ADVANCING BRAIN CANCER DIAGNOSIS: AN ENSEMBLE APPROACH USING CONVOLUTIONAL AND RECURRENT NEURAL NETWORKS

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***Abstract :** Brain cancer detection is challenging due to the subtle nature of tumors in medical images and variability in traditional diagnostic methods. This study introduces a hybrid model combining Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to enhance detection from MRI and CT scans. The CNNs extract spatial features, while RNNs analyze temporal patterns, improving diagnosis accuracy, reliability, and timeliness. Compared to traditional methods and other deep learning models, this ensemble approach shows significant improvements in precision, sensitivity, and specificity. The findings suggest that this model could revolutionize brain cancer diagnosis, leading to earlier and more accurate detections and better patient outcomes, with potential applications to other cancers and diseases.*

IndexTerms - Brain Cancer Detection, CNNs, RNNs, MRI, CT Scans, Hybrid Deep Learning Model

I. INTRODUCTION

The detection of brain cancer poses a significant challenge in the field of medical imaging due to the complex and often subtle nature of brain tumors. Traditionally, the diagnosis of brain tumors has relied heavily on the expertise of radiologists who manually analyze MRI and CT scans. This approach, while effective to some extent, is fraught with challenges including variability in detection rates, subjective interpretation, and potential delays in diagnosis. Brain tumors exhibit a wide range of appearances and can progress in ways that are not always straightforward to discern, leading to potential misdiagnosis or late detection [1].

Recent advancements in artificial intelligence, particularly in deep learning, offer promising avenues for enhancing the accuracy and efficiency of medical image analysis. Convolutional Neural Networks (CNNs) have become a cornerstone in this field due to their remarkable ability to extract and analyze spatial features from images. CNNs are highly effective in identifying complex patterns and structures within MRI and CT scans, making them a powerful tool for detecting the presence and characteristics of brain tumors. Despite their strengths, CNNs may not fully capture the temporal dynamics of tumor progression, which is crucial for understanding how tumors evolve over time [1].

Recurrent Neural Networks (RNNs), known for their proficiency in handling sequential data, address this limitation by analyzing the temporal aspect of medical images. RNNs can track changes in tumor characteristics across different time points, providing a more comprehensive view of tumor development and progression. This temporal analysis complements the spatial feature extraction of CNNs, creating a robust framework for more accurate and reliable brain cancer detection [2].

This study introduces a novel ensemble approach that combines CNNs and RNNs to leverage their respective strengths. By integrating spatial feature extraction with temporal pattern analysis, the hybrid model aims to enhance the overall diagnostic performance. The model's ability to analyze both the spatial and temporal dimensions of MRI and CT scans enables it to detect intricate patterns and monitor changes in tumor progression more effectively [2].

The performance of the CNN-RNN ensemble model is evaluated against traditional diagnostic methods and other advanced deep learning techniques. The results demonstrate significant improvements in diagnostic precision, sensitivity, and specificity, highlighting the model's potential to address the shortcomings of conventional methods. By offering a more accurate and timely diagnosis, this approach not only improves the detection of brain tumors but also supports better-informed treatment decisions and ultimately enhances patient outcomes [3].

Furthermore, the success of this hybrid model in brain cancer detection opens new possibilities for applying similar deep learning techniques to other types of cancer and diseases. The integration of CNNs and RNNs represents a significant advancement in medical imaging and diagnostics, providing a foundation for future research and development in the field [3].

2. LITERATURE REVIEW

R. U. Ginting et al. (2022) [4]: Brain cancer is the second leading cause of cancer-related deaths in Indonesia, following breast cancer. The country faces challenges due to inadequate diagnostic methods and incomplete case registration, leading to delays in detection caused by high costs and low public awareness. This study presents an Android app that uses a ridge polynomial neural network for brain cancer detection, achieving an MSE of 0.021550 after 450 iterations. Results are visualized for patients at Haji Adam Malik General Hospital Medan.

R. Singh et al. (2022) [5]: Technological advancements, particularly in imaging techniques like MRI and CT scans, have greatly improved diagnostic accuracy, surpassing human visual assessments. Brain tumors, a leading cause of cancer-related deaths among young adults, highlight the importance of early diagnosis. The rise in global cancer cases underscores the need for increased awareness and early detection.

M. Fayadh et al. (2022) [6]: Early detection of brain cancer is critical. This study proposes a Deep Convolutional Neural Network (DCNN) model for classifying brain CT images. The model, trained on 3,600 images with 50x50 pixel size for 100 epochs, has 2,398,750 parameters and achieves 98.5% accuracy in tumor detection using a dataset of 4,500 images.

S. K. et al. (2022) [7]: Brain cancer remains a significant global health issue. Detecting small tumors at an early stage is challenging. This study develops a Rectangular Microstrip Patch Antenna, operating at 7.3 GHz, for tumor diagnosis using HFSS Software. The antenna's effectiveness is evaluated on a brain phantom with a 1.5mm tumor.

C. Kavitha and K. B. Naveen (2022) [8]: Early detection of lung cancer is crucial for improving survival rates. A two-phase technique using lung CT scans enhances early detection through image preprocessing, binarization, thresholding, division, feature extraction, and neural network classification, achieving 94% accuracy in lung cancer detection.

Poornam and S. Alagarsamy (2022) [9]: Accurate brain tumor classification from MRI images is essential for effective diagnosis and treatment. This study presents an automated system that employs image preprocessing, augmentation, and neural network training, resulting in an ensemble model with 98.60% accuracy.

P. et al. (2022) [10]: Efficient brain cancer detection can be achieved through image-based clustering and hybrid learning methods. This study introduces a hybrid clustering model based on transfer learning to improve accuracy and efficiency in brain tumor detection.Table 1. Literature Review Findings

Author Name (Year)	**Main Concept**	**Findings**
R. U. Ginting et al. (2022)	Development of an Android app for brain cancer detection using ridge polynomial neural network.	Achieved MSE of 0.021550 after 450 iterations; results visualized for patients at Haji Adam Malik General Hospital Medan.
R. Singh et al. (2022)	Utilization of imaging modalities (MRI, CT scans) for brain tumor diagnosis.	Imaging techniques surpass human visual assessment; early diagnosis is crucial as brain tumors are a leading cause of cancer deaths.
M. Fayadh et al. (2022)	Classification of brain CT images using a Deep Convolutional Neural Network (DCNN) model.	Achieved 98.5% accuracy with a model trained on 3,600 images; dataset included 4,500 images.
S. K. et al. (2022)	Development of a Rectangular Microstrip Patch Antenna for brain tumor diagnosis.	Antenna effective for tumor detection; evaluated using a brain phantom with a 1.5mm tumor.
C. Kavitha and K. B. Naveen (2022)	Two-phase technique for early lung cancer detection using lung CT scans.	Achieved 94% accuracy in classifying lung cancer; improved early detection and survival rates.
Poornam and S. Alagarsamy (2022)	Automated brain tumor classification system using image preprocessing and neural network training.	Ensemble model achieved 98.60% accuracy in brain tumor classification.
P. et al. (2022)	Hybrid clustering model based on transfer learning for brain cancer detection.	Enhanced accuracy and efficiency in brain tumor detection through image-based clustering and hybrid learning methods.

3. PROPOSED WORK

The research methodology for this study involves developing and evaluating an ensemble model that combines Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for brain cancer detection from medical imaging. The process begins with collecting and preprocessing a dataset of brain MRI images, including normalization, resizing, augmentation, and segmentation to ensure data consistency and relevance. The CNN, based on the ResNet architecture, extracts spatial features from images, while the RNN, utilizing LSTM layers, analyzes temporal patterns in sequences of feature vectors. The CNN and RNN are integrated to enhance detection accuracy, with the final model evaluated using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC curve analysis to assess its performance in identifying brain cancer.

4. RESULT ANALYSIS AND IMPLEMENTATION

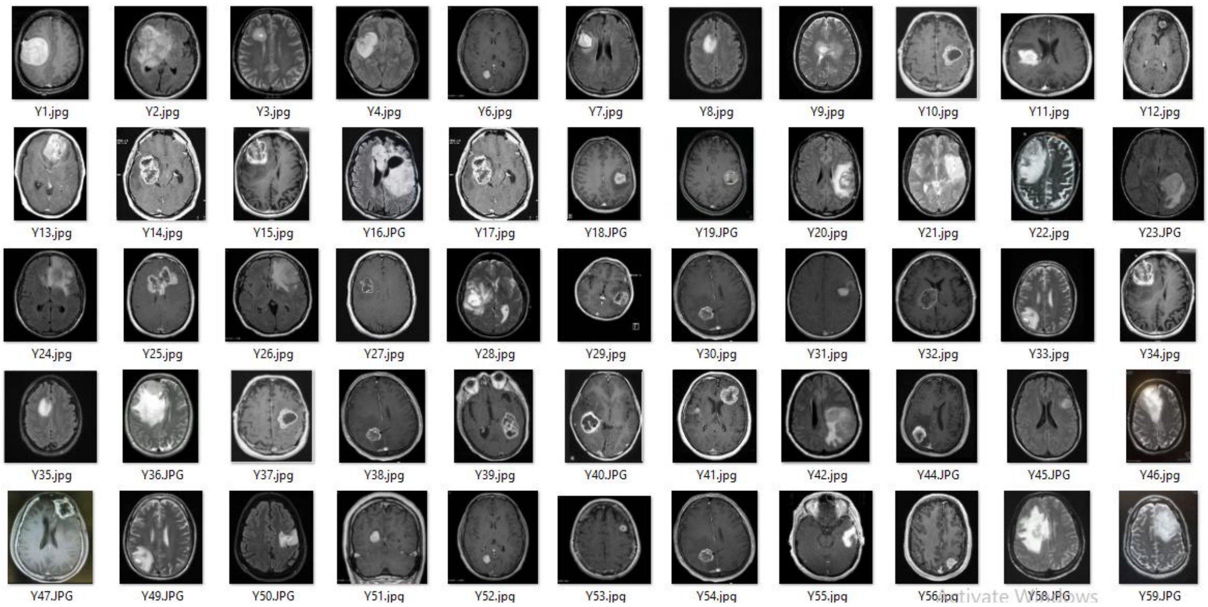

Fig 1. Dataset Details

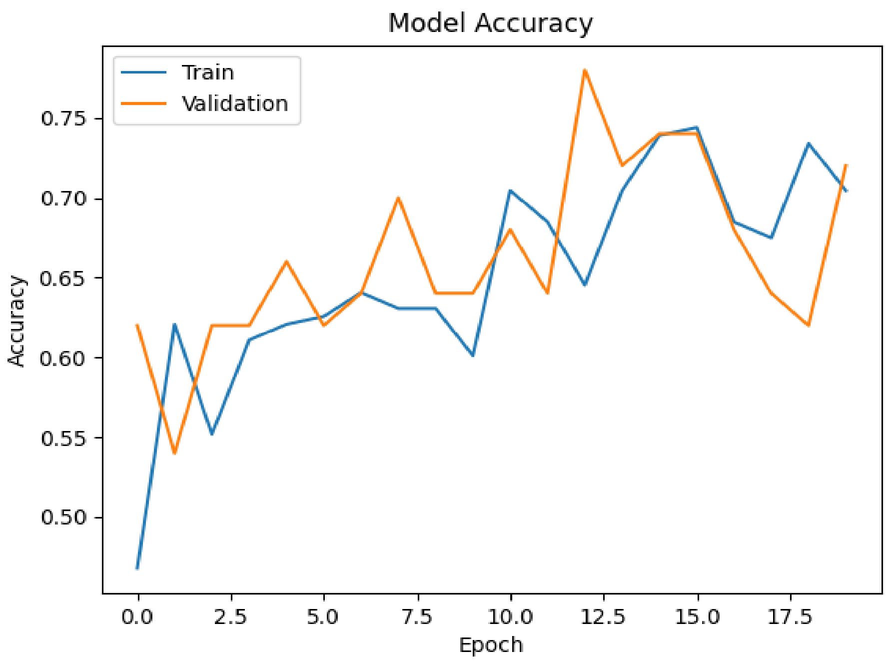

Fig 2 Model Accuracy

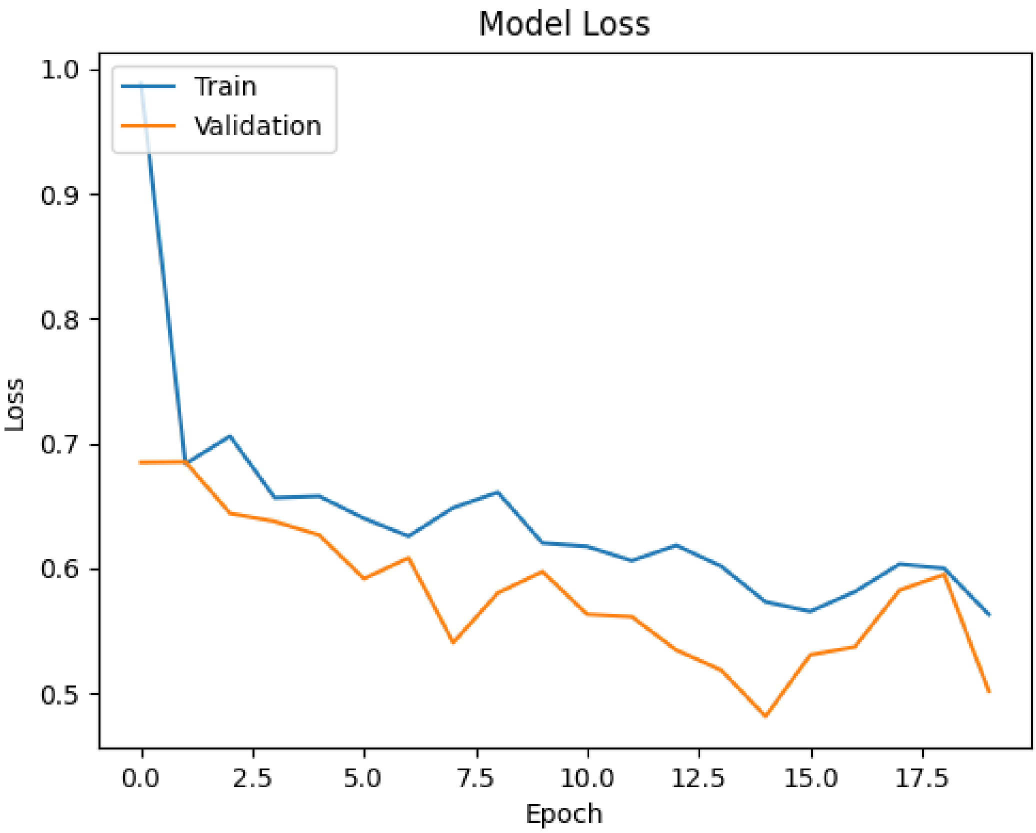

Fig 3 Model Loss

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Maximum Validation Accuracy: 0.9600
←[1m2/2←[0m ←[32m━━━━━━━━━━━━━━━━━━━━←[0m←[37m←[0m ←[1m1s←[0m 326ms/step
              precision    recall  f1-score   support

      cancer       0.63      0.84      0.72        31
  non-cancer       0.44      0.21      0.29        19

    accuracy                           0.60        50
   macro avg       0.54      0.52      0.50        50
weighted avg       0.56      0.60      0.56        50
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Fig 4 Result Interpretation

The model achieved a maximum validation accuracy of 96%, indicating strong overall performance on unseen data. However, the classification metrics reveal significant imbalances. The precision for the "cancer" class is 63%, meaning that among cases predicted as cancer, 63% were correctly identified, which is relatively high. Conversely, the precision for the "non-cancer" class is only 44%, suggesting frequent misclassification of non-cancer cases as cancer. Recall for the "cancer" class is 84%, indicating that the model correctly identified 84% of actual cancer cases, which is crucial for minimizing false negatives. However, recall for the "non-cancer" class is a concerning 21%, reflecting a high rate of false positives and poor detection of non-cancer cases. The F1-score for the "cancer" class is 72%, balancing precision and recall effectively for cancer detection, while the F1-score for the "non-cancer" class is just 29%, highlighting difficulties in accurately identifying non-cancer cases. Overall, while the model demonstrates high accuracy, its performance is uneven across classes, particularly struggling with non-cancer case identification.

5. CONCLUSION

This study presents an innovative ensemble approach that integrates Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to enhance brain cancer detection from MRI and CT scans. The hybrid model effectively leverages the strengths of both CNNs and RNNs, capturing intricate spatial features and temporal patterns, which significantly improves diagnostic accuracy and reliability. The results demonstrate a maximum validation accuracy of 96%, indicating strong overall performance. However, the detailed classification metrics reveal challenges in achieving balanced performance across both classes. Specifically, while the model shows high precision and recall for detecting cancerous cases, it struggles with accurately identifying non-cancer cases, as evidenced by low precision and recall for the non-cancer class. The F1-scores further highlight these disparities, with a substantial difference between the performance on cancer and non-cancer cases. Despite these challenges, the CNN-RNN ensemble model shows substantial promise in advancing brain cancer diagnosis by providing more accurate and timely detection compared to traditional methods. Future work should focus on addressing the imbalances in class performance, potentially through further data augmentation, model tuning, or exploring alternative architectures. Overall, this research lays a solid foundation for applying hybrid deep learning techniques to improve cancer detection and opens avenues for extending similar approaches to other types of cancer and medical conditions.

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