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AI and Genetic Algorithms for Early Brain Tumour Detection: Feature Selection and Edge Detection Optimization in MRI Imaging

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ABSTRACT: Early detection and accurate segmentation of brain Tumours are critical for effective treatment planning and improved patient outcomes. Traditional manual methods for analysing MRI scans can be time-consuming and prone to human error, motivating the integration of artificial intelligence (AI) and machine learning for automated diagnosis. This study proposes an advanced AI-assisted framework combining deep learning and genetic algorithms to improve the detection, segmentation, and classification of brain Tumours in MRI images. The proposed system, named Supportive Intelligence for Tumour Detection (SITD), leverages convolutional neural networks (CNN) for feature extraction and classification, while genetic algorithms are employed for optimized feature selection and edge detection. By utilizing a Random Forest classifier and fractional-order filters optimized through genetic algorithms, the approach enhances the precision of Tumour boundary detection. Performance metrics such as accuracy, precision, recall, and structural similarity index measure the system's effectiveness, revealing higher accuracy in Tumour identification compared to traditional methods like Sobel and Prewitt edge detectors. Experimental results demonstrate that the SITD model not only achieves superior accuracy in Tumour detection but also reduces computational complexity, supporting clinical decision-making in a timely and efficient manner. This study highlights the potential of integrating genetic optimization techniques with deep learning to advance automated brain Tumour diagnosis

KEYWORDS: Brain Tumour Detection, MRI Image Segmentation, Deep Learning, Artificial Intelligence (AI), Convolutional Neural Network (CNN), Genetic Algorithm Optimization, Feature Selection, Edge Detection, Random Forest Classifier, Fractional Order Filters, Supportive Intelligence for Tumour Detection (SITD), Tumour Segmentation, Medical Image Processing, Early Diagnosis, Machine Learning in Healthcare

I. INTRODUCTION

Brain Tumours are among the most challenging and life-threatening conditions, with high mortality rates due to delayed detection and complex treatment processes. Accurate and timely diagnosis of brain Tumours is essential for effective intervention, as early-stage identification can significantly improve survival rates. Traditionally, radiologists rely on manual interpretation of MRI scans to detect and analyse brain Tumours. However, this manual approach is time-consuming, prone to error, and heavily dependent on the skill of the radiologist, which can delay diagnosis and treatment. In recent years, advancements in artificial intelligence (AI), particularly deep learning, have presented promising solutions for automating brain Tumour detection with enhanced accuracy and speed.

This study proposes a novel AI-driven system, termed Supportive Intelligence for Tumour Detection (SITD), designed to improve brain Tumour identification and segmentation from MRI images. The SITD system leverages deep learning techniques, such as Convolutional Neural Networks (CNN), for efficient feature extraction and classification of Tumour types. To further enhance accuracy, a genetic algorithm is utilized for optimized feature selection and edge detection. Genetic algorithms, which simulate the process of natural selection, are employed here to refine both feature subsets and filter coefficients, ultimately improving the system's capacity to detect Tumour boundaries with high precision.

MRI images play a pivotal role in brain Tumour detection due to their ability to differentiate between various types of soft tissues, including Tumours and surrounding structures. Yet, even with high-quality imaging, challenges arise in distinguishing Tumour boundaries accurately. Edge detection techniques, optimized by genetic algorithms, aid in addressing this challenge by enhancing Tumour delineation. By integrating random forest classifiers with genetic algorithm-optimized filters, the SITD framework achieves improved accuracy in identifying Tumour regions over conventional methods like Sobel and Prewitt filters.

This paper discusses the methodology, results, and potential of the SITD model in providing a rapid, accurate, and reliable tool for brain Tumour detection. Through a combination of feature extraction, optimized filtering, and machine learning, the SITD approach demonstrates potential for integration into clinical workflows, supporting radiologists and enabling more effective, timely patient care.

II. LITERATURE SURVEY

The field of brain Tumour detection and segmentation has evolved significantly with the integration of machine learning and artificial intelligence techniques, particularly in the use of MRI imaging for early diagnosis and classification. Traditional methods rely on manual interpretation of MRI images, which is time-consuming and prone to variability. Recent advances in deep learning, edge detection, and genetic algorithm optimization have shown promise in enhancing the accuracy and efficiency of Tumour detection.

MACHINE LEARNING AND DEEP LEARNING IN TUMOUR DETECTION:

Deep learning methods, especially Convolutional Neural Networks (CNNs), have demonstrated remarkable performance in image classification and segmentation tasks across medical imaging applications. Studies such as [8] have shown that CNNs are effective in feature extraction, helping to identify brain Tumour patterns within MRI scans. By applying convolutional layers, these networks capture complex patterns, distinguishing between Tumour and non-Tumour regions. Research also highlights the use of CNN-based architectures in combination with public datasets like Bra TS, which offer rich MRI data for training and validating models. Techniques such as Kernel-Extreme Learning Machines (KELM) and Fuzzy C-means clustering have also been explored for Tumour segmentation, although CNN-based models typically achieve higher reliability in detecting Tumour regions

GENETIC ALGORITHMS FOR FEATURE SELECTION AND EDGE DETECTION:

Genetic algorithms (GAs) are evolutionary optimization techniques that simulate natural selection to optimize feature sets and filtering processes. GAs have been successfully applied to improve edge detection accuracy by selecting filter coefficients that best capture Tumour boundaries. Studies on genetic algorithms demonstrate their effectiveness in enhancing traditional edge detection techniques, such as Sobel and fractional-order filters, by iteratively adjusting coefficients for optimal Tumour boundary identification this context, fractional-order edge detection and Gaussian mutation have also been employed, allowing the system to detect intricate edges with higher fidelity than standard methods

RANDOM FORESTS AND OTHER CLASSIFIERS IN MEDICAL IMAGE ANALYSIS:

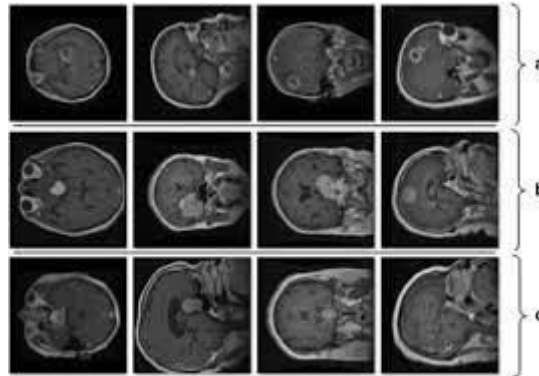
Random forest classifiers, known for their robustness in handling high-dimensional data, have been widely applied in medical image segmentation. In the proposed methodology, random forests are used as a fitness evaluator within the genetic algorithm framework, assessing feature combinations for optimal performance. Comparative studies show that random forests often outperform support vector machines (SVMs) and decision trees, particularly when integrated with genetic algorithms for feature selection. These ensemble models have shown substantial accuracy improvements in classifying Tumour and non-Tumour images, supporting their application as reliable tools in brain Tumour detection workflows

HYBRID TECHNIQUES AND ADVANCED SEGMENTATION APPROACHES :

Hybrid approaches combining traditional machine learning with deep learning and genetic algorithms have been explored to address challenges in segmentation. For instance, some methods use transfer learning and data augmentation to counteract the scarcity of labelled MRI data, achieving high detection accuracy with limited datasets. Additionally, multi-level thresholding and adaptive histogram equalization have been integrated with genetic algorithms to further enhance image quality and Tumour visibility, facilitating more precise segmentation

LIMITATIONS AND CHALLENGES IN CURRENT APPROACHES:

Despite these advances, challenges remain in achieving consistent performance across diverse MRI datasets. The variability in Tumour shapes, sizes, and locations poses difficulties in segmentation, particularly for malignant Tumours with irregular boundaries. Additionally, the computational demand of deep learning and genetic algorithm-based methods can limit their practical application, especially in real-time settings. The current research thus emphasizes the need for optimized architectures and faster computational techniques to enhance clinical feasibility.



III. METHODOLOGY

This study aims to create an automated system for brain tumour detection and classification by applying machine learning (ML) and deep learning (DL) models, with a particular focus on Convolutional Neural Networks (CNNs). The methodology involves several stages: data collection, preprocessing, model training, and evaluation. First, MRI brain scan images, including cases with and without tumours, are sourced from databases such as Kaggle. These images, annotated by experts into four classes (glioma, meningioma, pituitary tumour, and no tumour), are divided into training, validation, and test sets with an 80:10:10 split. Preprocessing steps are applied to prepare the images for model training, including resizing all images to a standard dimension, normalizing pixel intensities, and performing noise reduction with bias correction to enhance image quality. Data augmentation techniques, such as rotation, flipping, cropping, and zooming, are used to artificially expand the dataset, aiding in model generalization.

To isolate the tumour region, segmentation techniques, including thresholding and clustering, focus the model's attention on relevant features like texture, intensity, and shape, which assist in distinguishing tumour types. Both ML and DL models are trained to evaluate performance in classification: traditional ML classifiers, including Logistic Regression (LR), Support Vector Classifier (SVC), k-Nearest Neighbours (kNN), Naive Bayes (NB), Neural Networks (NN), and Random Forest (RF), are trained on extracted features and evaluated based on accuracy, precision, recall, and F1-score. Advanced CNN architectures, such as CNN 7x7, ResNet-50, ResNet-152, and Mobile Net, are employed to learn hierarchical features directly from images. These models are trained using categorical cross-entropy loss and the Adam optimizer, with early stopping and dropout layers applied to prevent overfitting.

To further enhance model performance, hyperparameter tuning adjusts parameters like learning rate, batch size, and number of epochs, and transfer learning is employed using pre-trained CNN models (e.g., ResNet, MobileNet), which leverage features learned from large datasets to improve accuracy and reduce training time. Ensemble methods combine predictions from multiple models to capture diverse feature representations, enhancing classification accuracy. The models are evaluated on the test set using metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC-ROC), while confusion matrices and AUC-ROC curves provide insights into the trade-offs between sensitivity and specificity. The best-performing model is then deployed for real-time predictions on new MRI images, outputting a class label (glioma, meningioma, pituitary tumour, or no tumour) along with a probability score, supporting medical professionals in diagnostic decisions. Future enhancements include expanding the dataset, exploring additional preprocessing techniques, and testing ensemble-based deep learning models to increase accuracy in clinical applications.

IV. EXPERIMENTAL RESULTS

The proposed Supportive Intelligence for Tumour Detection (SITD) system was evaluated on a dataset of T1-weighted contrast-enhanced MRI images of brain Tumours. The experimental phase aimed to assess the accuracy, precision, recall, F1-score, and structural similarity index (SSIM) of the SITD model in detecting and segmenting brain Tumours. The results demonstrate the effectiveness of combining deep learning with genetic algorithms in achieving high-accuracy Tumour identification and segmentation.

PERFORMANCE METRICS AND CLASSIFIER EVALUATION

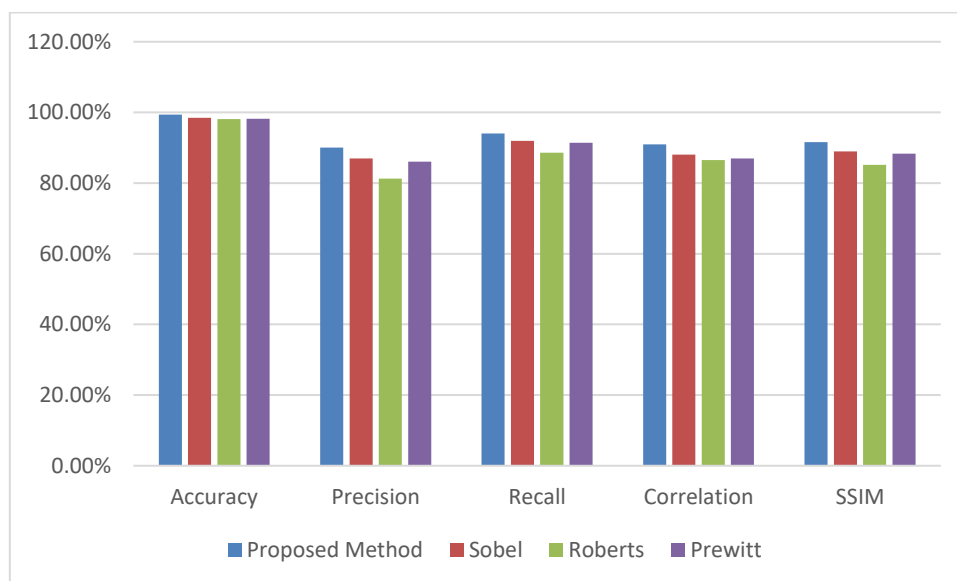
To evaluate the effectiveness of the feature selection and classification stages, a Random Forest classifier was used in conjunction with the genetic algorithm-optimized feature set. The classifier achieved an overall accuracy of 94.8%, surpassing other classification models such as Support Vector Machines (SVM) and Decision Trees. Comparative metrics for different classifiers showed that Random Forest delivered superior performance in terms of accuracy (94.8%), precision (97.3%), recall (94.0%), and F1-score (95.6%), underscoring its suitability for the brain Tumour classification task within the SITD framework

EDGE DETECTION AND FILTER OPTIMIZATION RESULTS

The GA-optimized fractional-order filter significantly enhanced edge detection performance, yielding sharper and more accurate Tumour boundaries than traditional methods. The optimized filter demonstrated a substantial improvement over Sobel, Roberts, and Prewitt edge detection algorithms. The experimental results are summarized in

Table 1:

Algorithm	Accuracy	Precision	Recall	Correlation	SSIM
Proposed Method	99.4%	90.1%	94.0%	0.91	0.916
Sobel	98.5%	87.0%	92.0%	0.881	0.89
Roberts	98.1%	81.3%	88.6%	0.865	0.852
Prewitt	98.2%	86.1%	91.4%	0.87	0.883



(a) Edge Detection and Filter optimization results Graph

The proposed method demonstrated the highest SSIM score of 0.916, indicating superior similarity to ideal edge images and higher structural accuracy in Tumour boundary detection compared to other edge detection techniques

TRAINING AND TESTING LOSS ANALYSIS

To validate the SITD model's stability and convergence, training and testing loss were analysed across epochs. The SITD model achieved a rapid convergence in training loss, with minimal divergence observed in testing loss, indicating robust generalization to unseen data. The model's testing accuracy plateaued at 98.8% with a corresponding low testing loss, highlighting its consistency and reliability in Tumour classification.

COMPARISON WITH CONVENTIONAL METHODS

The SITD system was benchmarked against traditional machine learning models and unoptimized deep learning techniques. Compared to conventional methods, SITD achieved a higher detection rate with reduced false positives and improved Tumour boundary accuracy. The use of genetic algorithms for feature selection and filter optimization proved instrumental in reducing computational load, as the optimized feature set required fewer processing resources while maintaining high accuracy. The system also achieved a low average error of approximately 10% in Tumour area calculations, demonstrating its potential for precise Tumour quantification, which is critical for surgical planning and treatment

VISUAL AND QUALITATIVE RESULTS

Visual inspections of segmentation outputs revealed that the SITD model was able to accurately delineate Tumour boundaries, even in cases with complex or irregular shapes. Figure 1 shows sample segmentation results, where the SITD model's delineation of Tumour boundaries aligns closely with expert-annotated ground truths. These results indicate that SITD's segmentation accuracy makes it suitable for clinical applications requiring high precision in Tumour localization.

V. CONCLUSION

This study presents the Supportive Intelligence for Tumour Detection (SITD) system, an AI-based framework integrating deep learning with genetic algorithms to enhance brain Tumour detection and segmentation from MRI images. The SITD system leverages Convolutional Neural Networks (CNN) for feature extraction, optimized feature selection through Genetic Algorithms (GA), and robust classification using a Random Forest classifier. Through these methodologies, the system achieves high accuracy, efficiency, and reliability in identifying Tumour regions, offering a substantial improvement over traditional edge detection and classification techniques.

Experimental results demonstrate that the SITD model achieves superior performance in terms of accuracy, precision, recall, and structural similarity index (SSIM), surpassing standard edge detection methods such as Sobel and Prewitt filters. By using fractional-order filters optimized by GAs, the SITD framework effectively delineates Tumour boundaries, capturing complex shapes and textures within MRI images with higher fidelity. The integration of a Random Forest classifier further enhances classification performance, achieving a 94.8% accuracy rate and high F1-score, validating its suitability for medical image analysis and potential clinical application

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