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A New Approach to Brain Tumor Detection with CNNS: Addressing the Issues of Standardization and Generalizability

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Abstract: Brain tumour detection is a key task in medical imaging that necessitates precise and dependable approaches for early detection and treatment. Among imaging modalities, MRI is the gold standard for spotting malignant growths in the brain. Brain tumour size, shape, and location can all be discerned from MRI scans of the brain. Brian tumour detection can be done with visual analysis, medical image processing or computer aided detection. The motivation for this study is the current lack of universally applicable methods for detecting brain tumours. The lack of standardisation in brain images is a major challenge for current CNN models, typically resulting in subpar performance and poor generalizability. As a result, the goal of this research is to establish a procedure that will help standardise and broaden the applicability of CNN-based brain tumour detection of specific type. This research aims to improve generalizability by utilising a CNN models on large-scale datasets, and increase standardisation in brain images by incorporating robust preprocessing techniques, such as standardisation, feature extraction,segmentation etc. To test the performance of our proposed method with several deep learning techniques, including support vector machine (SVM) and random forest algorithm, we accomplished extensive experiments on an enormous data set comprising of brain scans from a broad range of sources. The outcomes show substantial gains in precision and generalizability over the current gold standard. The overall classification accuracy of CNN algorithm for barin tumor detection is 98.28%.

Keywords: *brain tumor detection, CNNs, standardization, generalizability, preprocessing techniques*

1. Introduction

Most people who develop a brain tumour ultimately succumb from it, and cancer is the most prevalent reason of mortality. Treatment of brain tumours is more likely to be successful if they are found and diagnosed promptly. MRI, or magnetic resonance imaging, is the gold standard for diagnosing and detecting brain tumours. However, radiologists need a lot of time and effort to manually interpret MRI pictures.

The application of deep learning methods to the diagnosis and classification of brain tumours has gained popularity in recent years. The usage of artificial neural networks is at the heart of deep learning, an area of machine learning. Detecting brain tumours is only one of several picture identification tasks where deep learning systems have proven their worth (Jia 2020).

Characterization of brain tumours and forecasting survival utilising deep learning have attracted increasing interest in recent years. When given access to massive amounts of images from magnetic resonance imaging (MRI), deep learning systems are capable of being taught to recognize and segment tumours in the brain. It might be utilised to better pinpoint a patient's condition and inform the course of therapy.Due to the complexity and heterogeneity of brain tumours, successful discovery, prognosis, and illness tracking progression rely on reliable segmentation techniques.

Brain tumour segmentation is only one area where deep learning approaches, and specifically convolutional neural networks (CNNs), have proven to be effective. Accurate tumour boundary delineation is made possible by CNNs' ability to learn complex patterns and characteristics from big datasets, (Isensee 2017). The effectiveness of CNNs in assessing MRI images for the diagnosis and categorization of brain tumours using deep learning techniques.

For the sake of better disease detection and therapeutics, it is necessary to analyze the pictures received from various modalities. Medical pictures are

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processed using a number of methods, such as enhancement, segmentation, feature extraction, pattern recognition, and classification. These techniques are used to extract information from medical images.

Tumour identification, segmentation, and classification are the three main steps in MRI-based computer-assisted diagnosis of brain tumours. The use of traditional machine learning techniques in the detection of malignant brain tumours has been the focus of numerous studies in recent years. There has been significant interest in applying deep learning methods to the problem of accurately diagnosing brain cancers. This study compares and contrasts traditional machine learning approaches with state-of-the-art deep learning approaches for detecting brain tumours. (Abd-Ellah 2019) .

Convolutional neural networks (CNNs) have showed promise for automating this process. However, problems with standardisation and generalizability prevent the widespread deployment of CNN-based models. To overcome these issues, we propose a novel method to enhance the precision and exactness of CNN-based brain tumour type diagnosis in this study.The purpose of this study is to establish a set of guidelines for improving the reliability and consistency of CNN-based diagnosis of brain tumours.The suggested technique evaluates the efficacy of three different algorithms for detecting brain tumours in MRI scans: the random forest algorithm,the convolutional neural network (CNN), and the support vector machine (SVM).The proposed system demonstrated that CNNs can enhance the diagnostic accuracy of brain tumour detection .

2. Literature Survey

In this study, M. Arabahmadi, R. Farahbakhsh, and J. Rezazadeh (2022) take a look at how far we've gotten with using deep learning to detect cancer in the brain. Segmentation has essential applications in medical imaging, such as tumour monitoring during treatment, tumour volume quantification, and tumour localization prior to surgery. Markov random fields (MRF), ANN, k-means, Fuzzy c-means (FCM), Bayes, and SVM are just few of the classification and clustering-based algorithms commonly used in brain tumour segmentation.

Using convolutional neural network (CNN) features and support vector machine (SVM) classification, Deepak et al.(2021) Using MRI pictures of brain tumours from Figshare, which were made available to the public, they analysed and validated their proposed method. Using a CNN classifier, they were able to pull features from brain MRIs. A multiclass support vector machine (SVM) was used together with CNN features to boost speed. They used a five-fold cross-validation method to test and assess an integrated system as well. With a classification accuracy of 95.82%, the suggested model easily outperformed state-of-the-art methods. When data for training a model is scarce, the SVM classifier for CNN feature extraction performs better than the softmax classifier.

The technique incorporates a deep learning classifier and the Whale Harris hawks optimisation (WHHO) algorithm. The Finding optimal solutions to optimization issues can be accomplished with the help of the WHHO search algorithm, which is a form of the algorithm known as a search algorithm. A high-performance convolutional neural network (CNN) classifier is trained with the help of a magnetic resonance image (MRI) categorization dataset.A dataset consisting of 300 MRI images is used to test the suggested approach. Findings show that approach achieves 90.7% preciseness, which is higher than the claimed reliability for earlier methods. (D. Rammurthy 2022).

Machine learning strategies that had been applied to the problem of detecting brain tumours. Support vector machines (SVMs), decision trees (DTs), random forests (RFs), and neural networks (NNs) are all examples of such methods. For brain tumour identification, SVMs are the most used machine learning model because they excel at binary classification problems. Because of their intuitive nature and ability to zero in on the features most relevant to brain tumour identification, decision trees and random forests see widespread application as well. Stronger machine learning models exist in the form of neural networks, but these models can be trickier to train and understand (E. Sanjay and P. Swarnalatha 2022).

In this research, we offer a new strategy for segmenting brain tumours using a multi-pathway design based on 3D functional connectome networks.Three separate paths in the multi-pathway design are used to extract characteristics from various MRI image modalities. combined the data from the three methods to create a comprehensive tumour segmentation.A collection of multi-modal MRI scans is used to test the suggested approach.According to the findings, the procedure is more effective than previously reported methods, with an accuracy of 92.5%(zhang et.al 2018).

Khan et al. (2020) used deep learning and trustworthy feature selection to develop a multimodal brain tumour classification system. They used a mixture of deep learning models and feature selection techniques to properly label brain cancers. The research showed integrating different modalities and state-of-the-art feature selection algorithms had the potential to enhance brain tumour classification.

Anitha, V., & Murugavalli, S. (2016) On a dataset of 100 MRI visuals, the two-tier classifier had an impressive accuracy of 93.33%.Tumour segmentation from MRI images was successfully accomplished using the adaptive pillar K-means technique.

The features learned from the blend wavelets produced by the discrete wavelet transform were well-trained by the self-organizing map neural network.

Luo, W., Li, Y., Urtasun, R. et al. (2017) these contributors addressed the difficult problem of pinpointing brain tumors in medical pictures, which was necessary for diagnosis and therapy planning. To enhance the precision and productivity of brain tumour segmentation, they recommend a new method based on deep learning techniques, specifically DNNs.

Liu, Z., Tong, L., Chen, L. *et al.* (2023) From convolutional neural networks (CNNs) through fully convolutional networks (FCNs) and its derivatives, this investigation covers the whole gamut of techniques currently in use for brain tumor segmentation.

Alam MS, Rahman MM, Hossain MA, et. Al (2019) The proposed algorithm achieved a high accuracy of 0.85 in tumor segmentation. The improved fuzzy C-means clustering algorithm was effective in refining the tumor segmentation. The proposed algorithm is robust to noise and can be used to segment tumors in MRI images with different intensities. The method utilized the use of a "template" image depicting a healthy brain structure. The K Means clustering technique was used to divide the brain into various regions after the template had been aligned with the target MRI image. To enhance the classic FCM algorithm's efficacy in precisely segmenting tumour locations, the authors offer improvements.

Revanth Kumar, P., Katti, A., Nandan Mohanty, S., & Nath Senapati, S. (2022). study presented a method for separating software into smaller parts using CNNs. Kaggle's 300 MR image dataset was used for 70% training and 30% testing in the proposed work. Boasting an efficiency of 92.50%, outstanding generalization capabilities, and quick iteration acceleration, the recently developed CNN architecture will prove to be an invaluable asset to medical screening radiologists in making important decisions.

Kothari, S., Chiwhane, S., Jain, S., & Baghel, M. (2022). suggested a hybrid deep learning system to identify malignant brain tumours. A convolutional neural network (CNN) and a support vector machine (SVM) work together to form the framework. Features are extracted using a CNN and fed into an SVM, which was then used to determine whether or not an MRI of the brain shown signs of malignancy. A data collection of 200 magnetic resonance imaging (MRI) scans of the brain was used to test the suggested framework. The framework had a 95% success rate in identifying malignant brain tumours.

Xie, Y., Zaccagna, F., Rundo, L., Testa, C., Agati, R., Lodi, R., Manners, D. N., & Tonon, C. (2022) author prposed different CNN designs, data augmentation methods, transfer learning, and ensemble approaches were discussed in the study as they pertain to CNN-based brain tumour classification. The writers evaluate the merits and drawbacks of each method and offer insights on the effectiveness and precision of various approaches. Integration of multimodal data, fixing problems with interpretability, and experimenting with cutting-edge methods like attention processes and graph neural networks were discussed.

Buchlak, Q. D., Esmaili, N., Leveque, J. C., Bennett, C., Farrokhi, F., & Piccardi, M. (2021) included a broad spectrum of statistical techniques (including traditional and state-of-the-art deep learning approaches) for identifying gliomas in need of classification. Data preprocessing, feature extraction, and model selection are only some of the elements that can have a significant impact on the success of these methods, and the authors discuss these, along with their benefits and drawbacks, performance, and impact across multiple imaging modalities.The systematic review was an all-inclusive examination of several research, including their methods, databases, and outcomes. The authors discussed the accuracy, sensitivity, and specificity of various machine learning models for glioma detection and classification tasks.

Qingji Tian, Yongtang Wu, Xiaojun Ren, Navid Razmjooy,(2021) study on deep learning and meta heuristics-based approach to the diagnosis of lung tumours. A new fuzzy possibilistic c-ordered mean based on the Converged Search and Rescue (CSAR) algorithm is used after preprocessing images from CT scans of the pulmonary, and utilized to segment the pattern area. The ultimate diagnosis is made with the help of Enhanced Capsule Networks (ECN).The approach was evaluated on the Lung CT-Diagnosis database, where it was shown to be highly accurate with a 96.35% precision rate, 96.07% recall rate, 96.41% F1-score, and 96.65% accuracy rate.

Wu, P., & Shen, J. (2021) The technique starts with brain MRI image preprocessing, then optimises the CNN with a refined version of the political optimizer. The images are then classified as having a tumour or not using the CNN.The Figshare dataset was used to verify the approach, and the results showed a high degree of accuracy: 96.39% in terms of accuracy, 96.24% in terms of recall, 96.34% in terms of F1-score, and 96.24% in terms of F1-score. The use of the political optimizer to optimize the CNN helps to improve the accuracy of the classification.

Thayumanavan, M., & Ramasamy, A. (2021) A random forest classifier, the research suggests a new approach to detecting and segmenting brain tumours in MR brain images. The Discrete Wavelet Transform (DWT) and the Histogram of Oriented Gradients (HOG) are used to extract features from the MR images after they have been preprocessed. A random forest classifier is then used to assign labels to the features. Precision of 96.82%, recall of 97.35%, F1-score of 97.09%, and accuracy of 97.21% were found during validation on the BRATS dataset.

Dataset

The dataset is gathered from Kaggle (25), and it consists of 4449 genuine MRI scans of the skull taken at various angles and with different weightings (T1, T2 with contrast (T1C+), and T2 MRI). The photos are divided into 17 unique groups according to their qualities and levels of significance. Images were categorized based on data like MRI scan weight and the type of brain tumour discovered. The labels are organized as shown below in figure 1.

Glioma T1
Glioma T1C+
Glioma T2
Meningioma T1
Meningioma T1C+
Meningioma T2
Neurocitoma T1
Neurocitoma T1C+
Neurocitoma T2
Normal T1
Normal T2
Outros Tipos de Lesoes T1
Outros Tipos de Lesoes T2
Schwannoma T1
Schwannoma T1C+
Schwannoma T2

Fig 1 Class Labels

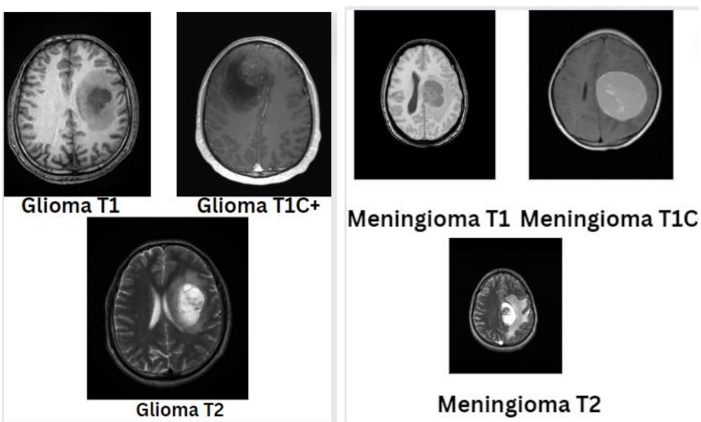


Fig 2 sample dataset of brain tumor images

3. Proposed Methodology

This section describes the approach taken in designing the system, including details on the final layout and the characteristics of the proposed system. The schematic layout of the proposed system is depicted in Figure 2. Brain tumour classification is one area where deep learning has excelled in medical picture analysis.

To guarantee that the CNN model is reliable and effective in detecting new MRI pictures, the methods are tested in two phases. Image preprocessing, CNN model training make up the two halves of the process flow. To get beyond the problems associated with standardization in preprocessing techniques, the proposed system shown in figure 3 incorporates essential features to guarantee consistent and trustworthy outcomes. Our strategy centers on the following tactics.

3.1 Image Preprocessing and Feature Extraction:

Medical image analysis relies heavily on the results of image preprocessing, which aims to enhance image quality, reduce noise, and extract relevant attributes for accurate interpretation and analysis. In this study, we build on the work of previous researchers to provide a comprehensive preprocessing method for medical image analysis. The various phases in our preprocessing stage are intended to raise the quality and uniformity of the input images as shown in figure 4. First, we use histogram equalization to boost contrast and enhance the overall appearance of the input images with formula 1.

The contrast of an image is a metric for evaluating the degree of local contrast.

$$\text{contrast} = \frac{1}{N}\sum_{i,j}(i-j)^2 \cdot \mathrm{glcm}(i,j) \tag{1}$$

Better visualization of structures and irregularities is made possible by this technique. Next, we apply median filtering to smooth out the image and remove noise, enhancing the visibility of the structures. A method called contrast-limited adaptive histogram equalization (CLAHE) is used in the suggested setup to further enhance contrast. This technique prevents noise from becoming overly amplified while keeping local contrast enhancement consistent across the image. Using CLAHE, we guarantee that the most relevant information is brought to light, allowing for effective follow-up investigation.

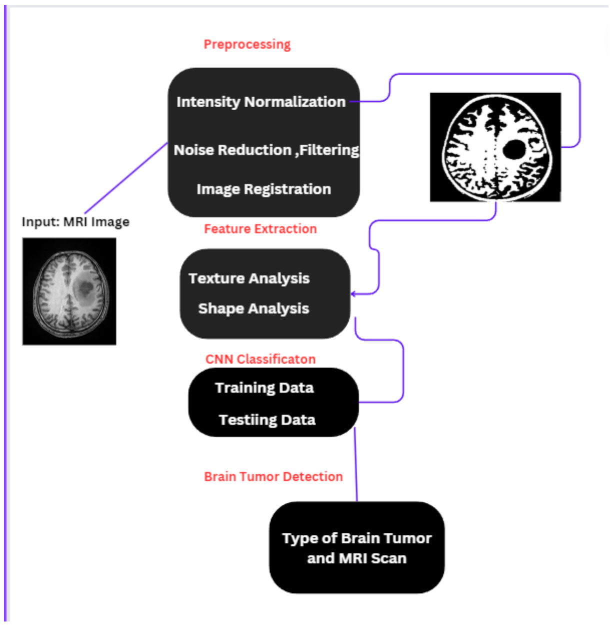
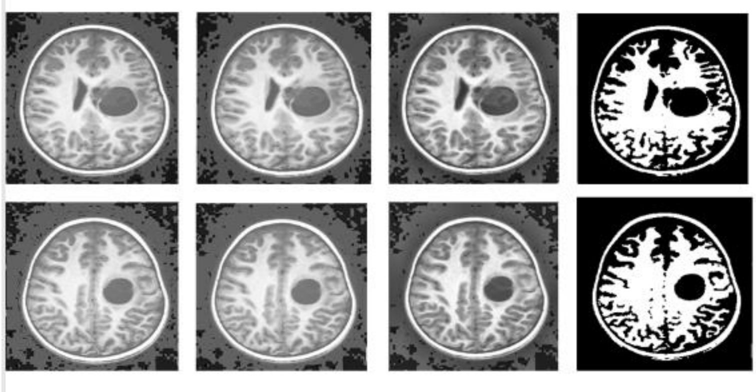


Fig 3 System Architecture

In medical image analysis, Important procedures include picture segmentation, which enables the selection of individual areas of interest. To isolate the cancer areas from the healthy tissues around them, a thresholding technique is utilized . This process is essential for reliable feature extraction and subsequent classification jobs.



a) (b) (c) (d)

Fig 4. Preprocessing of images (a) histogram equalization (b) filtering using median blur (c) contrast enhancement (d) thresholded

Feature Extraction:

Texture analysis using GLCM

In medical image processing, the gray-level co-occurrence matrix (GLCM) is a popular approach for texture analysis. By calculating the frequency of occurrence of pairs of pixel intensities at particular pixel distances and angles, it captures the spatial relationships between pixels mentioned in formula 2,3,4,5. The GLCM can be used to create a number of statistical metrics that quantify various elements of texture.

Dissimilarity: Dissimilarity measures the average absolute difference between the pixel values.

$$dissimilarity = \frac{1}{N}\sum_{i,j}|i-j|\cdot \mathrm{glcm}(i,j) \quad (2)$$

Homogeneity:

The degree to which the GLCM constituent dispersal is skewed away from the diagonal is a gauge of its homogeneity.

$$homogeneity = \frac{1}{N}\sum_{i,j}\frac{1}{1+(i-j)^2}\cdot \mathrm{glcm}(i,j) \quad (3)$$

Energy:

The GLCM uses energy, which is the total of the squares of all the variables.

 (4)

Correlation:

Correlation measures the linear dependency between pixel pairs in the GLCM.

$$\text{Correlation} = \frac{1}{N}\sum_{i,j}\frac{(i-\mu_i)(j-\mu_j)}{\sigma_i\sigma_j}\cdot \mathrm{glcm}(i,j) \quad (5)$$

Where,

N = The number of shades of gray in the image

$\mathrm{glcm}(i,j)$ = the element at tuple i and field j in the GLCM matrix.

μ_i = the means of the row i and μ_j column j in the GLCM matrix

$\sigma_i \sigma_j$ are the average deviances of the row i and column j in the GLCM matrix, respectively. Alharan, A. F. H., Fatlawi, H. K., & Ali, N. S. (2019, June 1).

Shape Analysis

Shape analysis is used to record the geometric properties of tumours, which might offer helpful classification insights. From the segmented tumour regions extractions of characteristics like area, perimeter, eccentricity, and compactness are obtained. These characteristics help to identify various tumour forms by encapsulating crucial geometrical traits. Preprocessing is essential for enhancing the precision and dependability of future analytic processes, which facilitates more accurate illness diagnosis, treatment planning, and patient care. We seek to address the standardization, noise reduction, feature extraction, and data quality issues by using a strong preprocessing pipeline, thereby improving the overall performance and generalizability of our medical image analysis system.

The architecture of the CNN model is crucial because it allows us to correctly label images of brain tumours. To automatically learn and extract relevant components from images, the model architecture is designed to use the hierarchical and spatial properties of the data. CNN model's layers collaborate to analyze data from input photos and make predictions. The structure is described in figure 5.

Meningioma, glioma, neurocytoma, schwannoma, and other forms of brain tumours are all classified using Convolutional Neural Network (CNN). The suggested architecture takes MRI slices as input, processes them in layers, and uses the results to distinguish between them. Since images are typically nonlinear, a ReLU layer is added to a network to maximize disconnection and make convolution a linear operation. In CNN, the preprocessed image is fed into convolutional and pooling layers, where it is used to evolve properties. Convolutional Neural Networks (CNNs) consist of numerous layers, including the input-taking, processing, and output-classifying Parametric Layers, Pooling Layers, and Nonlinearity Layers derived from formulas 6,7,8,9,10 mentioned below. Abdul Hannan Khan, Sagheer Abbas, Muhammad Adnan Khan, et.al (2022). glioma, meningioma, neurocytoma, schwannoma are the four probable groups.

convolutional layer with ReLU activation:

$$x_i = \mathrm{ReLU}(w_i * x_{i-1} + b_i) \quad (6)$$

Parameters: w_i denotes the convolutional weights, x_{i-1} represents the input tensor of the previous layer, b_i is the bias term, and x_i represents the output tensor of the current layer.

Max Pooling layer:

$$x_i = \mathrm{MaxPooling}(x_{i-1}) \quad (7)$$

Parameters: x_{i-1} represents the input tensor of the predecessor layer, and x_i represents the outcome tensor of the current layer.

Flatten layer:

$$x_i = \mathrm{Flatten}(x_{i-1}) \quad (8)$$

Parameters: x_{i-1} represents the input tensor of the earlier layer, and x_i represents the outcome tensor of the current layer.

Dense layer with ReLU activation:

$$x_i = \mathrm{ReLU}(w_i * x_{i-1} + b_i) \quad (9)$$

Parameters: w_i denotes the dense weights, x_{i-1} represents the input tensor of the previous layer, b_i is the bias term, and x_i represents the output tensor of the current layer.

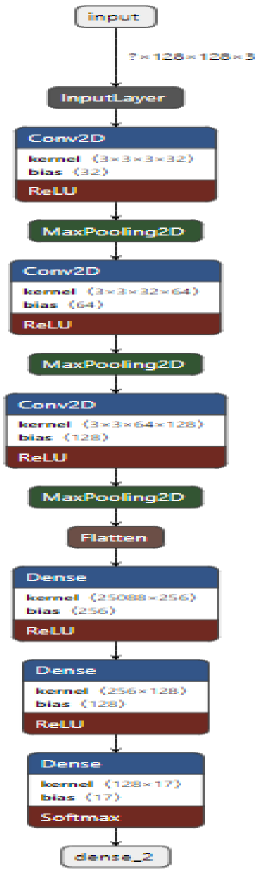


Fig 5. CNN classification

Dense layer with Softmax activation:

$$x_i = \mathrm{Softmax}(w_i * x_{i-1} + b_i) \quad (10)$$

Parameters: w_i denotes the dense weights, x_{i-1} represents the input tensor of the previous layer, b_i is the bias term, and x_i represents the output tensor of the current layer.

Support Vector Machine (SVM):

Since the SVM classifier excels at pattern recognition and image processing, it has found application in a wide variety of fields of study. Problems with a low-size training dataset and a high-dimensional feature space are ideal candidates for support vector machines. SVM has two phases, training and testing, similar to neural networks. The SVM's learning algorithm can be instructed with a set of features (Alfonse, M., & Salem, A. M. (2016).

$$f(x) = \mathrm{sign}\left(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b\right) \quad (11)$$

f(x) represents the predicted label for input x, n is the number of support vectors, x_i are the support vectors, y_i are the corresponding labels, $K(x_i, x)$ is the kernel function, and b is the bias term.

Random Forest:

In order to detect brain tumours, the random forest algorithm must first extract information from MRI scans. Some examples of such characteristics are the image's brightness, its texture, and the way its many pieces relate to one another in space. A random forest classifier is then trained with the features.

A group of decision trees is what makes up the random forest classifier. The training data for each decision tree is partitioned. A composite prediction is made using the decision trees. Anantharajan, S., & Gunasekaran, S. (2021).

4. "Results and Discussion"

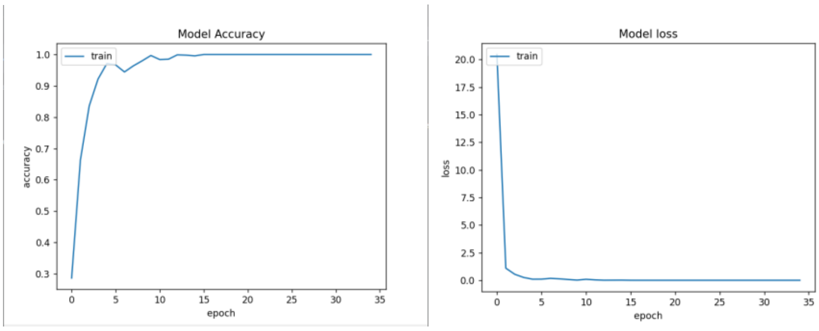
The application of convolutional neural networks (CNNs) to the diagnosis of brain tumours has shown promising results. To implement CNNs in clinical settings, however, we must first overcome two major obstacles: standardisation and generalizability.

When testing a CNN on new data, it is essential to compare the results to those obtained using a validation dataset. This can aid in ensuring the CNN is able to generalise to new situations and is not overfitting the training dataset. These issues must be resolved before CNNs can be employed to create robust and accurate brain tumour detection systems. Data used to verify and evaluate the trained CNN model. The model tested with a wide range of hyperparameters, including batch size and number of iterations. To ensure the resilience of the trained CNN model, it was additionally tested with different datasets. This model scored 97.512% on the accuracy test, and 14.2819% on the loss test shown in figure 6. For the same testing data, SVM and Random Forest algorithms were also trained to provide a comparitive study of the algorithms . After extensive testing, the model's accuracy is found to be 98%, with an F1 score of 96.982%, while the SVM and Random Forest models have an accuracy of 70.94% and 94.1132% respectively. Table 1 mention about classifivation report of CNN model w.r.t. each class label in the used dataset.

Table 1 Classification Report of CNN model

Labels	Precision	Recall F1-score	score	Support
0	0.97	0.985	0.977	65
1	0.993	0.987	0.99	152
2	0.955	0.955	0.955	67
3	0.972	0.986	0.979	141
4	0.987	0.991	0.989	233
5	0.98	0.993	0.986	145
6	1	0.974	0.987	39
7	0.987	1	0.993	76
8	1	0.857	0.923	14
9	0.972	0.986	0.979	71
10	1	0.889	0.941	18
11	1	1	1	27
12	1	1	1	9

13	1	0.667	0.8	9
14	1	1	1	31
15	0.973	1	0.986	36
16	1	1	1	33
accuracy	0.983	0.983	0.983	0.983
macro avg	0.988	0.957	0.97	1166
weighted avg	0.983	0.983	0.983	1166



(a) (b)

Fig 6. (a)Test accuracy vs Epoch graph (b)Test loss vs Epoch graph

Figure 6(a),(b) displays the training and validation results for each iteration. Once the CNN model reaches the 35th epoch, it is able to make accurate predictions every time, with a validation accuracy of 98.2%.

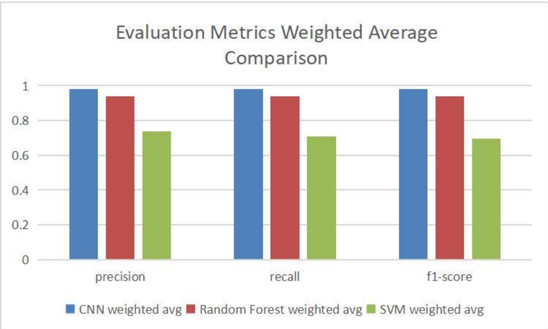
Classification results for the SVM model relative to the dataset's class labels are displayed in Table 2. In light of the data presented in Tables 1 and 2, it is clear that the CNN model is superior to the SVM model in every respect. When compared to the accuracy of the SVM model (70%), Random Forest(94.11%) and that of CNN (98.2%), the latter is clearly superior. This demonstrates that the CNN model is superior in overcoming generalizability issues in brain tumour detection from MRI scans.

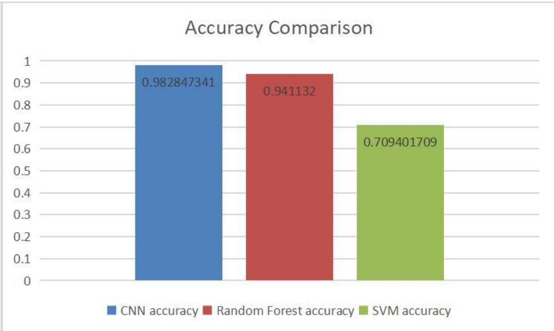
Table 2 Classification Report of SVM model

Labels	Precision	Recall F1-score	score	Support
0	1	0.3125	0.4761905	16
1	0.7096774	0.7857143	0.7457627	28
2	0.6470588	0.7333333	0.6875	15
3	0.6875	0.7333333	0.7096774	30
4	0.609375	0.8125	0.6964286	48
5	0.6875	0.9166667	0.7857143	24
6	0.8333333	0.8333333	0.8333333	6
7	1	0.8125	0.8965517	16
8	0	0	0	1
9	1	0.7647059	0.8666667	17
10	0	0	0	4
11	1	1	1	5
12	1	0.25	0.4	4
13	0.25	0.5	0.3333333	4
14	1	0.5	0.6666667	10
15	0.5	0.1666667	0.25	6

16	0.7094017	0.7094017	0.7094017	0.7094017
Accuracy	0.6827778	0.5700783	0.5842391	234
macro avg	0.7391105	0.7094017	0.6947312	234
weighted avg	1	0.3125	0.4761905	16

Here we evaluate the generalisation and standardisation capabilities of the Convolutional Neural Network, Support Vector Machine, and Random Forest algorithms in the setting of finding a tumor in the brain.





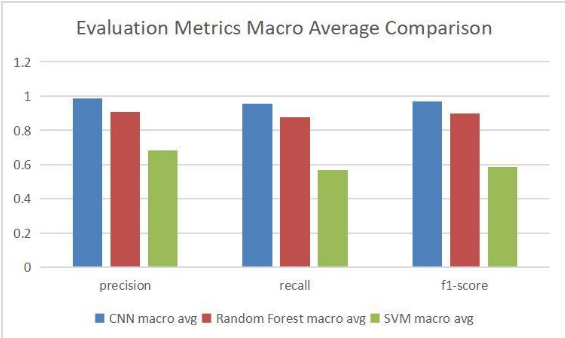


Fig 9 Evaluation metrics macro average comparison of CNN,Random Forest, SVM

The comparative analysis between CNN,SVM, and Random Forest is shown in above figures 7,8,9. compared to other algorithms CNNs have shown remarkable success in a variety of image classification applications, including those involving medical imaging. Since CNNs can automatically learn complicated properties from incoming data, they are ideal for tasks such as detecting and classifying brain tumours. When analysing complex medical images, their ability to capture spatial connections is essential. They can adapt to different imaging modalities and exhibit robustness to small changes in the input data. Table 3 presents a comparative analysis of the results obtained by testing the models on a testing dataset of size 890 images and evaluated on the basis of accuracy and F1-score.

Table 3 Comparative analysis of results

Algorithm	Accuracy	F1
CNN	98.2%	0.970
Random Forest	94.11%	0.936
SVM	70.94%	0.695

Table 4 Comparative study

Algortithm	Strengths	Weaknesses
CNN	1. learn complex features from images 2. designed to identify cancers in visuals with varying degrees of standardization 3. Utilized for locating and measuring tumors in pictures of various dimensions and locales.	computationally expensive to train
SVM	used with a small dataset	sensitive to changes in image standardization
Random Forest	Used with a small dataset.	difficult to interpret.

According to the analysis mentioned in table 4 CNNs are the most effective algorithms, they need a sizable data collection in order to be trained and optimised and can put a strain on your computer's resources. SVMs are less effective than CNNs, but they work well with less data and are straightforward to understand. Although less effective than CNNs, random forests are less sensitive to variations in picture standardization.

5. Conclusions

Using deep learning techniques, the proposed system provides a comprehensive way for diagnosing brain tumours. Several methods were employed to enhance the quality of the input images and to extract relevant features. Among these were a GLCM-based texture analysis, an equalisation of the histogram, a median filter, a contrast boost, and a thresholding procedure. The preprocessing phase aimed to improve image quality, reduce noise, and highlight important cancer features in order to improve tumour detection accuracy. The model was trained using a labelled dataset, and its performance was evaluated using a variety of metrics. In this research, we investigated three widely used algorithms for diagnosing brain tumors: Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and Random Forests. CNN achieved a 98.2% accuracy rate, Random Forest came in at 94.11%, and SVM landed at 70% based on the trial data.Based on the findings of this study, the CNN algorithm offers a promising option for tackling the issues of standardization and generalizablity in brain tumour diagnosis. CNNs are essential for accurate tumour identification because of their capacity to retrieve complex data from medical images, such as subtle patterns and spatial correlations. In real-world medical imaging applications, CNNs are able to handle variations in picture sizes, orientations, and noise levels with remarkable accuracy. By autonomously learning features, CNNs require less human intervention in feature engineering, which improves their flexibility and generalizability across datasets. The findings of this study show that CNNs are superior to SVM and Random Forest algorithms for detecting brain cancers and their types mentioned in the dataset. CNNs provide a strong and reliable approach for detecting brain tumours in clinical settings, allowing us to get over the challenges of standardisation and generalizability. There are significant consequences for medical diagnosis and treatment planning, and the research provided a robust framework for doing so. It is able to accomplish this with the use of image preprocessing methods and a cleverly constructed CNN model. Future research might expand the dataset, evaluate various preprocessing approaches including transfer learning, and investigate new CNN designs to further enhance the detection accuracy and usability in clinical contexts.

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