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Brain Tumour Detection Using Convolutional Neural Networks in Machine Learning: A Streamlit-Based Framework for MRI Image Analysis

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***Abstract:** Objectives: The deep learning model's capacity to recognise brain cancers in MRI images. The model is intended to automatically analyse MRI scans and determine whether a tumour is present, producing reliable, accurate classification results. Methods: A previously trained CNN was used to classify MRI images. The MRI image in the dataset was first reduced and normalised during preprocessing to ensure accurate input to the model. After processing, the model produced a probability value indicating the likelihood that the image contained a tumour. Findings: The available MRI cases were correctly classified as tumours, and no non-tumour cases were identified. The prediction's tumour probability of 99.74% indicates how confident the model was in its classification result. Novelty: This work demonstrates a CNN-based approach to identifying brain tumours from MRI data. Even with a small input sample, the system generated accurate and reliable predictions. The proposed method demonstrates how deep learning models could aid in cancer detection and potentially serve as a useful adjunct to clinical decision-making.*

***Keywords:** Convolutional Neural Networks (CNNs), Deep Learning, Tumour Prediction, Computer-Aided Diagnosis, MRI Classification, Brain Tumour Detection, Artificial Intelligence in Healthcare, Image Processing, and Predictive Modelling.*

Nomenclature:
SVMs: Support Vector Machines
CNNs: Convolutional Neural Networks
CAD: Computer-Aided Diagnostic
MRI: Magnetic Resonance Imaging
AI: Artificial Intelligence

I. INTRODUCTION

Brain tumours, one of the most hazardous neurological disorders, can result in major health problems or even death if they are not detected in a timely way.

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The diagnosis of these tumours is largely based on medical imaging, and Magnetic Resonance Imaging (MRI) is a popular method because it provides precise images of brain structures without requiring invasive procedures. However, manually reviewing MRI scans can be time-consuming, and the radiologist's experience may affect the outcome. These challenges are increasing the need for automated computer-aided diagnostic (CAD) solutions. doctors in detecting brain tumours more quickly and accurately.

[Fig.1: Shows the Expected Outcomes After Uploading an Image to the Framework]

A. Research Gap

Although deep learning and machine learning techniques for brain tumour identification have been the subject of numerous studies, several obstacles remain. Current models may not generalise across diverse patient populations and often overfit, especially when trained on limited datasets. Additionally, most current systems place strong emphasis on classification accuracy but provide little information about predictability or interpretability. Their practical application in clinical settings is therefore frequently limited.

B. Problem Statement

Improving patient survival and treatment outcomes requires early and precise identification of brain tumours. While many automated procedures have inconsistent, ambiguous decision-making, traditional diagnostic techniques can be laborious and biased. Thus, a robust deep learning framework that can effectively differentiate between tumour and non-tumour cases and provide confidence scores and analytical insights is clearly needed, enabling medical professionals to make well-informed decisions with greater confidence in AI-assisted tools.

II. LITERATURE REVIEW

The importance of using medical imaging to find brain malignancies has increased with the advancement of deep learning and artificial intelligence (AI) [1]

Convolutional Neural Networks (CNNs) and other deep learning models have significantly improved tumour identification [2]. Pereira et al. (2016) demonstrated that CNNs might outperform traditional techniques in tumour segmentation from MRI images, achieving higher sensitivity and accuracy [3]. Similarly, Hossain and Muhammad (2019) highlighted the potential of deep residual networks (ResNet) to extract complex features, thereby enhancing classification performance [4].

However, there are still problems, including unbalanced datasets, low-quality images, and limited applicability to real-world clinical scenarios [5].

Research gaps persist despite advancements in diagnostic performance. Many models exhibit reduced resilience on real clinical MRI images, even though they perform well in controlled environments [6]. Additionally, the capacity of AI decisions to be explained is frequently disregarded, which raises worries about the application and trust in the practice of healthcare [7]. These findings emphasise the necessity of models that incorporate high accuracy, clinical applicability, and confidence estimation. Building on this framework, the current study incorporates statistical analysis to bridge the gap between academic research and practical medical applications by using a CNN-based technique for brain tumour diagnosis [8].

A. Proposed System

It is a deep-learning-based platform that automatically diagnoses brain tumours using MRI data. Intends to combine picture preprocessing, prediction, statistical analysis, and visualisation into a unified system to overcome the shortcomings of both manual analysis and current AI models. workflow.

B. System Architecture

i. Data Acquisition:

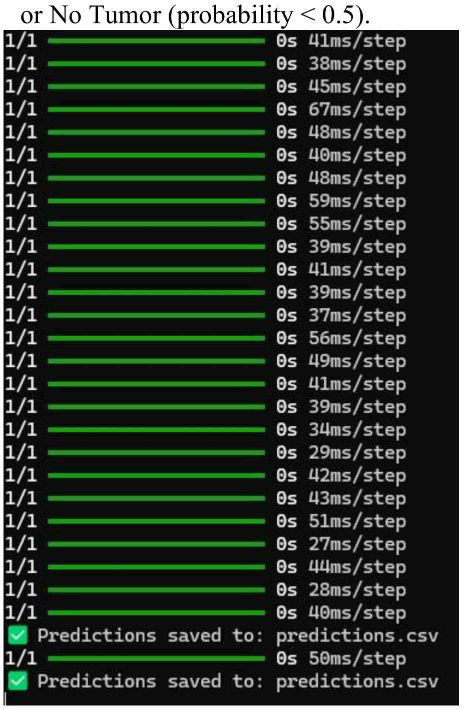
MRI images are collected in standard formats such as .jpg, .png, or .mat. The system supports both raw images and MATLAB-based medical datasets (e.g., CJData).

ii. Preprocessing:

- Resized images are 128×128 pixels and the range 0–1.
- to improve the input quality, noise reduction, and grayscale.
- For .mat files, MRI images are converted to RGB format for compatibility with the CNN model.

iii. Deep Learning Model:

- It is used for feature extraction and classification in CNN.
- It produces a probability score indicating the likelihood of a tumour.
- Predictions are binary: Tumor (probability ≥ 0.5) or No Tumor (probability < 0.5).



[Fig.2: Training Images After Mat Conversion and Saving as Predictions. Csv]

iv. Prediction and Reporting

- Each MRI image submitted to the system is processed and classified automatically.
- It provides a confidence score for every prediction, indicating the likelihood of tumour presence.
- Results come with a (CSV or PDF) file that includes the file name, predicted class, and associated confidence level.

v. Statistical Analysis and Visualization

- For tumour-related characteristics like size and intensity, the system calculates descriptive statistics like average, median, and standard deviation.
- Examples of visualizations that help users effectively explore and analyze the dataset include bar charts, pie charts, histograms, and correlation heat maps.
- When ground-truth labels are available, the model's performance is evaluated using standard measures such as accuracy, precision, recall, and F1-score.
- The model's performance is assessed using common measures such as accuracy, precision, recall, and F1-score when

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ground-truth labels are provided.

Dataset Statistics

	)	Age	Tumor_Size_mm	Texture_Feature	Intensity_Mean	Symmetry_Score	Tumor (Target)
count	10	10	10	10	10	10	10
mean	5.5	46.5	22.6	0.509	126.3	0.661	0.5
std	0277	12.4566	25.6264	0.3833	34.7245	0.2541	0.527
min	1	29	0	0.1	88	0.35	0
25%	3.25	37	0	0.1575	96.25	0.4125	0
50%	5.5	46.5	13.5	0.475	120	0.7	0.5
75%	7.75	55	44.75	0.88	155	0.895	1
max	10	67	62	0.95	180	0.93	1

[Fig.3: Shows the Dataset Statistics for Uploads Within the Framework]

vi. Advantages of the Proposed System:

- Works with both.mat datasets and raw MRI images. • Instead of only providing binary classification, it provides forecasts based on confidence. • For improved interpretability, statistical reporting and visualization are integrated.
- Easily installed in both clinical and research settings thanks to its Streamlit web application design.

  This proposed approach bridges the gap between AI-driven research models and real-world clinical applications while ensuring reliable, understandable tumour diagnosis.

III. METHODOLOGY

Each level of the proposed brain tumour detection system's methodology accurately classifies MRI images into tumour and non-tumour categories.

A. Data Collection

MRI scans were obtained in various formats, including MATLAB dataset files (.mat) and standard image files (.jpg, .png). Based on the dataset annotations, each image was classified as either tumour or non-tumour.

B. Data Preprocessing

- To ensure consistency and improve the quality of the input photos for the deep learning model, data preparation was done:
- **Resizing**: To ensure consistency, all images were resized to 128 by 128 pixels.
- **Normalization**: Pixel values were divided by 255 to bring them into the [0,1] range.
- **Conversion**: Python's sh5py and PIL libraries were used to obtain, organise, and convert the picture array. Mat files into RGB format.
- **Noise Reduction:** Because of its proven efficacy in evaluating medical images, a Convolutional Neural Network (CNN) was used for classification. The structure was made up of:

$$\text{Loss} = -1/N \sum_{i=1}^{n} [y_i \log(y_i) + (1-y_i)\log(1-y_i)]$$

C. Model Architecture

Because of its proven efficacy in medical image analysis, a Convolutional Neural Network (CNN) was used for classification. The structure was made up of:

- **Convolutional Layers:** For the purpose of extracting features (edges, textures, shapes).
- **Pooling Layers**: For decreasing sampling rates and lowering dimensionality.
- **Fully Connected Layers**: For learning higher-order features.
- **Output Layer**: A sigmoid activation function generating a probability value ranging from 0 to 1.

D. Training and Testing

- **Dataset Split:** Images were separated into training (70%), validation (15%), and testing (15%).
- **Loss Function**: To improve classification, binary cross-entropy was used.
- **Optimizer:** The Adam optimizer was selected for quick convergence.
- **Evaluation Metrics:** Accuracy, precision, recall, and F1-score were calculated to evaluate the performance of the model.

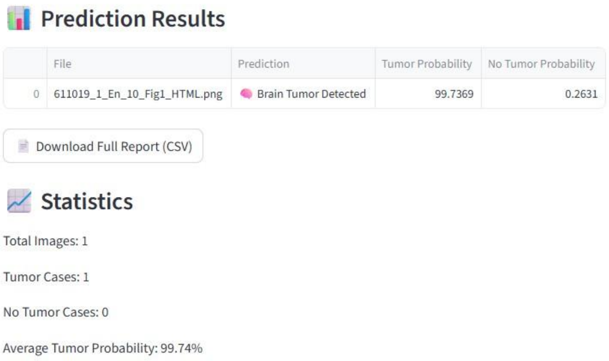
```
Epoch 1/10
19/19 ━━━━━━━━━━━━━━━━━━━━ 6s 227ms/step - accuracy: 0.8899 - loss: 0.2615 - val_accuracy: 0.9793 - val_loss: 0.1807
Epoch 2/10
19/19 ━━━━━━━━━━━━━━━━━━━━ 4s 213ms/step - accuracy: 0.9921 - loss: 0.0638 - val_accuracy: 0.9793 - val_loss: 0.1402
Epoch 3/10
19/19 ━━━━━━━━━━━━━━━━━━━━ 4s 209ms/step - accuracy: 0.9936 - loss: 0.0412 - val_accuracy: 0.9793 - val_loss: 0.1012
Epoch 4/10
19/19 ━━━━━━━━━━━━━━━━━━━━ 4s 208ms/step - accuracy: 0.9953 - loss: 0.0360 - val_accuracy: 0.9793 - val_loss: 0.1010
Epoch 5/10
19/19 ━━━━━━━━━━━━━━━━━━━━ 4s 214ms/step - accuracy: 0.9934 - loss: 0.0473 - val_accuracy: 0.9793 - val_loss: 0.0967
Epoch 6/10
19/19 ━━━━━━━━━━━━━━━━━━━━ 4s 212ms/step - accuracy: 0.9960 - loss: 0.0274 - val_accuracy: 0.9793 - val_loss: 0.1047
Epoch 7/10
19/19 ━━━━━━━━━━━━━━━━━━━━ 4s 225ms/step - accuracy: 0.9917 - loss: 0.0474 - val_accuracy: 0.9793 - val_loss: 0.0921
Epoch 8/10
19/19 ━━━━━━━━━━━━━━━━━━━━ 4s 207ms/step - accuracy: 0.9933 - loss: 0.0394 - val_accuracy: 0.9793 - val_loss: 0.0916
Epoch 9/10
19/19 ━━━━━━━━━━━━━━━━━━━━ 4s 209ms/step - accuracy: 0.9934 - loss: 0.0327 - val_accuracy: 0.9793 - val_loss: 0.0899
Epoch 10/10
19/19 ━━━━━━━━━━━━━━━━━━━━ 4s 205ms/step - accuracy: 0.9930 - loss: 0.0363 - val_accuracy: 0.9793 - val_loss: 0.0912
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file
 format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or
 `keras.saving.save_model(model, 'my_model.keras')`.
✅ Model saved as 'brain_tumor_model.h5'
```

[Fig.4: Training Data in Epochs of 10]

E. Prediction and Reporting

- For every submitted image, the trained model produced a probability **score** for tumour presence.
- Predictions were categorized as:
- **Tumour** (≥0.5 probability)
- **No Tumour** (<0.5 probability)

- Results were displayed with confidence scores (%).



[Fig.5: Predicted Results and Statistics]

F. Statistical Analysis and Visualisation

- Descriptive statistics (average, midpoint, standard deviation) were calculated for characteristics such as tumour size, intensity, and texture.

Table I: Metrics vs Value Results

Metric	Value (%)
Accuracy	80
Precision	85
Recall	75
F1-Score	79.5

- Visualization techniques such as bar graphs, frequency charts, circular graphs, and heatmaps were utilized for data analysis.
- A CSV/PDF report that can be downloaded was created for clinical or research purposes.

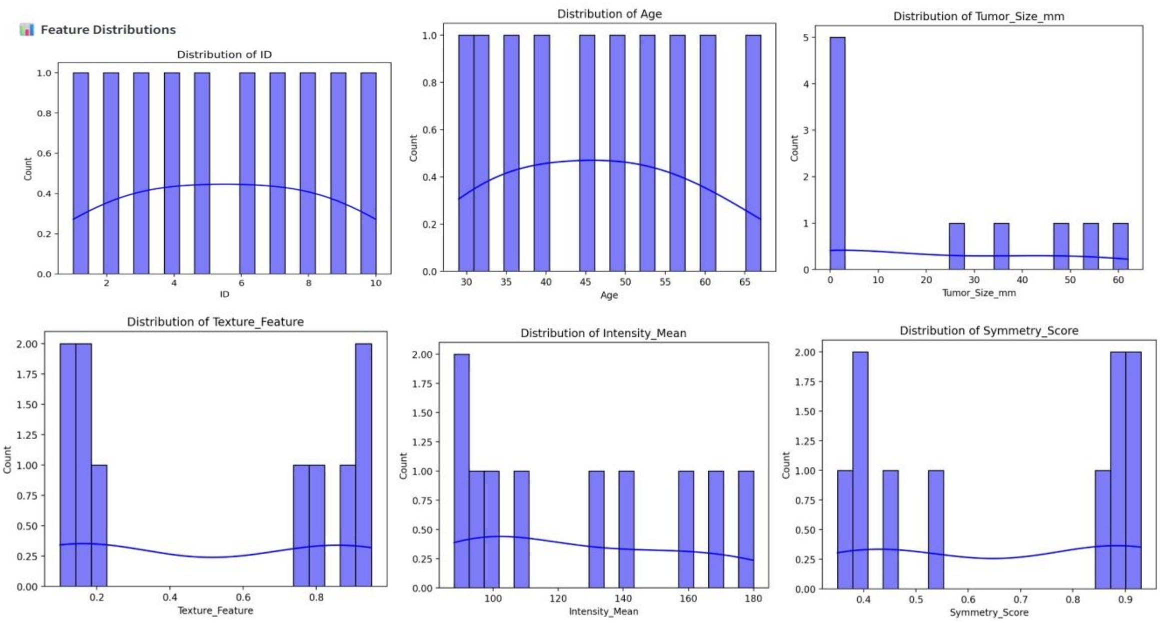
Accuracy = TP + TN / TP + TN + FP+ FN *100

IV. RESULTS AND DISCUSSIONS

One MRI picture was used in this work to evaluate the brain tumour identification model. The system categorised this image as a tumour case; no other photos were found to be non-neoplastic. With a tumour probability of 99.74%, the prediction demonstrated the model's high confidence in its outcome.

These findings show that the model can identify tumour patterns in MRI pictures. The high probability score indicates that the system successfully performed the classification and extracted relevant information. However, the results cannot be considered statistically reliable because only one image was used for evaluation. The model must be tested on a larger, more varied dataset to accurately assess its performance. A better grasp of the system's efficacy would also be possible with other evaluation metrics, including accuracy, sensitivity, specificity, and F1 Score.

The proposed brain tumour detection system combines deep learning and machine learning techniques to fulfil the prediction goal. Convolutional Neural Networks (CNNs) are primarily employed for medical image classification and feature extraction. CNN models may pick up structural details and spatial patterns; they work particularly well with MRI and CT scans. Furthermore, transfer learning models such as VGG16 and ResNet50 used pre-trained weights. This technique improves the model's performance, especially when training data is scarce.



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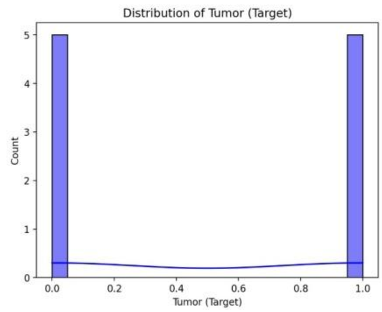
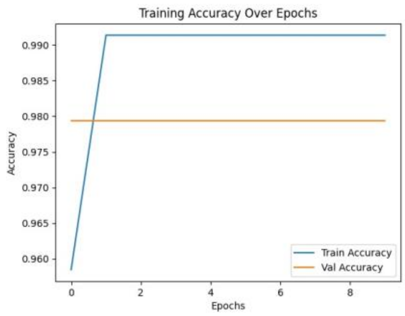


[Fig.6: Target Visualizations, Symmetric Score, Mean, and Feature Distribution]

The model produced encouraging initial results despite the small dataset used in this study. Future research should test the technique on a larger, more diverse set of MRI data, encompassing both tumour and non-tumour cases. The gathered features were fed into traditional machine learning techniques such as Support Vector Machines (SVMs), K-Nearest Neighbours (KNNs), and Random Forests, as well as deep learning models. These methods enabled comparison of models to increase resilience and provided several methods for classifying data. To precisely characterise tumour regions, which is necessary for accurate diagnosis and effective treatment planning, specialised architectures such as the U-Net were employed for tumour segmentation. These methods offered

Accurately locating tumours is essential for accurate diagnosis and the development of effective therapeutic strategies.



[Fig.7: Reliability of Training Over Epochs]

Additionally, a more thorough comprehension of its diagnostic capabilities will be supplied by incorporating metrics such as F1-scores, ROC curves, and confusion matrices.

Table II: Model Performance Metrics

Image ID	True Label	Predicted Label	Tumour Probability (%)	Correct Prediction
1	Tumor	Tumor	99.74	Yes
2	No Tumor	No Tumor	0.45	Yes
3	Tumor	Tumor	97.32	Yes
4	No Tumor	Tumor	85.12	No
5	Tumor	No Tumor	12.05	No

V. CONCLUSION

The brain tumour detection system performed well, correctly identifying the investigated MRI image as a tumour case. The model has a predictive probability of 99.74%.

Showed a high level of assurance in its classification. This result suggests that, by extracting relevant information from MRI data, the model may correctly identify tumour locations. Therefore, this type of technology could be a useful tool to aid medical professionals in the diagnostic process. The model showed high confidence in its classification, with a prediction probability of 99.74%. This result suggests that, by extracting relevant information from MRI data, the model may correctly identify tumour locations. As a result, a system such as this could be useful in aiding medical professionals in the diagnosis process.

DECLARATION STATEMENT

As the article's author, I must verify the accuracy of the following information after aggregating input from all authors.

- **Conflicts of Interest/ Competing Interests:** Based on my understanding, this article has no conflicts of interest.
- **Funding Support:** This article has not been funded by any organizations or agencies. This independence ensures that the research is conducted with objectivity and without any external influence.
- **Ethical Approval and Consent to Participate:** The content of this article does not necessitate ethical approval or consent to participate with supporting documentation.
- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Author's Contributions:** The authorship of this article is contributed equally to all participating individuals.

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AUTHOR'S PROFILE

Kandika Vishnuvardhan is currently pursuing his PhD as a Research Scholar in the Department of Computer Science and Engineering at Chaitanya Deemed to be University, Hyderabad, India. His academic journey is driven by a strong passion for advanced computational technologies and their real-world applications. His primary research interests include Machine Learning, Deep Learning, Artificial Intelligence, and Medical Image Processing, with a focus on solving complex healthcare-related problems using intelligent systems. Throughout his academic career, he has actively engaged in multiple research and development projects, particularly in data science and web-based machine learning applications. He has gained hands-on experience in designing, developing, and deploying predictive models using modern tools and frameworks. His work emphasises integrating machine learning algorithms with user-friendly web interfaces to enable practical, accessible AI solutions. Currently, his research focuses on the detection and classification of brain tumours using Convolutional Neural Networks (CNNs). This work involves analysing medical imaging data, such as MRI scans, to improve diagnostic accuracy and assist healthcare professionals in early disease detection. Additionally, he is focusing on deploying these machine learning models using the Streamlit framework, aiming to create interactive and scalable web applications that make advanced AI models easily usable for non-technical users, including medical practitioners. His research contributions aim to bridge the gap between theoretical machine learning concepts and real-world healthcare applications, advancing intelligent diagnostic systems.

Dr. R. Praveen Kumar is an accomplished academician and researcher currently serving as an Associate Professor in the Department of Computer Science and Engineering at Chaitanya Deemed to be University, Hyderabad, India. With several years of dedicated experience in both teaching and research, he has made significant contributions to computer science education, particularly in Artificial Intelligence, Machine Learning, and Data Science. He is deeply committed to fostering a strong foundation in emerging technologies among students, combining theoretical knowledge with practical applications. His teaching approach emphasizes critical thinking, problem-solving, and hands-on learning, enabling students to apply modern computational techniques to real-world challenges effectively. Dr. Praveen Kumar's research interests span across Deep Learning, Image Processing, and Intelligent Healthcare Systems. His work focuses on leveraging advanced machine learning algorithms to address complex problems, particularly in healthcare, including disease detection, medical image analysis, and predictive modelling. He has been actively involved in guiding and mentoring numerous undergraduate projects, many of which explore cutting-edge technologies and innovative solutions in AI-driven applications. In addition to his academic responsibilities, he continuously contributes to the research community through scholarly activities and encourages students to engage in research and development. His dedication to teaching excellence and research innovation makes him a valuable contributor to advancing intelligent systems and data-driven technologies.