AI-Driven Algorithms for Brain Tumour Detection and Classification

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***Abstract*—This Detecting brain tumours in their early stages is crucial. Brain tumours are classified by biopsy, which can only be performed through definitive brain surgery. A dataset containing 3000 Magnetic Resonance Imaging (MRI) brain images comprising images of glioma, meningioma, pituitary gland tumours, and healthy brains were used in this study. First, preprocessing and augmentation algorithms were applied to MRI brain images. In this report, we present the results of our brain tumour detection project using various machine learning models. The dataset consists of 1500 tumour images and 1500 non-tumour images, making it a balanced dataset. We have evaluated the performance of several models We analyse each model's accuracy, precision, recall, F1-score, true positive and negative, false positive and negative, and area under the curve (AUC) to compare their performance. These models effectively distinguish between tumour and no tumour images, providing reliable results.**

I. INTRODUCTION

Tumours are abnormal growths that can be either malignant or benign. There are over 200 different types of tumours that can affect humans. Brain tumours, specifically, are a serious condition where irregular growth in brain tissue impairs brain function. The number of deaths caused by brain tumours has increased by increased by 300% in the last three decades. If left untreated, brain tumours can be fatal. Diagnosing and treating brain tumours is challenging due to their complexity. Early detection and treatment are crucial for improving survival rates. Brain tumour biopsy requires surgery, so there is a need for non-invasive diagnostic methods. Magnetic Resonance Imaging (MRI) is commonly used for diagnosing brain tumours. They can cause a range of symptoms, such as:

- Headaches,
- Seizures,
- Vision problems,
- Muscle twitching and shaking in the body,
- Drowsiness, nausea, and vomiting.

Recent advancements in machine learning, particularly deep learning, have enabled the identification and classification of medical imaging patterns. Machine learning techniques have shown success in various medical applications, including disease prognosis, diagnosis, image classification, and tissue segmentation. Due to the variation in pathology and potential limitations of human specialists, computer-assisted interventions and computational intelligence techniques can assist in tumour identification and classification. Machine learning, especially deep learning, plays a vital role in analysing, segmenting, and classifying cancer images, particularly brain tumours. These methods enable accurate and reliable tumour identification, distinguishing them from other diseases. In this study, we propose models that consider previous suggestions and limitations. We compare seven modelling methods to determine any significant differences in performance.

II. LITERATURE OVERVIEW

Over the years, researchers have explored various techniques and approaches to improve the accuracy and efficiency of brain tumour detection. In this literature review, we will summarise some key studies and their contributions to the field of brain tumour detection. One of the fundamental challenges in brain tumour detection is the presence of inhomogeneous intensities and unclear boundaries within tumour images. Researchers have addressed this challenge by applying intensity normalisation or bias field correction techniques to balance the effect of magnetic field inhomogeneity. Additionally, features such as intensities, neighbourhood information, and texture have been widely utilised in different studies. Several segmentation techniques have been proposed for brain tumour detection. Here, we highlight a few notable ones: 1. Spatial Clustering: It is important to differentiate between image segmentation and image clustering. In image segmentation, grouping is performed in the spatial domain, while image clustering is conducted in the measurement space. 2. Split and Merge Segmentation: This technique involves initially considering the entire image and splitting it into quarters. This process is repeated until a homogeneity criterion is satisfied. In the merge method, adjacent segments of the same object are merged or joined. 3. Region Growing: In the region growing method, neighbouring points are connected to each other to expand the region. The success of this method is often dependent on the selection of an appropriate threshold value. It is worth noting that these are just a few examples of segmentation techniques used in brain tumour detection. Many other methods and algorithms have been developed and evaluated in the literature. Additionally, researchers have explored the application of machine learning techniques in brain tumour detection. Various machine learning algorithms, such as support vector machines (SVM), k-nearest neighbours (KNN), random forests, and neural networks, have been utilised for classification tasks. These algorithms leverage features extracted from brain images to distinguish between tumour and non-tumour regions. Benchmark datasets, such as the MICCAI BraTS dataset, have played a crucial role in evaluating and comparing different algorithms. These datasets provide standardised data for researchers to optimise and compare their algorithms, leading to advancements in brain tumour detection.

III. Methodology

Data preparation

Image Augmentation

1. Geometric transformations: randomly flip, crop, rotate, stretch, and zoom images. You need to be careful about applying multiple transformations on the same images, as this can reduce model performance.
2. Colour space transformations: randomly change RGB colour channels, contrast, and brightness.

IV. MODELS

1. Support Vector Classifier

Support Vector Classifier (SVC) is a popular classification algorithm that separates data points by finding the optimal hyperplane in a high-dimensional feature space. It aims to maximise the margin between different classes while considering support vectors

2. K-Nearest Neighbour

K-Nearest Neighbours (KNN) is a non-parametric algorithm that classifies an input based on its nearest neighbours in the feature space. It assigns a class label to the input based on the majority vote of its k nearest neighbours.

3. Neural Networks

Neural Networks, or Artificial Neural Networks, are composed of interconnected nodes (neurons) arranged in layers. They are capable of learning complex patterns and relationships in the data through a process called training, which involves adjusting the weights between neurons

4. Random Forest

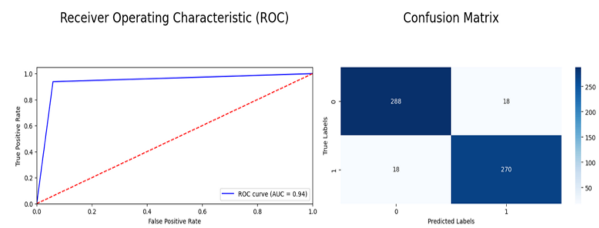
Random Forest is an ensemble learning method that combines multiple decision trees to make predictions. Each decision tree is trained on a subset of the data, and the final prediction is determined by averaging or voting among the individual trees

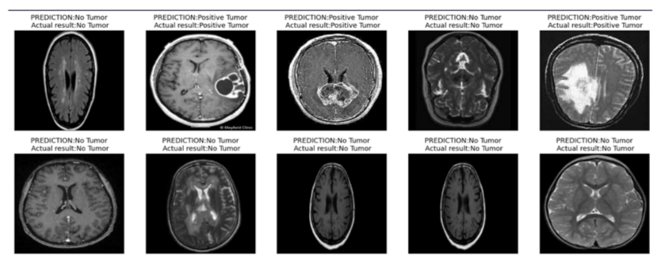
V. EXPERIMENT

1. Support Vector Machine

SVC (Support Vector Classifier) also demonstrates strong performance in the brain tumour detection task with an accuracy of 94%. It achieves a precision of 0.94, indicating a high percentage of correct predictions for brain tumour cases.
The recall score of 0.94 highlights the model's ability to effectively identify actual brain tumour images.
With an F1-score of 0.94, SVC achieves a balanced combination of precision and recall.
The AUC value of 0.94 indicates the model's good discriminatory power in distinguishing between tumour and no tumour images.

	precision	recall	f1-score	support
0	0.94	0.94	0.94	306
1	0.94	0.94	0.94	288
accuracy			0.94	594
macro avg	0.94	0.94	0.94	594
weighted avg	0.94	0.94	0.94	594

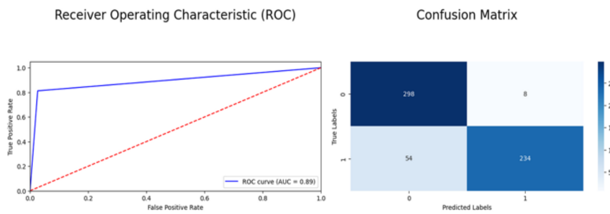


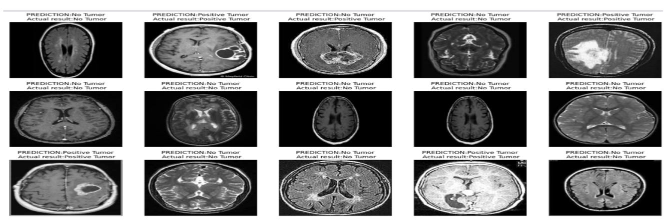


2. k-Nearest Neighbour

KNN (k-Nearest Neighbours) demonstrates satisfactory performance in the brain tumour detection task with an accuracy of 90%. It achieves a precision of 0.85, indicating a reasonably high percentage of correct predictions for brain tumour cases. The recall score of 0.97 highlights the model's ability to effectively identify actual brain tumour images. With an F1-score of 0.91, kNN achieves a relatively balanced combination of precision and recall. kNN exhibits a relatively high number of false negatives, indicating that it incorrectly classifies a significant number of tumour images as no tumour images. The AUC value of 0.89 suggests that the kNN model has reasonable discriminatory power in distinguishing between tumour and no tumour images.

	precision	recall	f1-score	support
0	0.85	0.97	0.91	306
1	0.97	0.81	0.88	288
accuracy			0.90	594
macro avg	0.91	0.89	0.89	594
weighted avg	0.90	0.90	0.89	594

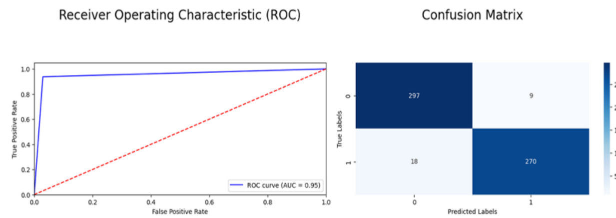


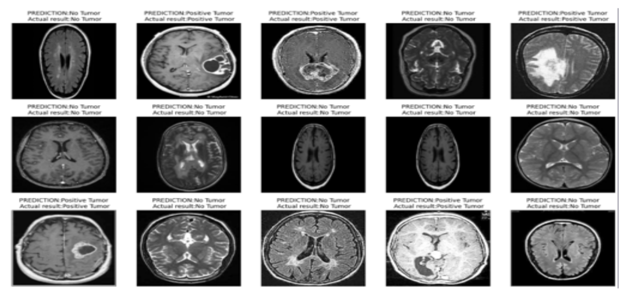


3. Nerual Networks

Neural Networks exhibit strong performance in brain tumour detection, achieving an accuracy of 95%. The model demonstrates a high precision of 0.94, indicating that it correctly predicts brain tumour cases with a 94% accuracy. With a recall score of 0.97, the model effectively identifies actual brain tumour cases. The F1-score of 0.96 reflects a well-balanced combination of precision and recall, indicating the model's strong overall performance.

	precision	recall	f1-score	support
0	0.94	0.97	0.96	306
1	0.97	0.94	0.95	288
accuracy			0.95	594
macro avg	0.96	0.95	0.95	594
weighted avg	0.95	0.95	0.95	594



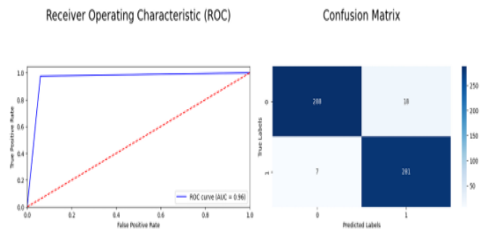


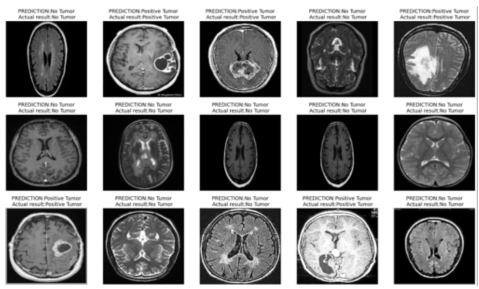
Neural Networks excel at capturing complex patterns and features in the input images, leading to accurate predictions.The AUC value of 0.95 signifies the Neural Networks' excellent discriminatory power in distinguishing between tumour and no tumour images

4. Random Forest algorithm

Random Forest demonstrates excellent performance in the brain tumour detection task. With an accuracy of 96%, the model achieves a high level of correctness in classifying brain tumour images. The precision score of 0.98 indicates that when the model predicts a brain tumour, it is correct 98% of the time. The recall score of 0.94 highlights the model's ability to effectively identify actual brain tumour cases.The F1-score of 0.96 reflects a balanced combination of precision and recall, indicating a strong overall performance of the Random Forest model compared to other

	precision	recall	f1-score	support
0	0.98	0.94	0.96	306
1	0.97	0.98	0.96	288
accuracy			0.96	594
macro avg	0.96	0.96	0.96	594
weighted avg	0.96	0.96	0.96	594





VI. CONCLUSION

· After carefully evaluating the performance of multiple machine-learning models on the brain tumour detection dataset, we can draw the following conclusions :

(i) Neural Networks, and Random Forest showcase the highest performance in terms of accuracy, precision, recall, and F1-score. These models effectively distinguish between tumour and no tumour images, providing reliable results.

(ii) SVC and kNN models also demonstrate respectable performance, maintaining a good balance between precision and recall. They achieve accuracy levels above 90%, making them viable alternatives for brain tumour detection.

(iii) The Random Forest model appears to be the best-performing mode

In conclusion, considering the overall performance metrics and their respective strengths, the Random Forest model appears to be the best-performing model. Random Forest achieved an accuracy of 96%, precision of 0.98, recall of 0.94, and an F1-score of 0.96. It correctly identified 288 tumour images with only 18 false positives and 7 false negatives. The model demonstrated strong discriminatory power with an AUC value of 0.96.

VII. REFERENCES

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GITHUB LINK