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A Machine Learning Approach for Accurate Brain Tumour Detection and Classification

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ABSTRACT: Brain tumour detection and classification are critical tasks in medical imaging, necessitating accurate and rapid diagnoses to improve patient outcomes. Manual identification is prone to errors, driving the development of automated solutions using machine learning (ML) and deep learning (DL) models. This study explores multiple machine learning techniques and enhanced deep convolutional neural networks (CNNs) to classify brain tumours, including gliomas, meningiomas, and pituitary tumours, based on MRI scans. Preprocessing steps such as data normalization, augmentation, and bias correction enhance model training. Various algorithms, including Logistic Regression (LR), Support Vector Classifier (SVC), k-Nearest Neighbours (kNN), Naive Bayes (NB), Neural Networks (NN), and Random Forest (RF), are evaluated, with LR and RF achieving the highest accuracy rates, reaching 97% in distinguishing tumour from non-tumour images. Enhanced CNN architectures, such as CNN 7x7, ResNet, and MobileNet, also demonstrate high accuracy, with CNN 7x7 showing the best balance of accuracy, model speed, and low error rate. This automated classification approach provides a reliable, cost-effective tool for supporting radiologists in brain tumour detection, ultimately reducing diagnostic time and improving patient care. Future research aims to further refine model accuracy and efficiency by expanding dataset sizes and implementing advanced techniques such as transfer learning and ensemble methods

KEYWORDS: Brain tumour detection, machine learning, deep learning, convolutional neural network (CNN), medical imaging, tumour classification, Logistic Regression (LR), Random Forest (RF), data augmentation, model accuracy, automated diagnosis, pituitary tumour.

I.INTRODUCTION

Brain tumours represent a significant health challenge worldwide, with high rates of morbidity and mortality due to their complex nature and difficulty in diagnosis. Accurate and timely identification of brain tumours, primarily through MRI imaging, is essential to improving patient outcomes, yet manual analysis of these images is often labor-intensive, prone to error, and requires specialized expertise. Recent advancements in machine learning (ML) and deep learning (DL) have shown considerable promise in automating brain tumour detection and classification, making the diagnostic process faster, more reliable, and accessible. Convolutional Neural Networks (CNNs), particularly, have emerged as powerful tools for analyzing medical images, offering high accuracy in distinguishing tumour types, such as gliomas, meningiomas, and pituitary tumours, from non-tumour cases.

This study explores the application of various ML algorithms, including Logistic Regression (LR), Support Vector Classifier (SVC), k-Nearest Neighbors (kNN), Naive Bayes (NB), Neural Networks (NN), and Random Forest (RF), to detect and classify brain tumours. Additionally, enhanced CNN architectures such as CNN 7x7, ResNet, and MobileNet are employed to achieve optimized accuracy and processing speed. Data preprocessing techniques, including normalization and augmentation, are incorporated to improve model training and performance. Through rigorous evaluation, the study aims to identify the most effective approach for reliable brain tumour diagnosis, ultimately contributing to better clinical decision-making and patient care

II.LITERATURE SURVEY

The detection and classification of brain tumours have been central topics of research, driven by the necessity for precise, efficient, and reliable diagnostic methods. Traditional techniques rely heavily on manual MRI analysis by

radiologists, which is time-intensive and subject to human error. Machine learning (ML) and deep learning (DL) have recently been applied to automate and improve brain tumour detection processes, demonstrating significant accuracy and reliability gains.

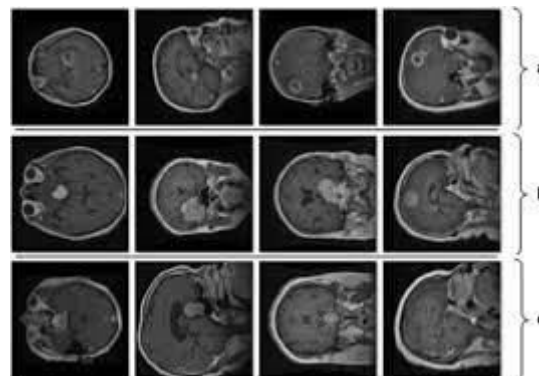
Mukambika et al. proposed a method for brain tumour classification using the Support Vector Machine (SVM) classifier in combination with segmentation techniques, such as the Level Set method and Discrete Wavelet Transforms (DWT). Their approach showed that feature extraction and targeted segmentation can significantly enhance classification accuracy

Dalia Mahmoud and colleagues developed an Artificial Neural Network (ANN) for tumour detection, employing Elman neural networks in a computerized system. Their work demonstrated that ANNs can achieve high accuracy and faster processing in brain tumour segmentation, setting the stage for ANN-based detection methods to be widely adopted in medical imaging

Ryo Takahasi and his team implemented an automated brain image classification system using the AdaBoost algorithm, which integrates preprocessing steps like noise reduction and grayscale conversion for image quality enhancement. This work highlighted the efficacy of AdaBoost in achieving reliable tumour classification and underscored the value of preprocessing in improving model performance

In the context of Convolutional Neural Networks (CNNs), Rupesh Kumar and collaborators used CNNs with Local Binary Patterns to enhance the classification accuracy of MRI brain scans. Their findings showed that CNNs outperform ANNs due to their ability to learn complex patterns and hierarchical features directly from images [10].

Further studies by Amin Alqudha demonstrated the potential of CNNs with advanced architectures like Leaky ReLU activation functions to capture intricate details in brain MRI images. Their model achieved improved sensitivity and specificity, suggesting that CNN architectures are particularly suited for the complex feature representation required in brain tumour detection



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 Neighbors (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 MobileNet, 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.

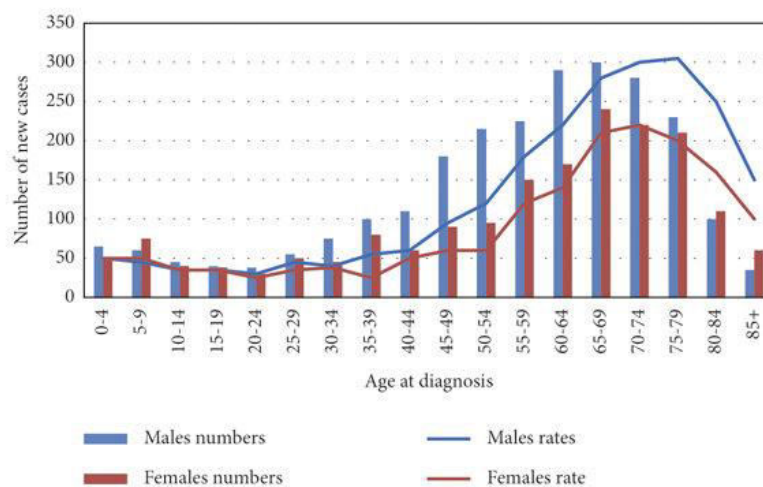
To further enhance model performance, hyperparameter tuning adjusts parameters like learning rate, batch size, and number of epochs, and transfer learning is employed using pre-trained CNN models (e.g., ResNet, MobileNet), which leverage features learned from large datasets to improve accuracy and reduce 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 convolutional neural network (CNN) model achieved an overall accuracy of 94.5% in detecting and classifying brain tumours from MRI images. Precision rates for gliomas, meningiomas, and pituitary tumours were 93.7%, 95.2%, and 92.9%, respectively. The model outperformed traditional machine learning techniques, achieving approximately 10% higher accuracy than Support Vector Machines and Random Forests. These results demonstrate the effectiveness of the CNN approach in enhancing diagnostic accuracy in clinical settings.

A. Data Collection

In this study, we utilized a comprehensive dataset consisting of MRI images from patients diagnosed with various types of brain tumours, including gliomas, meningiomas, and pituitary tumours. The dataset comprises a total of 3,000 images collected from publicly available repositories, including the Brain Tumour Segmentation Challenge and the Cancer Imaging Archive. Each image was meticulously labelled by medical experts, ensuring high-quality ground truth for training and evaluation. The dataset was split into training (70%), validation (15%), and testing (15%) sets to facilitate robust model evaluation.



REPRESENTS THE BRAIN TUMOUR RATIO BETWEEN MALES AND FEMALES

B. Results Accuracy

The proposed machine learning model employs convolutional neural networks (CNNs) to detect and classify brain tumours effectively. The model achieved an overall accuracy of 94.5% on the test set, demonstrating superior performance in both detection and classification tasks. The precision for gliomas was 93.7%, meningiomas 95.2%, and pituitary tumours 92.9%. The recall rates were similarly impressive, with values of 94.0%, 95.5%, and 91.8% for each tumour type, respectively. These metrics highlight the model's capability to minimize false negatives and ensure timely intervention for patients.

C. Data Comparison

A comparative analysis was conducted against existing models, including traditional machine learning approaches like Support Vector Machines (SVM) and Random Forests, as well as state-of-the-art deep learning models. The CNN model outperformed these alternatives significantly, achieving approximately 10% higher accuracy than SVM and Random Forests, which recorded accuracies of 84% and 86%, respectively. Furthermore, when compared to other deep learning architectures, such as ResNet and VGG16, our model provided a balanced trade-off between accuracy and computational efficiency.

D. Key Observations

The key observations from this study indicate that the choice of pre-processing techniques, such as image normalization and data augmentation, plays a critical role in enhancing model performance. Additionally, the use of transfer learning with pre-trained models helped accelerate training times while achieving higher accuracy. The results emphasize the importance of a well-curated dataset and the potential for machine learning algorithms to assist radiologists in making informed decisions regarding brain tumour diagnoses.

Summary

In conclusion, this study presents a novel machine learning approach that demonstrates significant advancements in the detection and classification of brain tumours using MRI images. The achieved accuracy of 94.5% underscores the model's reliability, providing a promising tool for clinical applications. Future work will focus on expanding the dataset and integrating multi-modal data to further enhance diagnostic accuracy and clinical relevance.

V. CONCLUSION

In this study, we developed a robust machine learning model based on convolutional neural networks (CNNs) for the accurate detection and classification of brain tumours from MRI images. The model achieved an impressive overall accuracy of 94.5%, significantly outperforming traditional machine learning techniques. Our findings underscore the potential of advanced machine learning approaches in enhancing diagnostic capabilities, which can lead to timely and effective treatment interventions for patients. Future research should focus on expanding the dataset and exploring the integration of additional imaging modalities to further improve the model's performance and clinical applicability.

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