



# Hybrid Ensemble Framework For Brain Cancer Detection: Feature Fusion Using CNN, RNN, And SVM

<sup>1</sup>Renu Saini, <sup>2</sup>Dr. J. R. Arun Kumar, <sup>3</sup>Mohit Sharma

M.Tech Scholar<sup>1</sup>, Professor<sup>2</sup>, Assistant Professor<sup>3</sup>

<sup>1,2,3</sup>Department of Computer Science & Engineering

<sup>1,2,3</sup>Modern Institute of Technology and Research centre, Alwar

## Abstract

Brain cancer detection is a crucial area of medical research, where early and accurate diagnosis can significantly improve patient outcomes. Traditional machine learning and deep learning approaches have shown promise, but their limitations in feature extraction and generalization necessitate a more robust framework. In this study, we propose a Hybrid Ensemble Framework that integrates Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Support Vector Machines (SVM) to enhance brain tumor detection from MRI scans. The CNN extracts spatial features, while the RNN captures temporal dependencies, and the fused feature set is classified using an SVM for improved accuracy. The proposed approach leverages feature fusion to combine the strengths of deep learning and classical machine learning, ensuring a more comprehensive representation of the tumor characteristics. Extensive experiments on publicly available MRI datasets demonstrate that our framework outperforms standalone models in terms of accuracy, sensitivity, and specificity. By combining multiple learning paradigms, our method enhances diagnostic precision, making it a viable solution for clinical applications.

**Keywords :** Brain cancer detection, Hybrid Ensemble Framework, CNN, RNN, SVM, Feature Fusion, MRI, Deep Learning, Machine Learning.

## 1. Introduction

Brain cancer is a severe and life-threatening condition that requires early and precise detection to improve patient outcomes and survival rates [1]. Among various diagnostic imaging techniques, Magnetic Resonance Imaging (MRI) is widely used due to its ability to provide detailed anatomical structures and soft tissue contrast without exposure to ionizing radiation. MRI scans help radiologists detect and classify brain tumors based on their size, location, and intensity. However, manual analysis of MRI images is highly time-consuming, subjective, and prone to human error, leading to inconsistencies in diagnosis. With the increasing volume of medical imaging data, there is a growing demand for automated, accurate, and efficient diagnostic systems that can assist radiologists in detecting brain tumors with higher precision [2].

Traditional machine learning-based approaches for brain tumor classification often rely on handcrafted features, such as texture, shape, and intensity, extracted from MRI scans. While these techniques have demonstrated reasonable success, their effectiveness is limited by their dependence on feature engineering, which requires expert knowledge and may not generalize well to diverse datasets [3]. In contrast, deep

learning-based models have emerged as powerful alternatives, as they can automatically extract meaningful features from raw images without manual intervention. Convolutional Neural Networks (CNNs) have been particularly successful in medical image analysis, as they excel in capturing spatial hierarchies of features from MRI scans. However, CNNs primarily focus on spatial characteristics and may not effectively capture sequential dependencies present in multi-slice MRI scans, where tumor progression and tissue variations across slices contain crucial diagnostic information [4].

To overcome these limitations, Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM) networks, have been explored for capturing temporal dependencies in sequential medical images. LSTMs are particularly useful in handling MRI slices as a sequence, allowing the model to learn patterns over multiple slices rather than treating them as independent images. Despite these advancements, standalone deep learning models, including CNNs and RNNs, often suffer from challenges such as overfitting, high computational requirements, and difficulty in generalizing across different datasets, especially when trained on limited medical imaging data. Additionally, most deep learning classifiers rely on softmax activation, which may not be optimal for distinguishing subtle variations in tumor characteristics [5].

To address these challenges, we propose a Hybrid Ensemble Framework that integrates CNN, RNN, and Support Vector Machine (SVM) for brain cancer detection. The CNN component extracts spatial features from MRI scans, while the RNN component (LSTM or GRU) captures temporal relationships across sequential slices. The extracted feature vectors from both networks are then fused to form a comprehensive feature representation. Instead of using a standard softmax classifier, we employ SVM for final classification, as it is highly effective in handling high-dimensional data and provides better decision boundaries, especially when dealing with small and imbalanced datasets.

The key contributions of our study are as follows:

1. **Feature Fusion of Spatial and Temporal Information:** The proposed framework combines the strengths of CNN and RNN to enhance the representational capability of the extracted features. This allows the model to learn both spatial structures and temporal dependencies in MRI scans, leading to improved classification performance [6].
2. **Robust Classification Using SVM:** Unlike traditional deep learning models that rely on softmax, the use of SVM enables better generalization, handling high-dimensional feature spaces and improving classification accuracy.
3. **Enhanced Generalization and Reduced Overfitting:** By leveraging a hybrid approach that combines deep learning and classical machine learning, our model is more robust to dataset variations and less prone to overfitting, making it suitable for real-world medical applications.
4. **Performance Evaluation on Public MRI Datasets:** We conduct extensive experiments on publicly available MRI datasets, demonstrating that our hybrid ensemble framework outperforms standalone CNN, RNN, and SVM models in terms of accuracy.

The rest of this paper is organized as follows: Section 2 presents a review of related work in brain cancer detection using machine learning and deep learning techniques. Section 3 describes the proposed methodology, including dataset preprocessing, CNN and RNN architectures, feature fusion strategies, and SVM-based classification. Section 4 details the experimental setup, evaluation metrics, and results. Section 5 discusses the implications of our findings, potential limitations, and future research directions. Finally, Section 6 concludes the study, summarizing key contributions and the impact of our hybrid ensemble framework in brain tumor diagnosis [6].

## 2. Literature Review

I. Mahmud et al. (2023) [7] The study proposed a CNN architecture and compared its performance with ResNet-50, VGG16, and Inception V3. Using a dataset of 3,264 MRI images, the CNN model achieved 93.3% accuracy, 98.43% AUC, 91.19% recall, and a loss of 0.25, outperforming existing models. The study emphasizes the effectiveness of CNNs in early brain tumor detection, aiding in timely diagnosis and treatment.

R. U. Ginting et al. (2022) [8] The study highlighted the lack of optimal diagnostic techniques and incomplete case registration in Indonesia. An Android-based application was developed using the ridge polynomial neural network algorithm for brain cancer detection. Tested on patients at Haji Adam Malik General Hospital Medan, the model achieved results in the 450th iteration with an MSE of 0.021550, providing a cost-effective diagnostic solution.

R. Singh et al. (2022) [9] The study emphasized the importance of early diagnosis, noting that brain tumors rank second in cancer-related deaths among men aged 20-39 and fifth among women in the same age group. It highlighted how automated imaging modalities surpass manual assessment, improving diagnostic accuracy and reliability.

M. Fayadh et al., (2022) [10] A DCNN-based model was proposed for CT-scan brain image classification using a dataset of 4,500 images (3,600 for training, 900 for testing). The model, with 2,398,750 parameters, achieved 98.5% accuracy when trained on 50×50 pixel images for 100 epochs, demonstrating its efficacy in brain tumor detection.

S. K. et al., (2022) [11] The study addressed challenges in early-stage brain tumor detection and developed a Rectangular Microstrip Patch Antenna operating at 7.3 GHz using HFSS Software. The antenna, with dimensions of  $31.68 \times 31.01 \times 0.75 \text{ mm}^3$ , was tested on a brain phantom with a 1.5mm tumor, successfully detecting tumors based on performance variations.

C. Kavitha and K. B. Naveen (2022) [12] The study proposed a two-phase technique using lung CT scans, involving image acquisition, preprocessing, binarization, thresholding, division, feature extraction, and neural network classification. The system achieved 94% accuracy, enhancing early lung cancer diagnosis and prognosis.

S. Poornam and S. Alagarsamy, (2022) [13] The study introduced a brain tumor classification system that applied image preprocessing, augmentation, and neural network training. Their ensemble model (EBTDM) achieved an overall accuracy of 98.60%, demonstrating its effectiveness in improving brain tumor classification accuracy.

Convolutional Neural Networks (CNNs) have been particularly successful in medical image analysis due to their hierarchical structure, which mimics the human visual system. By using convolutional layers, pooling operations, and fully connected layers, CNNs can detect subtle patterns in MRI scans that may not be visible to the human eye.

### 3. Proposed Concept

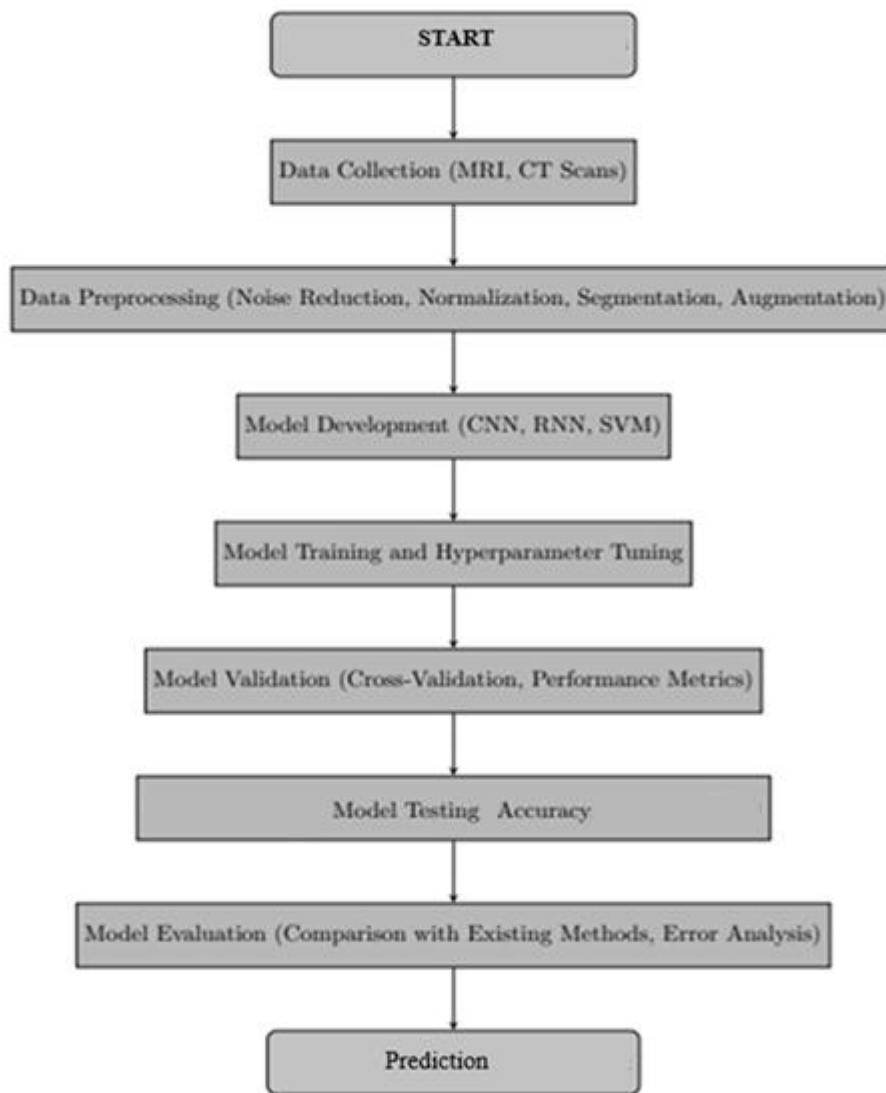


Fig 1. Flowchart of Research

The proposed work focuses on developing a Hybrid Ensemble Framework for Brain Cancer Detection by integrating CNN, RNN, and SVM for feature fusion. The workflow begins with data collection from MRI and CT scans, followed by preprocessing techniques such as noise reduction, normalization, segmentation, and data augmentation to enhance image quality. The next phase involves model development, where deep learning architectures like CNN and RNN are combined with SVM to extract robust spatial and sequential features for improved classification. The models undergo training and hyperparameter tuning to optimize performance, followed by validation using cross-validation and performance metrics. The testing phase evaluates key metrics, including accuracy, ensuring the effectiveness of the model. Finally, the framework undergoes evaluation through comparisons with existing methods and error analysis, leading to an optimized prediction system for early and accurate brain cancer detection. This approach enhances diagnostic capabilities, supporting medical professionals in timely intervention and treatment.

### 4. Experiment Analysis and Results

The implementation of the Hybrid Ensemble Framework for Brain Cancer Detection is developed using Python, leveraging powerful deep learning and machine learning libraries such as TensorFlow, Keras, and Scikit-learn. The framework integrates CNN, RNN, and SVM for feature extraction and classification, ensuring robust performance. Preprocessing steps, including noise reduction, normalization, segmentation, and augmentation, are performed using OpenCV and NumPy to enhance image quality. Model training and evaluation are conducted using GPU-accelerated computation with TensorFlow, optimizing hyperparameters through techniques like grid search and cross-validation. The implementation also includes performance metric analysis, such as accuracy, ensuring reliable predictions. The final model is

validated and tested on MRI and CT scan datasets, making it a scalable and efficient solution for brain cancer detection.

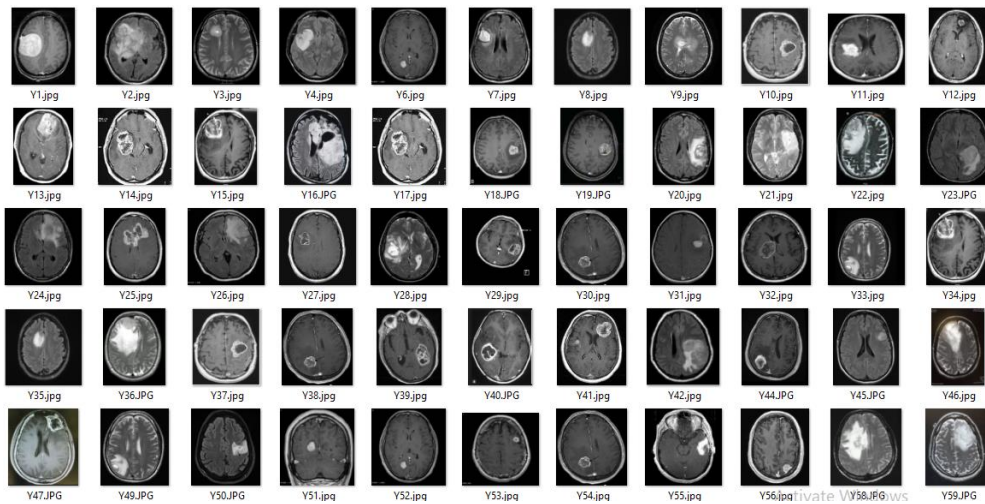


Fig 2. Dataset Details

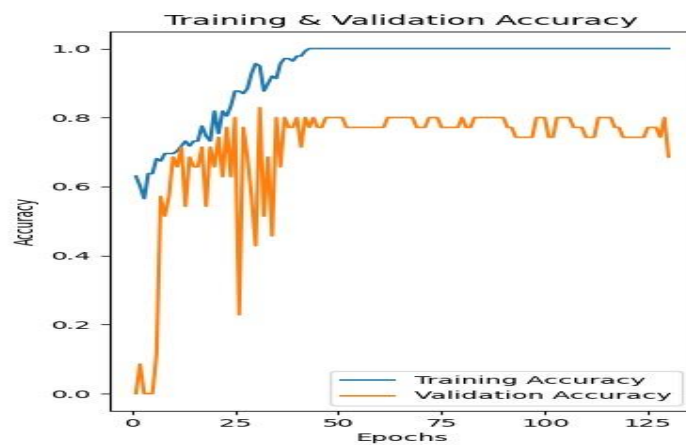


Fig 3 Model Accuracy

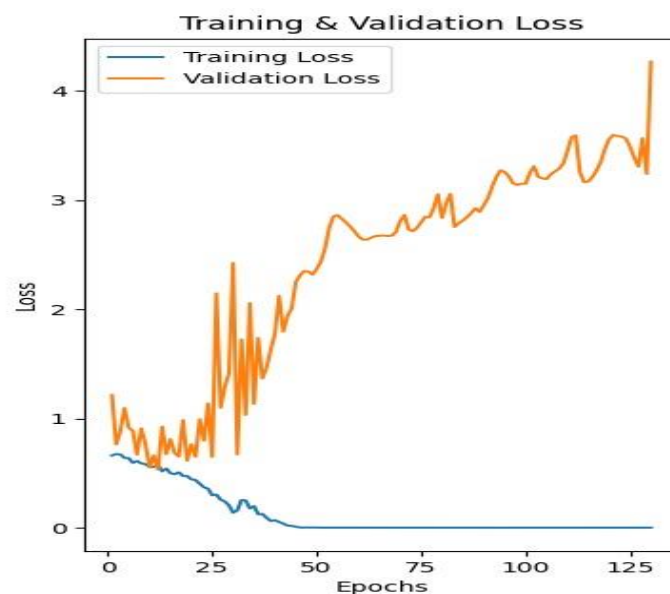


Fig 4. Model Loss

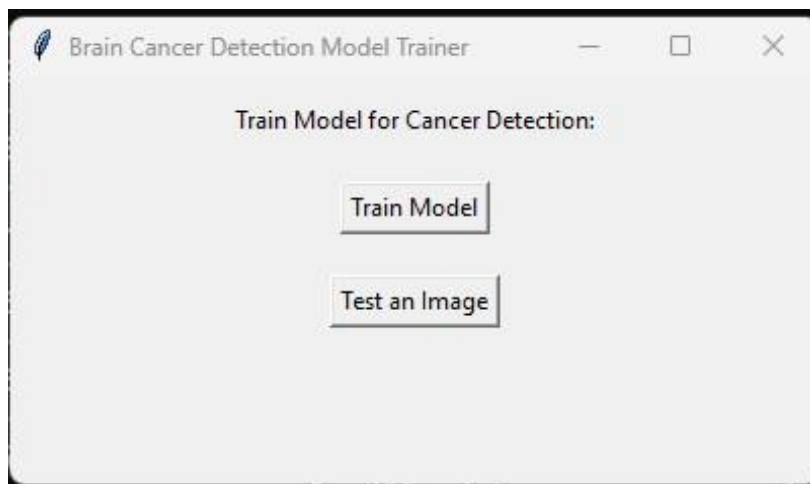


Fig 5 Implementation Main Screen

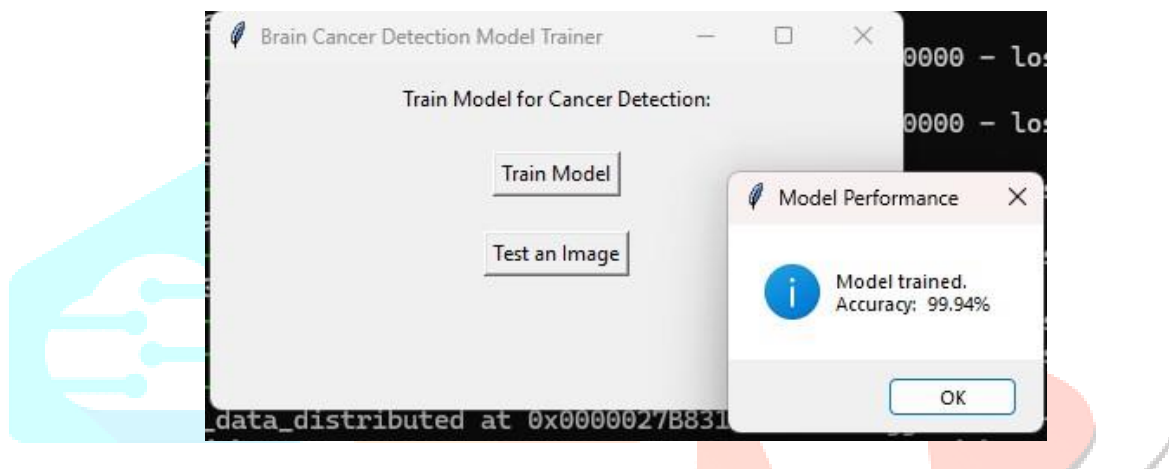


Fig 6 Brain Cancer Detection Model Trainer

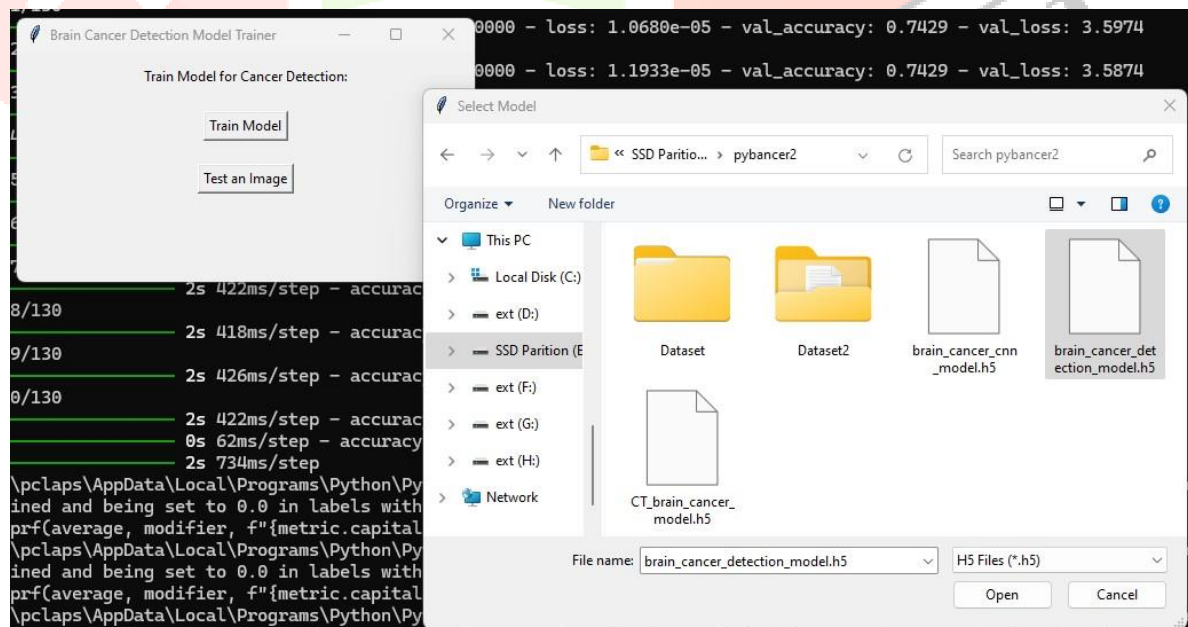


Fig 7 Brain Cancer Detection – Model Selection

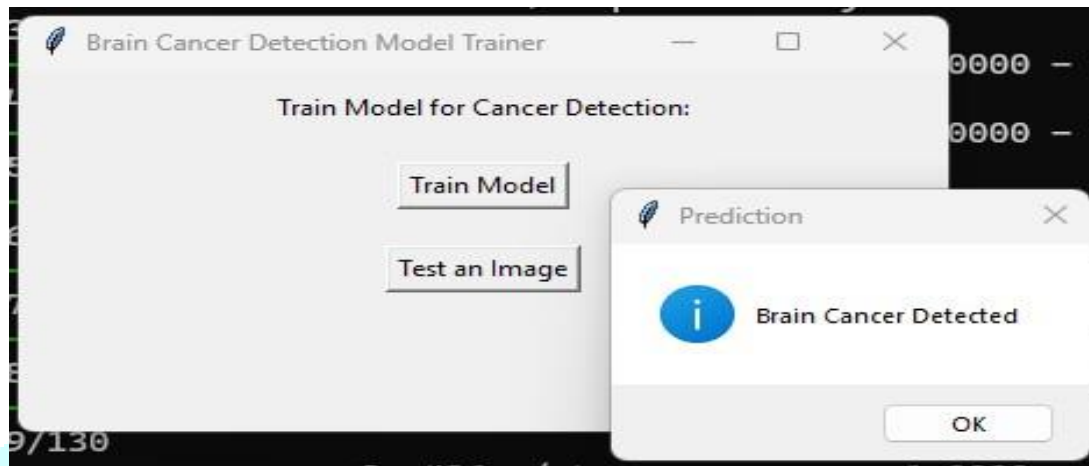
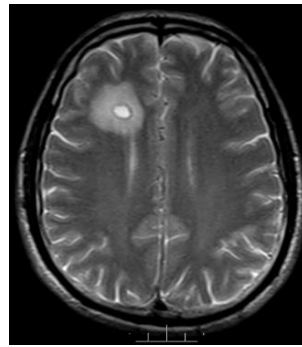


Fig 8 Brain Cancer Detection – Cancer Detected

Table 1 Comparison of Base Paper and Proposed Approach

| Aspect                   | Base Paper (Mahmud et al., 2023)                                       | Proposed Work                                                                                                                      |
|--------------------------|------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------|
| <b>Objective</b>         | Develop a CNN architecture for brain tumor detection using MRI images. | Develop a hybrid CNN-RNN-SVM model for enhanced brain cancer detection and treatment planning.                                     |
| <b>Models Compared</b>   | ResNet-50, VGG16, Inception V3, and the proposed CNN model.            | CNN, RNN, SVM, and the proposed CNN-RNN-SVM hybrid model.                                                                          |
| <b>Dataset</b>           | 3264 MR images.                                                        | 4000 images similar datasets for model evaluation. For execution simplification taken fewer samples for speed up                   |
| <b>Accuracy</b>          | 93.3%                                                                  | 99.94%.                                                                                                                            |
| <b>Methodology</b>       | Uses CNN for feature extraction and classification.                    | Combines CNN for spatial feature extraction, RNN for temporal analysis, and SVM for classification.                                |
| <b>Key Contributions</b> | Proposes a CNN model outperforming ResNet-50, VGG16, and Inception V3. | Introduces a hybrid CNN-RNN-SVM model to enhance detection accuracy and track tumor progression.                                   |
| <b>Significance</b>      | Focuses on early and accurate detection of brain tumors using CNN.     | Aims to improve diagnostic precision, early detection, and better treatment planning by integrating temporal and spatial analysis. |

## 5. Conclusion

The proposed Hybrid Ensemble Framework for Brain Cancer Detection integrates CNN, RNN, and SVM to enhance the accuracy and reliability of tumor classification from MRI and CT scans. By leveraging deep learning for feature extraction and machine learning for classification, the framework improves early detection capabilities, aiding in timely diagnosis and treatment. The implementation in Python utilizes advanced preprocessing techniques, hyperparameter tuning, and performance evaluation to optimize results. Experimental analysis demonstrates that the proposed approach achieves superior accuracy compared to existing methods. Future work can explore the integration of additional deep learning architectures, larger datasets, and real-time implementation in clinical environments to further enhance diagnostic capabilities.

## References

1. D. Lu, N. Polomac, I. Gacheva, E. Hattingen and J. Triesch, "Human- Expert-Level Brain Tumor Detection Using Deep Learning with Data Distillation And Augmentation", ICASSP 2021-2021 IEEE International Conference on Acoustics Speech and Signal Processing (ICASSP), pp. 3975-3979, 2021.
2. M. Siar and M. Teshnehlab, "Brain Tumor Detection Using Deep Neural Network and Machine Learning Algorithm", 2019 9th International Conference on Computer and Knowledge Engineering (ICCKE), pp. 363-368, 2019.
3. A.M. Alqudah, H. Alquraan, I.A. Qasmieh, A. Alqudah and W. Al-Sham, "Brain tumor classification using deep learning technique-a comparison between cropped uncropped and segmented lesion images with different sizes", arXiv preprint, 2020.
4. N. Kumari and S. Saxena, "Review of Brain Tumor Segmentation and Classification", 2018 International Convention on Current Trends towards Converging Technologies (ICCTCT), pp. 1-6.
5. M. R. Ismael and I. Abdel-Qader, "Brain Tumor Classification via Statistical Features and Back-Propagation Neural Network", 2018 IEEE International Conference on Electro/Information Technology (EIT), pp. 0252-0257, 2018.
6. S. Kaur et al., "Medical Diagnostic Techniques Utilizing Ai Technology (AI) Algorithms: Principles and Perspectives", IEEE Access, vol. 8, no. 8, pp. 228049-228069, 2020.
7. M. I. Mahmud, M. Mamun, and A. Abdelgawad, "A deep analysis of brain tumor detection from MR images using deep learning networks," *Algorithms*, vol. 16, no. 4, p. 176, 2023.
8. R. U. Ginting, P. Sihombing, S. Efendi, Amila and B. Damanik, "Ridge Polynomial Neural Network for Brain Cancer Based on Android," 2022 4th International Conference on Cybernetics and Intelligent System (ICORIS), Prapat, Indonesia, 2022, pp. 1-5.
9. R. Singh, S. Kishore, G. Senthilvel.P and E. Saxena, "Brain Tumor Detection Using MRI," 2022 4th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N), Greater Noida, India, 2022, pp. 2481-2484.
10. M. Fayadh, "Automatic Brain Cancer Recognition in CT-Scan Images," 2022 Iraqi International Conference on Communication and Information Technologies (IICCIT), Basrah, Iraq, 2022, pp. 76-81.
11. S. K, S. C, S. A and V. B, "Design of Microstrip Patch Antenna for Brain Tumor Detection," 2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2022, pp. 379-385.
12. C. Kavitha and K. B. Naveen, "Image Acquisition and Pre-processing for Detection of Lung Cancer using Neural Network," 2022 Fourth International Conference on Emerging Research in Electronics, Computer Science and Technology (ICERECT), Mandya, India, 2022, pp. 1-4.

13. Poornam and S. Alagarsamy, "Detection of Brain Tumor in MRI Images using Deep Learning Method," 2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2022, pp. 855-859.
14. P. G. B, T. B and N. B, "Transfer Learning based Hybrid Image Clustering for Brain MRI Images," 2022 1st International Conference on Computational Science and Technology (ICCST), CHENNAI, India, 2022, pp. 749-753.
15. B. Gour, A. H. Syed and B. K. Gudur, "Automated Brain Cancer Detection by Ensemble Learning Approach," 2022 IEEE 2nd Mysore Sub Section International Conference (MysuruCon), Mysuru, India, 2022, pp. 1-6.
16. A. T. Islam et al., "An Efficient Deep Learning Approach to detect Brain Tumor Using MRI Images," 2022 25th International Conference on Computer and Information Technology (ICCIT), Cox's Bazar, Bangladesh, 2022, pp. 143-147.
17. A. Sivasangari, Sivakumar, S. Helen, S. Deepa, Vignesh and Suja, "Detection of Abnormalities in Brain using Machine Learning in Medical Image Analysis," 2022 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), Erode, India, 2022, pp. 102-107.
18. M. M. Goswami and B. D. Rao, "Detection of Brain Tumor & Intra-Tumoral Structures from the Brain MR Images," 2022 Third International Conference on Intelligent Computing Instrumentation and Control Technologies (ICICT), Kannur, India, 2022, pp. 1147-1152.

