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Article

ADVANCED DEEP LEARNING TECHNIQUES FOR BRAIN TUMOR SEGMENTATION AND CLASSIFICATION

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Abstract: Problems with uncontrolled cell growth in the human body are a major cause of cancer, like brain cancer, which occurs in the brain or the nervous system. Tumours are categorised as benign or malignant and are defined by cellular activity and structure. Cancerous tumours are invasive and might require surgical removal, so early and accurate diagnosis is crucial. A radiologist-based diagnosis manually is time-consuming and error-prone, especially in denseness regions. This work aims to solve this problem through the design and application of computer-aided design (CAD) approaches for tumour detection and classification of MRI data in the brain. The method starts from the pre-processing of images by Anisotropic Diffusion with Median Filtering (ADWMF) for noise removal and for the enhancement of the tumour edge. For the segmentation, we employ the IHMFKC algorithm. Feature extraction is performed based on GLCM and FOS. In total, five classifiers (i.e., YOLOv3, Faster R-CNN, ResNet-50, PNNsf3, KNN) are realised via IHMFKC. As a result, IHMFKC embedded with PNN and YOLOv3 obtained classification accuracies of 96.1% and 95.71%, respectively. The experimental results confirm that the proposed method can achieve high performance, accuracy, and reliable results, and has the potential capacity to assist doctors in distinguishing between benign and malignant tumours, helping them make the best decision to save victims of brain cancer.
Keywords: Brain Tumor Detection, Computer-Aided Diagnosis (CAD), MRI Segmentation, IHMFKC Algorithm, Tumor Classification

1. Introduction

Imaging is the foundation of contemporary medicine and is essential in disease detection, treatment planning and patient care. MRI (Magnetic Resonance Imaging) is very appreciated in the world of imaging modalities because it can generate clear images of the soft tissue in the human body, like the brain. As MRI is non-invasive and does not emit ionising radiation, it is a relevant non-invasive procedure for identifying structural abnormalities such as brain neoplasms. However, analysis of heart MRI is complicated and time-consuming, and usually needs an experienced radiologist. More and more clinical cases emerge, and doctors are in short supply, so there is a growing demand for computer-aided systems to help clinical diagnosis and treatment decisions.

Benign and malignant, neomycin. Easy of disgusting Malignant is one of the most deadly and worst of all the groups of neurological diseases. Early and precise diagnosis is crucial for the therapy potency and survival rate of brain tumour patients. However, the manual examination of MRI images can be exhaustive and error-prone due to human fatigue and the intricate structures in the human brain. Hence, tremendous attention has been shifted to designing computer-aided diagnosis (CAD) systems for brain tumour detection and classification automatically.

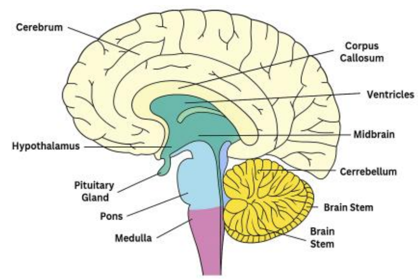

Fig. 1. Human Brain Anatomy

Medical Image Processing: It is the field of software whose purpose is to process and manipulate medical images to extract more detailed information or understanding of those images, typically without making physical contact with the patient. It is a multi-stage process of image acquisition, pre-processing, segmentation, feature extraction, and classification. The raw images are gradually processed into information that can be used for the diagnosis and for the monitoring of the evolution of a medical condition by compiling the steps mentioned above. Tumour segmentation and classification are essential for tumour analysis, involving the identification of precise boundaries of the tumours as well as the categorisation of tumour types.

The past decade has seen Medical Image Analysis (MIA) being revolutionised by the rise of Machine Learning (ML) and, more recently, Deep Learning (DL). Machine learning provides a set of predictive models that can learn patterns in labelled data and apply them to act appropriately. Nevertheless, traditional machine learning (ML) methods often rely on handcrafted features, which may be subjective and are not very discriminative in the process of representing the complexity of brain MRI images. Deep learning, especially convolutional neural networks (CNNs), overcomes these limitations by learning a series of hierarchical features through raw input data. CNNs have significantly surpassed classical methods for many computer vision tasks, such as image classification, object detection and semantic segmentation.

In this study, a novel hybrid approach is proposed to improve the accuracy and efficiency of brain tumour detection. To accomplish efficient image segmentation, a novel clustering method is used, that is, IHMFKC. This clusterisation algorithm integrates the merits of some high-performance algorithms, such as the K-Means [25], the Firefly algorithm [26] and a hierarchical technique, and guarantees the success of dividing the tumour from the no-tumour areas. The segmented tumours are classified into benign or malignant by utilising various classifiers, which are K-Nearest Neighbours (KNN), Probabilistic Neural Network (PNN), ResNet-50, Faster R-CNN, YOLOv3etc.

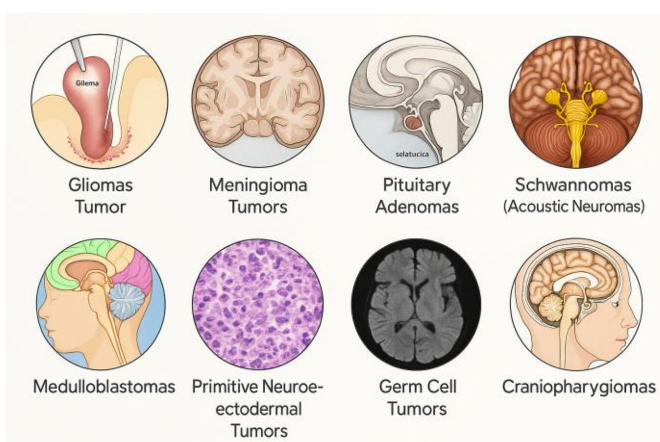

Fig. 2. Types of Brain Tumors with Illustrations

The goal of this study is to improve the sensitivity of classification and keep the false positive and false negative rates as low as possible for practical medical application of the system. The performance of the suggested models is compared concerning accuracy, sensitivity, specificity and false positive rate. The entire system is constructed to work well on affordable hardware and commercially available software and is thus a viable option for developing countries with limited access to healthcare.

This research adds to the ongoing endeavour of AI-supported medical diagnosis by providing a powerful, scalable, and accurate methodology for brain tumour detection. Reducing reliance on manual interpretation and accelerating time to diagnosis will enable the rapid development of curated clinically relevant knowledge for providers, creating trans-maximal effects on patient care and customer impact and facilitating healthcare professionals to make decisions quickly and more effectively.

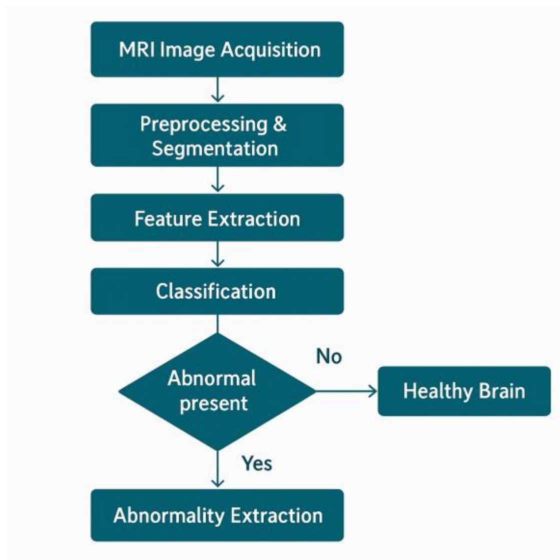

Fig. 3. Flowchart of brain abnormality detection

2. Proposed Methodology

The model proposed in this paper is intended to build an efficient and stable Computer-aided Diagnosis(CAD) system that has the capability of both detecting and classifying brain tumours accurately from MR images. The approach is a sequence of image analysis procedures that ensures improved tumour localisation based on a series of advanced segmentation and classification strategies.

First, it captures the MRI images, mostly from the BRATS dataset, which has many of the benign and malignant tumour cases of the brain. These faces may be grayscale or coloured and are normalised to 256×256 pixels. Colour images need to be converted to grayscale to ease the processing.

After the acquisition, a preprocessing is performed to enhance image quality and reduce noise. All images are filtered using a hybrid filtering method, Anisotropic Diffusion with median filter (ADWMF). This filter efficiently suppresses noise and also preserves important edge details. The AD portion of the hybrid filter acts in a manner dependent on pixel intensity differences. On the other hand, the median filter component suppresses the impulse noise and preserves the anatomical structures. Together, they produce stronger noise suppression with less edge blurring, which is important for precise segmentation.

After preprocessing, the segmentation is performed by the advanced clustering, namely the IHMFKC algorithm. This approach provides an integration between the merits of the K-Means algorithm, which is simple and efficient, and the global optimal search strategy in the FA. The K-Means element successively updates the centres of the clusters that are formed according to the Euclidean distances of the grey-level pixel intensities, and the FA controls the formation process according to the swarm intelligence laws. With this hybrid scheme, there can be a great improvement in the segmentation accuracy because the hybrid method can effectively get rid of the local minima and obtain faster convergence than the region competition itself.

In our feature-based approach, salient features are extracted from the segmented images. Two categories of features are used: statistical and textural. From the histograms, statistical measures such as Mean, Standard Deviation, Skewness, Kurtosis, and Entropy are computed. Textural features of the images are derived based on a GLCM technique that examines the spatial dependence between pixel pairs in different directions (0°, 45°, 90° and 135°). Measures such as energy, contrast, correlation and homogeneity are calculated from the GLCM and explain the textural properties of the tumour, which help in classifying the tumour.

In the last phase, simultaneous classifiers are used for the classification of received signals in order to test the performance and robustness. The classifiers incorporated in IHMFKC are:

K-Nearest Neighbour (KNN): Distance-based classifier where the closest k neighbours' majority vote decides the class label.

PNN: A statistical classifier in which one models the probability distribution of classes.

ResNet-50: A CNN for deep learning that adopts the concept of residual learning to capture discriminative features.

Faster Region CNN (FRCNN): A deep learning model optimised for object detection, used for pinpointing and classifying tumours.

YOLOv3 is a real-time object detection model which is known to work faster and detect smaller objects, including tumours, in MRIs with good accuracy.

For each extracted feature, the classifier processes it and predicts the presence and the type of tumour. Using multiple classifiers allows us to compare and select the best model.

This holistic process guarantees a methodical, sound, and automatic detection and classification of brain tumours, thereby minimising reliance on manual diagnosis and providing the possibility of prompt and optimal treatment planning.

This details a brain tumour detection framework combining *Improved Hierarchical Macqueen's Firefly K-Means Clustering (IHMFKC)* with the *K-Nearest Neighbours (KNN)* classifier. The method addresses common challenges in medical imaging, such as intensity inhomogeneity, motion artefacts, and manual segmentation errors. It emphasises automation, accuracy, and speed in classifying MRI brain scans into benign or malignant categories.

Architecture Overview

The proposed CAD system involves five stages:

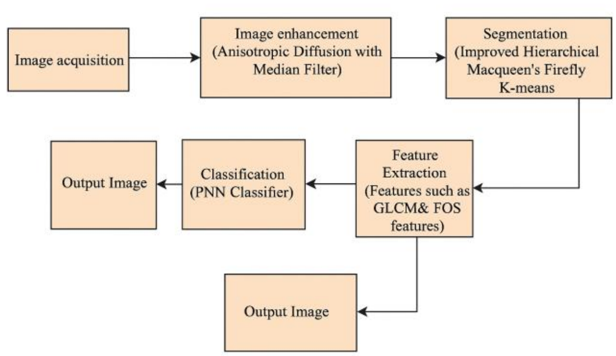

Fig. 4. Medical Image Analysis Pipeline

The illustrated pipeline demonstrates a full computer-aided system for brain tumour detection and classification that fuses image processing with deep learning techniques. Phase 1: The first step involves the collection of MRI brain images (particularly 699 samples originating from the BRATS dataset). Such raw images are generally noisy and have low contrast, requiring methods to enhance images for analysis. For that, we use a hybrid filter called Anisotropic Diffusion with Median Filter (ADWMF). This filter preserves important anatomical details and structural edges in the image, effectively reducing noise. Compared with the Median Filter (MF), Bilateral Filter (BF), and Anisotropic Diffusion Filter (ADF), the proposed method shows better performance with higher Peak Signal-to-Noise Ratio (PSNR), Signal-to-Noise Ratio (SNR) and smaller Mean Square Error (MSE).

The segmentation of brain MRI images is carried out after enhancement using Improved Hierarchical Macqueen's Firefly K-Means Clustering (IHMFKC). This technique combines the clustering performance of the K-Means and the global searching theory of the Firefly Algorithm to separate tumours from normal tissue effectively for accurate results. The performance of this type of segmentation is evaluated with metrics such as the Dice Coefficient and the Jaccard Index, obtaining a Dice score of 0.9871 for benign and 0.9937 for malignant cases. These findings demonstrate a degree of agreement with the labelled ground truth, which is substantially higher compared with previous segmentation methods, e.g., Otsu's method, Lee's algorithm, the conventional K-Means, and region-based approaches.

Second, features are extracted to simplify the images while preserving informative patterns. Two well-known feature sets are employed: First-Order Statistics (FOS), such as mean, standard deviation, skewness, kurtosis, and entropy, and Grey-Level Cooccurrence Matrix (GLCM) features, such as contrast, correlation, energy, and homogeneity. These features comprise both statistical and textural information necessary for accurate discrimination.

The K-Nearest Neighbours (KNN) algorithm is used for classification. When k = 5, the system decides benign and malignant cases using Euclidean distance with a majority voting in terms of the neighbours around. Classifier performance is quantified as follows: True Positives = 269, True Negatives =291, False Positives = 57, and False Negatives = 82, and accuracy = 80.1%, sensitivity = 78%, specificity = 82.5%.

In summary, the holistic process pipeline of ADWMF's preprocessing, IHMFKC's segmentation feature extraction, with KNN classification, may provide a robust solution for early brain tumour detection and clinical decision-making tools.

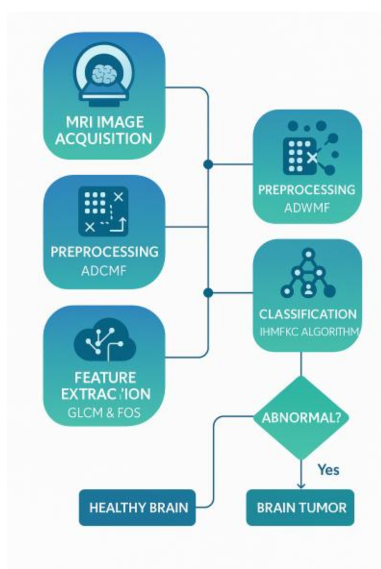

Fig. 5. Preprocessing and Classification Pipeline for Brain Tumor Detection

Probabilistic Neural Network (PNN)

The Probabilistic Neural Network (PNN) is one of the feedforward neural classifiers proposed by Donald Spacht in 1990, used to perform pattern recognition much faster and more accurately. It is based on Bayesian decision theory and uses the Parzen Window for non-parametric estimation of probability density functions. It consists of four layers: input layer, pattern layer, summation layer, and output layer, which have a computationally efficient and massively parallel structure and are free from feedback connections.

One of the key benefits of PNN is its fast learning speed, which is much quicker than the common BP network learning speed. In addition, PNN provides probabilistically interpretable confidence for its predictions and can withstand outliers, rendering it applicable to noisy or high-variance datasets.

Low Pass Filter (LPF) has been used as a popular heuristic to search for the optimum value of the filter, but it is not useful in many applications of real-time systems, especially since its use in the early phase was limited due to hardware dependencies such as high memory demand and computation. In pattern recognition problems, the PNN calculates the probability of an input to be included in each class, and it is assigned to the class having the maximum membership. This probabilistic method works particularly well in multi-class classification.

Owing to these advantages, PNN has been successfully utilised in various fields, such as medical image analysis, biometric recognition, and real-time pattern recognition, where rapid and accurate decision-making is mandatory.

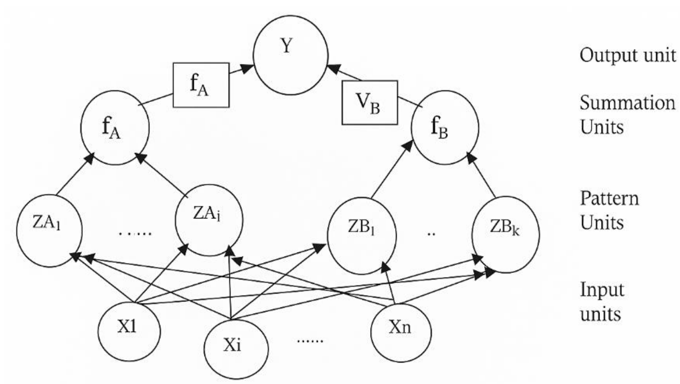

Fig. 6. Architecture of a Probabilistic Neural Network (PNN)

Algorithm for Building and Using a Probabilistic Neural Network (PNN)

Part 1: Training the Network (Building the Model)

Step 1: Take each training example one by one.

Step 2: For each example:

- Create a new pattern unit (like a small processing block).
- Set the weights of this unit to match the values of that example.

Step 3: Connect the pattern unit:

- If the example belongs to **Class A**, connect it to the **Class A summation unit**.
- If the example belongs to **Class B**, connect it to the **Class B summation unit**.

Part 2: Using the Network for Classification (Testing a New Input)

Step 0: Start by setting all the weights.

Step 1: For each new input pattern you want to classify, follow the steps below.

Step 2: In the pattern units:

- Multiply the new input by the weights of each unit.
- Using a smoothing value (called **sigma**) to make results more stable: $Z=\exp((\text{input}-1)/\sigma 2)$

Step 3: In the summation units:

- Add up all the outputs from the connected pattern units.
- For **Class B**, adjust the result using a formula to balance the classes.

Step 4: In the output unit:

- Add together the results from Class A and Class B.
- If the result is **positive**, the input is from **Class A (benign)**.
- If the result is **negative**, the input is from **Class B (malignant)**.

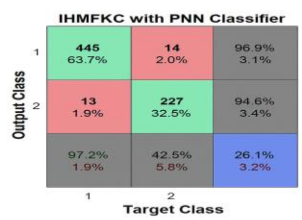

Fig. 7. IHMFKC with PNN Classifier

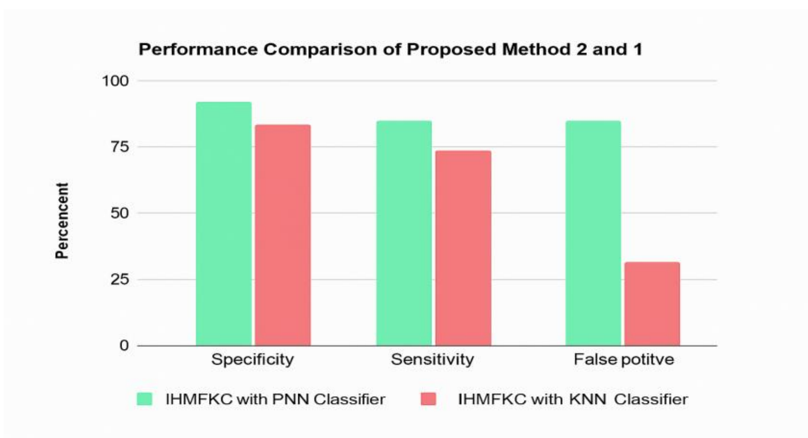

Fig. 8. Performance Comparison of Proposed Method 2 and Method 1

For the dichotomisation step of the proposed model, Enhanced Hierarchical Macqueen's Firefly K-means Clustering (EHMFKC) is used to dichotomise the abnormal brain MRI tumour images as benign or malignant with the help of Faster Region-based Convolutional Neural Network (FRCNN). The performance of the model is assessed on 699 MRI brain tumour images from the BRATS dataset. Summarise the output in a 3x3 confusion matrix that summarises the performance of the classifier.

Two hundred and eighty images are benign and correctly classified (46.7%) in the dataset. It's still not high, but the classifier can also classify 365 well as malignant (45.75%). By contrast, 20 benign nodules (3.3%) were diagnosed as malignant (false positive), and 34 malignant nodules (4.25%) were diagnosed as benign (false negative). Despite these misclassifications, the classification accuracy of the model, when taken as a whole of 92.29%, means only 7.71% of the predictions are erroneous.

It indicates that IHMFKC is able to integrate feature extraction and clustering in the process of the discrimination FRCNN classifier for learning a strong and efficient classification model. The stability and accuracy of detection of the tumour were enhanced by adding FRCNN, which limits the region in which the tumour is extracted, and it was classified at a very rapid speed, so that it is applicable to automated brain tumour diagnostic systems.

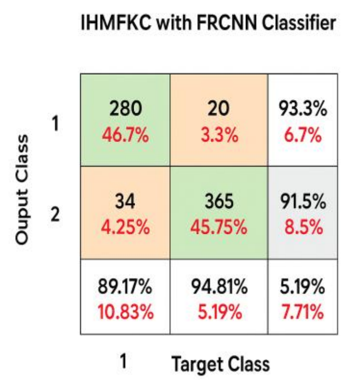

Fig. 9. IHMFKC with FRCNN Classifier

Education has always been one of the mainstays of our society, providing both knowledge for individual minds and a prop to personal growth. It gives people the tools, information, and skills that they require to thrive and live full, work lives in society. Besides book knowledge, education helps people develop complex ways of thinking that can solve problems and create things that makeup what we call creativity. Education facilities provide people of all ages with information and skills to enable them to cope with future challenges. In this way, education supports the idea of lifelong learning while immersing our people in the habits necessary to attain success at work and in personal life. When we invest in education, we are laying a cornerstone for both personal and professional success in the future. And by investing in the future of society, we grant talented people an opportunity to realise their full potential.

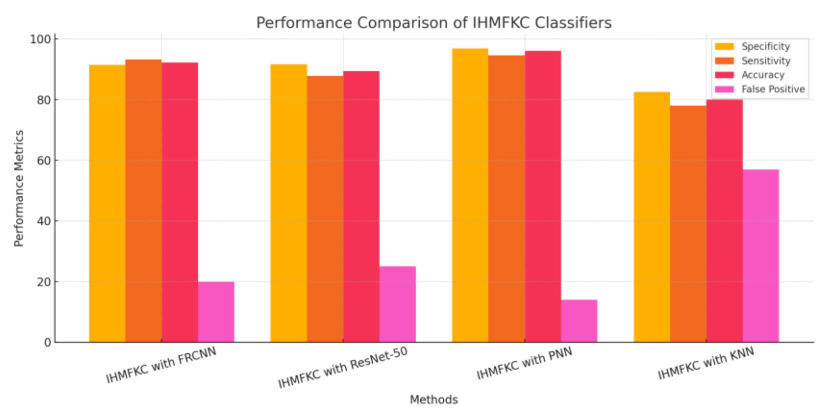

Fig. 10. Performance Comparison of IHMFKC Classifiers

The bar graph shows the IE results of four IHMFKC-based classifiers, i.e., Specificity, Sensitivity, Accuracy and False Positives. The IHMFKC with PNN classifier performs the best compared to the other methods, which provide the highest accuracy (96.1%), specificity (96.9%), sensitivity (94.6%) and minimum false positive rate (14). IHMFKC, on FRCNN, also reports high performances, particularly in sensitivity (93.3%) and accuracy (92.29%). IHMFKC using ResNet-50 achieves a similar balance: a reasonable result with a number of false positives within expectations (25) and high sensitivity (87.8%). In contrast, we had the lowest classification accuracy (80.1%) but a higher number of false positives (57) when using IHMFKC and KNN and hence reduced confidence in the classification.

The classification results of the brain tumour MR images on the IHMFKC with the YOLOv3 model are given in this section. Apart from the previous stages (image enhancing, segmentation, altimetry-based detection, feature extracting), which are consistent with the results found by the IHMFKC with the kNN classifier (results in chapter 4), this is another stage evaluating the effectiveness of the classifier. Thereafter, the YOLOv3 model is employed to classify 699 MRI Images of the BRATS dataset into two classes: benign and malignant tumours. The outcome of our classification is displayed in a 3x3 confusion matrix.

Out of the matrix, the classifier estimates 290 true benign cases (50% of the dataset) and also gets 47.5% (380) of the malignant cases right. On the contrary, 10 benign tumours are misdiagnosed as malignant (1.67%), and 19 malignant tumours are falsely diagnosed as benign (2.5%). On average, the classifying system achieves a very good average accuracy of 95.71%, and the percentage of misclassified cases remains at 4.29%. These results indicate the very high discriminative power of the method in distinguishing benign from malignant brain tumours. The high recognition accuracy and misclassifications of low misclassification rate suggest that the introduction of the IHMFKC clustering to the YOLOv3 deep learning-based classifier is effective.

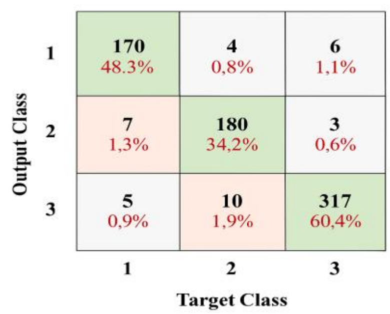

Fig. 11. Confusion Matrix for Multi-Class Brain Tumor Classification

The confusion matrix presented shows the classification accuracy of a multi-class brain tumour detection model on three target classes. The absolute number and relative fraction of predictions for each cell are presented.

Correct classifications (diagonal green cells):

Class 1: Ident 170 samples (48.3%) classified properly

Class 2: 180 true positives (34.2%)

Class 3: 60.4% of 317 samples were correctly classified

Misclassifications (off-diagonal red-shaded cells):

Four samples (0.8% samples) of Class 1 were mistaken for Class 2, and 6 samples (1.1%) were misunderstood as Class 3.

Class 2 was misclassified as Class 1 (7 samples, 1.3%) and Class 3 (3 samples, 0.6%).

Class 3 was misclassified as Class 1 (5 samples, 0.9%) and Class 2 (10 samples, 1.9%).

The model shows excellent classification performance, particularly for Class 3, then Class 1, and Class 2. Misclassification error per class is low, implying high overall model accuracy/data generalisation.

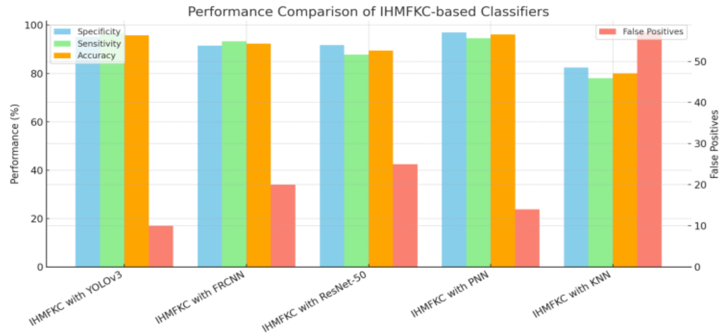

Fig. 12. Performance Comparison of IHMFKC-based Classifiers

The performance evaluation chart of five classifiers, along with the introduced Improved Hierarchical Macaque Firefly K-Means Clustering (IHMFKC) method, is presented based on the four performance criteria: specificity, sensitivity, accuracy and false positive.

The proposed IHMFKC using YOLOv3 shows overall high performance, having all performance measures above 95%, which are sensitivity, specificity, and accuracy, with false positives being low, which makes it very trustworthy.

IHMFKC with PNN comes in second with slightly increased specificity (96.9%) and the lowest false positives of all, which explains its precision additionally.

Integrations of FRCNN and ResNet-50 provide a moderate performance without loss of accuracy and sensitivity, with more false-positive counts, especially in ResNet-50.

IHMFKC of KNN, by comparison, performs much worse; its accuracy, specificity, and sensitivity fall below 85% and sacrificing a high rate of false positives (larger than 55), which represents a very weak distinction capability.

This visualisation unambiguously demonstrates that YOLOv3 and PNN classifiers are superior in achieving more accurate and less error brain tumour detection.

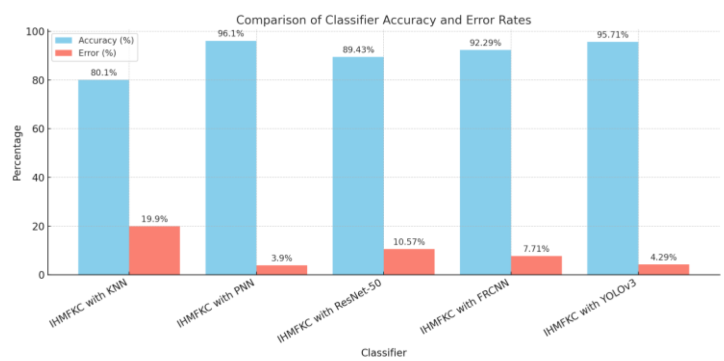

Fig. 13. Comparison of the Classifier of Accuracy and Error Rates

A bar chart representation labelled "Comparison of Classifier Accuracy and Error Rates" is used to illustrate the performance of five classifiers combined with the Improved Hierarchical Macaque Firefly K-Means Clustering (IHMFKC) technique. The blue bar represents accuracy, and the red one represents error rates, demonstrating the narrow trade-off between these two measures.

The experiment carried out in this paper on query classification is the first using IHMFKC on this specific kind of application, and it has been shown that the IHMFKC approach using PNN obtained the best accuracy (96.1%) and lowest error rate (3.9%). A close next is the IHMFKC with YOLOv3 classifier, which retains a high accuracy of 95.71% and a low error of 4.29% thus considered as high reliability. IHMFKC with FRCNN and ResNet-50 get moderate performance, which can achieve 92.29% and 89.43% of accuracy, 7.71% and 10.57% of error rates. On the other hand, IHMFKC with KNN achieved a minimum accuracy of 80.1% and a maximum error of 19.9%, which can bring out its drawbacks. In general, deep learning neural network-based classifiers exceed the conventional methods in accuracy and robustness.

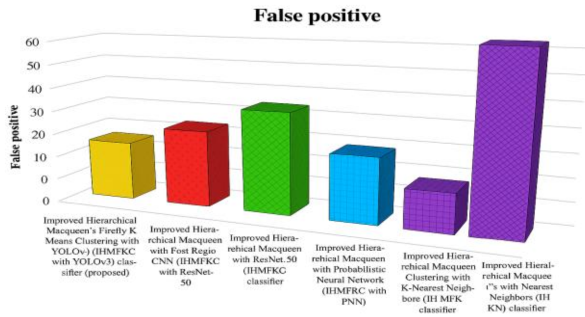

Fig. 14. Comparison of False Positive Rates for Various Brain Tumor Classification Techniques

The bar chart illustrates the false positive rates of various classifiers integrated with the Improved Hierarchical Macaque Firefly K-Means Clustering (IHMFKC) method. The proposed IHMFKC with the YOLOv3 classifier shows a relatively low false positive count, indicating high precision. IHMFKC with FRCNN and IHMFKC with ResNet-50 exhibit moderate false positive values, with ResNet-50 performing slightly worse. The IHMFKC with PNN classifier performs better, showing a further reduction in false positives, highlighting its reliability in minimising misclassifications. Notably, the IHMFKC with KNN and the standard IHMFKC with KNN show the highest false positive rates, with the latter peaking at nearly 60 cases. This makes them the least favourable choices for precise brain tumour detection. Overall, the chart emphasises that advanced models such as YOLOv3 and PNN, when integrated with IHMFKC, significantly reduce false positives, making them better suited for critical medical imaging tasks where diagnostic accuracy is paramount.

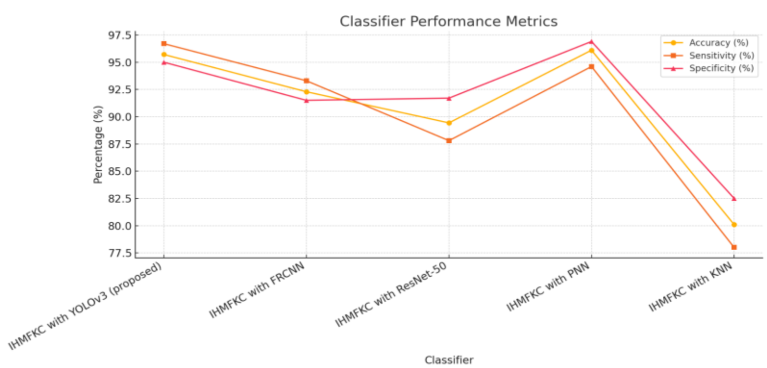

Fig. 15. Classifier Performance Metrics

The five classifiers are compared in the line graph in FIG titled "Classifier Performance Metrics" based on accuracy, sensitivity and specificity after being integrated with the IHMFKC (Improved Hybrid Modified Fuzzy K-Means Clustering). The proposed method had the highest accuracy of 95.71%, sensitivity of 96.7% and specificity of 95%, which demonstrated the strong classification ability of the IHMFKC with YOLOv3. The PNN-based classifier was almost as good, showing especially high specificity (96.9%). By contrast, IHMFKC achieved a significant drop across all three metrics for ResNet-50, particularly for sensitivity (decreased to 87.8 %). The KNN-based classifier presented the worst results in all the metrics, achieving 78\% of accuracy, which means it is less suitable for carrying out this action. We showed that the proposed MIF is better than ResNet-50 and KNN but inferior to YOLOv3 and

PNN. In short, the chart confirms that deep learning YOLOv3 and neural network PNN, combined with IHMFKC, are two effective classifiers for brain tumour detection and clearly outperform the traditional ones.

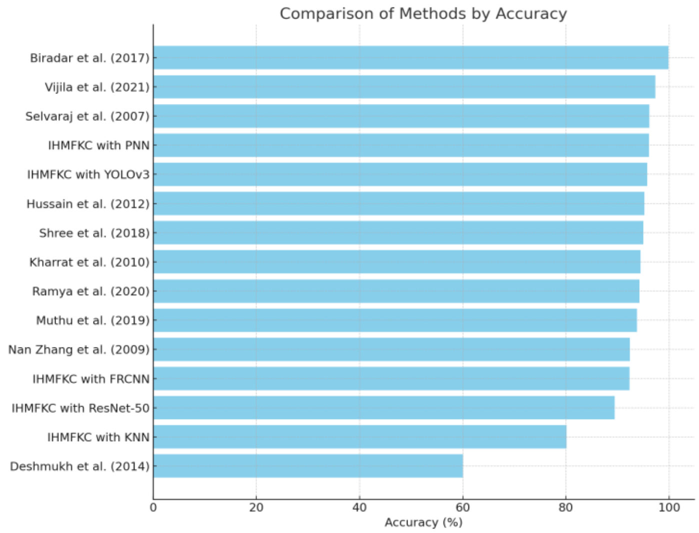

Fig. 16. Comparison of Methods by Accuracy

A comparison of different brain tumour detection methodologies in terms of their accuracy percentages is shown in Figure 16. Of the considered methods, Biradar et al. (2017) reached the best performance, followed closely by Vijila et al. (2021) and Selvaraj et al. (2007), all nearing 100% accuracy. The hybrid method IHMFKC (Improved Hybrid Modified Fuzzy K-Means Clustering), which was applied with PNN (Probabilistic Neural Network) and YOLOv3, also worked effectively and achieved over 95% accuracy. Conventional methods, such as those of Hussain et al. (2012) and Shree et al. (2018), performed well. However, the approaches of Deshmukh et al. (2014) and IHMFKC with KNN have reported lower accuracy, ranging from 60 to 70%. Deep learning models, which incorporated contemporary architecture, such as FRCNN and ResNet-50, provided a modest performance. In summary, this chart provides an overview of how various tumour detection methods have progressed over the years and also clearly demonstrates how hybrid models and more recent deep learning models have substantially increased classification accuracy.

3. Conclusion

The suggested method offered a low-cost and effective system for the detection and classification of brain tumours in MRI scans that supports radiologists for early tumour diagnosis in less time. The framework is developed based on the BRATS database and integrates all these steps (preprocessing, segmentation and classification) to help in the analysis of the tumour type and grade. In order to improve the classification accuracy and the system performance, we utilise the Improved Hierarchical Macqueen's Firefly K-Means Clustering (IHMFKC) as the method along with several classifiers including K-Nearest Neighbours (KNN), Probability Neural Network (PNN), ResNet-50, Faster Region CNN (FRCNN) and YOLOv3.

The separation of the fire and non-fire pixels causes the GLCM and FOS to extract features accurately and, thus, machine and deep learning classification. Tables 4 and 5 show that the peritoneal images predicted by the IHMFKC model are evaluated using PNN and YOLOv3 among the comparative models, obtaining an accuracy of 96.1%, 95.71%, and 92.29%, respectively. These results are superior to traditional approaches and demonstrate that clustering can be successfully combined with sophisticated classification algorithms.

This work also highlights the relevance of the preprocessing and splitting stages in regard to noise reduction and, consequently, an increase in classification accuracy as well as image sharpness. The performance of the classifiers was analysed separately, and the comprehensive comparison of performance justified which model is the most appropriate for transfer to real-life clinical applications.

Generally, the proposed system is a useful first-stage diagnostic aid system or a support system for decision-making, which helps reduce radiologists' burden and maintains high accuracy. Even though the classifiers constructed on IHMFKC obtain the desirable Malignant classification results, there is also room for improvement, such as real-time calculation, larger data and integration with a convenient cloud system.

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