acar, T. C. Akinci, and M. Yilmaz, "Automatic detection of brain tumors with the aid of ensemble deep learning architectures and class activation map indicators by employing magnetic resonance images," Z. Med. Phys., 2023, doi: 10.1016/j.zemedi.2022.11.010.

[10] M. A. Salam, S. Taha, and S. El_ahmdy, "Predicting Brain Tumor using Transfer Deep Learning," Int. J. Comput. Appl., vol. 184, no. 37, pp. 33–37, 2022, doi: 10.5120/ijca2022922445.

[11] M. M. Badža and M. C. Barjaktarović, "Classification of brain tumors from mri images using a convolutional neural network," Appl. Sci., vol. 10, no. 6, 2020, doi: 10.3390/app10061999.

[12] M. Lather and P. Singh, "Investigating Brain Tumor Segmentation and Detection Techniques," Procedia Comput. Sci., vol. 167, no. 2019, pp. 121–130, 2020, doi: 10.1016/j.procs.2020.03.189.

[13] D. Daimary, M. B. Bora, K. Amitab, and D. Kandar, "Brain Tumor Segmentation from MRI Images using Hybrid Convolutional Neural Networks," Procedia Comput. Sci., vol. 167, no. 2019, pp. 2419–2428, 2020, doi: 10.1016/j.procs.2020.03.295.

[14] M. K. Islam, M. S. Ali, M. S. Miah, M. M. Rahman, M. S. Alam, and M. A. Hossain, "Brain tumor detection in MR image using superpixels, principal component analysis and template-based K-means clustering algorithm," Mach. Learn. with Appl., vol. 5, no. May, p. 100044, 2021, doi: 10.1016/j.mlwa.2021.100044.

[15] M. Jian, X. Zhang, L. Ma, and H. Yu, "Tumor Detection in MRI Brain Images Based on Saliency Computational Modeling," IFAC-PapersOnLine, vol. 53, no. 5, pp. 43–46, 2020, doi: 10.1016/j.ifacol.2021.04.123.

[16] R. Vankdothu and M. A. Hameed, "Brain tumor MRI images identification and classification based on the recurrent convolutional neural network," Meas. Sensors, vol. 24, no. August, p. 100412, 2022, doi: 10.1016/j.measen.2022.100412.

[17] D. Rammurthy and P. K. Mahesh, “Whale Harris hawks optimization based deep learning classifier for brain tumor detection using MRI images,” J. King Saud Univ. - Comput. Inf. Sci., vol. 34, no. 6, pp. 3259–3272, 2022, doi: 10.1016/j.jksuci.2020.08.006.

[18] N. Kesav and M. G. Jibukumar, “Efficient and low complex architecture for detection and classification of Brain Tumor using RCNN with Two Channel CNN,” J. King Saud Univ. - Comput. Inf. Sci., vol. 34, no. 8, pp. 6229–6242, 2022, doi: 10.1016/j.jksuci.2021.05.008.

[19] R. M. Kronberg, D. Meskelevicius, M. Sabel, M. Kollmann, C. Rubbert, and I. Fischer, “Optimal acquisition sequence for AI-assisted brain tumor segmentation under the constraint of largest information gain per additional MRI sequence,” Smart Agric. Technol., vol. 2, no. 4, p. 100053, 2022, doi: 10.1016/j.neuri.2022.100053.

[20] A. Deshpande, V. V. Estrela, and P. Patavardhan, “The DCT-CNN-ResNet50 architecture to classify brain tumors with super-resolution, convolutional neural network, and the ResNet50,” Neurosci. Informatics, vol. 1, no. 4, p. 100013, 2021, doi: 10.1016/j.neuri.2021.100013.

[21] G. Saad, A. Suliman, L. Bitar, and S. Bshara, “Developing a hybrid algorithm to detect brain tumors from MRI images,” Egypt. J. Radiol. Nucl. Med., vol. 54, no. 1, 2023, doi: 10.1186/s43055-023-00962-w.

[22] S. Solanki, U. P. Singh, S. S. Chouhan, and S. Jain, “Brain Tumour Detection and Classification by using Deep Learning Classifier,” Int. J. Intell. Syst. Appl. Eng., vol. 11, no. 2s, pp. 279–292, 2023.

[23] D. K. Sahoo, S. Mishra, M. N. Mohanty, R. K. Behera, and S. K. Dhar, “Brain Tumor Detection using Deep Learning Approach,” Neurol. India, vol. 71, no. 4, pp. 647–654, 2023, doi: 10.4103/0028-3886.383858.

[24] H. Mohsen, E.-S. A. El-Dahshan, E.-S. M. El-Horbaty, and A.-B. M. Salem, “Classification using deep learning neural networks for brain tumors,” Futur. Comput. Informatics J., vol. 3, no. 1, pp. 68–71, 2018, doi: 10.1016/j.fcij.2017.12.001.

[25] M. Alnowami, E. Taha, S. Alsebaeai, S. Muhammad Anwar, and A. Alhawsawi, “MR image normalization dilemma and the accuracy of brain tumor classification model,” J. Radiat. Res. Appl. Sci., vol. 15, no. 3, pp. 33–39, 2022, doi: 10.1016/j.jrras.2022.05.014.

[26] [26 S. Tankala et al., “A novel depth search based light weight CAR network for the segmentation of brain tumour from MR images,” Neurosci. Informatics, vol. 2, no. 4, p. 100105, 2022, doi: 10.1016/j.neuri.2022.100105.

[27] K. Dang, T. Vo, L. Ngo, and H. Ha, “A deep learning framework integrating MRI image preprocessing methods for brain tumor segmentation and classification,” IBRO Neurosci. Reports, vol. 13, no. October, pp. 523–532, 2022, doi: 10.1016/j.ibneur.2022.10.014.

[28] J. Walsh, A. Othmani, M. Jain, and S. Dev, “Using U-Net network for efficient brain tumor segmentation in MRI images,” Healthc. Anal., vol. 2, no. August, p. 100098, 2022, doi: 10.1016/j.health.2022.100098.

[29] H. M. Rai and K. Chatterjee, “Detection of brain abnormality by a novel Lu-Net deep neural CNN model from MR images,” Mach. Learn. with Appl., vol. 2, no. October, p. 100004, 2020, doi: 10.1016/j.mlwa.2020.100004.

[30] A. S. M. Shafi, M. B. Rahman, T. Anwar, R. S. Halder, and H. M. E. Kays, “Classification of brain tumors and auto-immune disease using ensemble learning,” Informatics Med. Unlocked, vol. 24, p. 100608, 2021, doi: 10.1016/j.imu.2021.100608.

[31] F. M. Refaat, M. M. Gouda, and M. Omar, “Detection and Classification of Brain Tumor Using Machine Learning Algorithms,” Biomed. Pharmacol. J., vol. 15, no. 4, pp. 2381–2397, 2022, doi: 10.13005/bpj/2576.

[32] Y. Peng and J. Sun, “The multimodal MRI brain tumor segmentation based on AD-Net,” Biomed. Signal Process. Control, vol. 80, no. P2, p. 104336, 2023, doi: 10.1016/j.bspc.2022.104336.

[33] Harvard medical dataset. URL: http://www.med.harvard.edu/AANLIB/.

[34] Wang D, Tan D, Liu L. Particle swarm optimization algorithm: an overview. Soft Computing. 2018;22(2):387–408. https://doi.org/10.1007/s00500-016-2474-6.