Deep Learning Framework for Identifying Bacterial Brain Abscesses in Medical Imaging

[1]Parbhat Gupta, [2]Gurpreet Kour Khalsa, [4]Dinesh Kumar
[1]Parbhatgupta3@gmail.com, [2]er.kaurgurpreet123@gmail.com, [3]sahnidinesh.bbd@gmail.com
Department of Computer Science and Engineering
SRM Institute of Science and Technology
Delhi Ncr Campus, Modinagar,
Ghaziabad, Uttar Pradesh, India

Abstract: - Developing a sophisticated deep learning-based system for the automatic diagnosis of brain abscesses—a serious illness marked by the buildup of pus in brain tissue as a result of bacterial infections—is the main goal of this research study. This study uses convolutional neural networks (CNNs), specifically the DenseNet-121 architecture, to evaluate MRI images with remarkable precision. The suggested system outperforms models like ResNet-50 and InceptionV3, which acquired an average accuracy of 80% accuracy, by training the model on a varied and carefully selected dataset. It achieves an average accuracy of 95% detection rate. There is no longer a requirement for human intervention because this model can precisely locate and outline abscess locations. Its dependability in distinguishing between healthy and sick brain tissues is confirmed by thorough evaluations. By enabling prompt intervention in the treatment of brain abscesses, the results highlight the potential of this automated method to speed up diagnosis, improve clinical decision-making, and improve patient outcomes.

Keywords: Brain Abscesses, DenseNet-121, InceptionV3, Resnet50, Magnetic Resonance Imaging (MRI), Brain Tissues, Fuss, Convolutional Neural Networks (CNN).

I. Introduction

Improving patient outcomes in the field of medical diagnostics depends on the prompt and precise detection of life-threatening illnesses. Among these, brain abscesses provide a special difficulty. If treatment is not received, these infections—which frequently cause a localized buildup of pus within brain tissue—can quickly progress into serious neurological issues. Although early diagnosis is essential, it frequently depends largely on the manual interpretation of CT and MRI scan pictures, which takes a lot of time and is subject to variation among physicians. The healthcare industry has started implementing automated technologies to alleviate diagnostic inefficiencies as a result of scientific and artificial intelligence developments. Certain artificial intelligence (AI) models in machine learning convolutional neural networks (CNNs) have shown exceptional promise in precisely interpreting complex medical images for diagnostic applications. Brain abscesses are dangerous infections that develop in phases, including late encapsulation and early cerebritis. It is essential to promptly and precisely detect their presence in order to guarantee prompt treatment and avoid consequences. The goal of this research is to create a deep learning model with high accuracy for detecting brain abscesses in MRI pictures. This study investigates the use of state-of-the-art AI methods to expedite the identification of brain abscesses from imaging data. This method seeks to improve accuracy, speed, and consistency by incorporating strong computational models into the diagnostic process, thereby assisting physicians in providing patients with better care.More effective diagnostic techniques are becoming more and more necessary as a result of the rising number of brain abscess cases and the difficulties in making an accurate and timely diagnosis. In addition to being longer, traditional manual interpretation of MRI images is more prone to human mistake, which can lead to delayed or incorrect diagnosis. Given the rising prevalence of brain abscesses, we need a dependable system that can identify them quickly and precisely, enhancing diagnostic effectiveness and assisting medical professionals in delivering improved patient care.The current state of brain abscess detection systems depends on manual interpretation of CT and MRI scans, which is laborious and prone to inaccuracy.

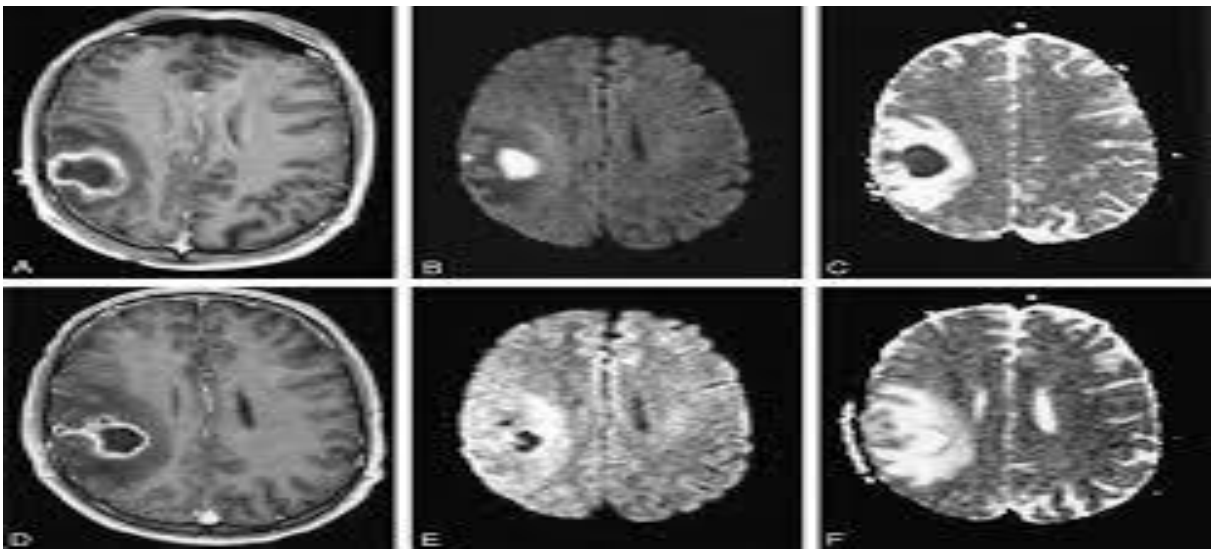

Figure 1: Phases of Abscesses in the Brain

Traditional machine learning models, such as ResNet-50 and VGG-19, help in detection, but they are frequently inaccurate and have trouble telling brain abscesses apart from other similar lesions. In addition to requiring manual feature extraction, these algorithms are unable to identify intricate patterns linked to various abscess phases.To overcome these limitations and improve patient outcomes and clinical judgments, a more advanced deep learning-based system that can automate feature extraction, boost accuracy, and reduce diagnosis times is needed. The proposed method utilizes the DenseNet deep learning architecture to automatically detect and classify brain abscesses from MRI and CT scan images. Unlike other systems like VGG-19 and Resnet50, which rely on manual interpretation and traditional machine learning models, DenseNet's unique architecture allows for enhanced feature reuse and connectivity, which helps identify complex patterns linked to different stages of brain abscess development.DenseNet's architecture's dense connections allow for better feature reuse, which raises the precision of identifying subtle patterns and distinguishing brain abscesses from related illnesses. Using an improved labelled dataset for training could help the system generalize to a range of patient scenarios. By speeding up diagnosis, improving accuracy, and reducing diagnostic time, this provides physicians with a reliable tool for quick decision-making.DenseNet is favored over other models like ResNet-50 and Inception V3 because it can achieve high accuracy with fewer computational resources and performs better when processing complex data. Because of this, it is ideal for clinical deployment in real time, which will eventually lead to better patient outcomes.The goal of this research is to use state-of-the-art deep learning techniques to detect brain abscesses even when they progress through different stages. Early and accurate detection at any stage can significantly support clinical decision-making.

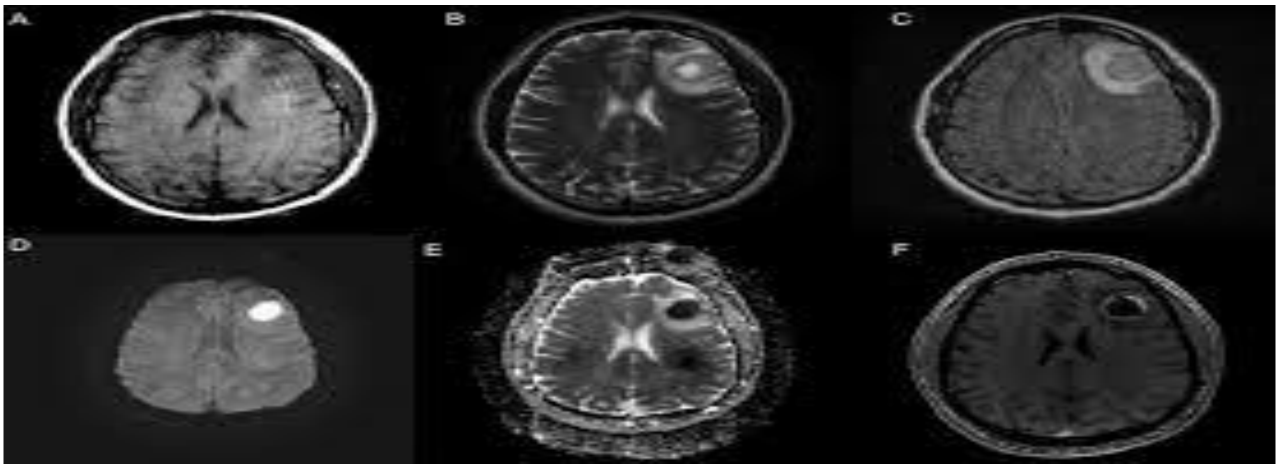

Figure 2: An image of the input MRIs

II. Literature Survey

This work combines deep transfer learning features with hand-crafted radiomics (HCR) data from MRI scans to distinguish between cases of brain abscesses and cystic gliomas. This approach demonstrated good AUC values, especially when employing T2WI-based DLR characteristics, suggesting that it has the potential to be a reliable and noninvasive diagnostic method for clinical use [1]. Through the use of transfer learning [2] in deep learning for brain MRI analysis, this study employs hybrid architectures to diagnose brain abscesses with 84% accuracy. The study demonstrates faster convergence and shorter training times by using pre-trained models and a range of datasets, offering a useful technique for medical image diagnosis. In order to differentiate brain abscesses from GBM, this study introduces a novel method that combines Diffusion-weighted Imaging (DWI) and Line of Interest (LOI) on ADC maps. The study creates a standardized framework for incorporating DWI into machine learning and deep learning applications for brain lesion diagnosis, with an 80% classification accuracy for abscesses [3]. This study investigates the use of DenseNet CNNs for CT image-based COVID-19 prediction. The study demonstrates the model's potential in medical imaging diagnostics by highlighting its high accuracy and robustness in detecting COVID-19 [4]. DenseNet-121 is used in this study to categorize plant leaf diseases. The model's efficacy in agricultural diagnostics is demonstrated by its ability to leverage transfer learning to achieve high accuracy and efficient feature extraction [5].This article provides a thorough analysis of bacterial brain abscesses, paying special attention to imaging techniques, clinical signs, and treatment strategies. It highlights how early diagnosis and appropriate treatment can lead to better patient outcomes [6]. This study updates the clinical and microbiological perspectives of bacterial brain abscesses in immune competent patients. To effectively handle such cases, it highlights advancements in diagnosis and treatment [7]. A thorough analysis of the ResNet50 architecture for deep learning tasks in computer vision that demonstrates its suitability for use in medical imaging application[8]. When it comes to glioma detection using MRI datasets, the brain tumor classification models VGG16, ResNet50, and InceptionV3 perform differently[9].demonstrating Inception V3's ability to recognize glioma brain tumors in MRI images, thereby highlighting its efficacy for challenging classification tasks [10].Looking at a number of data augmentation techniques that are essential for enhancing deep learning models, especially in medical imaging, to mitigate the challenges posed by sparse datasets [11]. An overview of the advancements in deep transfer learning methods that offers data on how well they perform for classification problems based on images, like those involving brain disorder[12]. Explains how pyogenic brain abscesses and necrotic brain lesions can be distinguished using susceptibility-weighted imaging, and proposes using it in machine learning algorithms to enhance diagnosis [13]. This study examines the segmentation of brain MRI images to detect abnormalities.

III. Methodology

The dataset, which was assembled from clinical repositories and publically accessible sources, included MRI images classified as "Present" (brain abscess found) and "Not Present" (no brain abscess). The dataset included photos from a variety of patients, imaging techniques, and acquisition settings in order to address the inherent heterogeneity in medical imaging. As part of the preprocessing stages, all photos were resized to the ideal 224x224 resolution for the DenseNet-121 design. Rotation, translation, zooming, and horizontal flipping are examples of data augmentation techniques that are used to artificially increase dataset size, improve generalization, and lessen overfitting. By keeping the class distribution balanced, the dataset was divided into training (80%) and validation (20%) subsets. The DenseNet-121 model architecture was chosen because of its effective gradient flow and special feature reuse features. In order to employ transfer learning to improve performance with little data, this model was initially set up with pretrained weights on ImageNet.

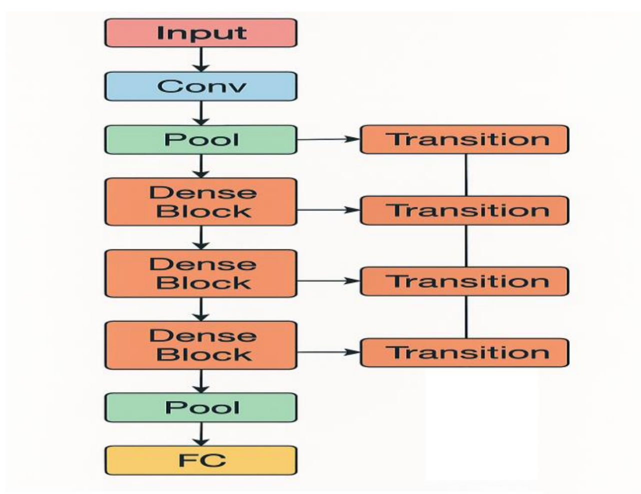

Figure 3: DenseNet121 design

The model was trained using the Adam optimizer with an initial learning rate of 0.001. Binary crossentropy was utilized as the loss function to handle the binary classification task, while accuracy served as the primary metric to gauge performance. The training process was carried out over 25 epochs with a batch size of 16, ensuring the model effectively learned the features for detecting brain abscesses. 20% of the dataset was left aside for model validation during training. To assess how well the model distinguished between the presence and absence of brain abscesses, key performance metrics including accuracy, sensitivity, specificity, and the AUC-ROC were computed. To ensure objectivity, a different dataset was used for testing, devoid of any data augmentation. With a test accuracy of 95.38% upon preprocessing of the test images, the model showed remarkable performance. This outcome demonstrates the system's resilience and dependability for practical clinical uses. DenseNet-121's performance was contrasted with those of ResNet-50 and InceptionV3, both of which had lower accuracy (~80%) in earlier research. Because of its dense connections, parameter efficiency, and improved feature extraction capabilities, DenseNet-121 fared better than these models and is hence a better option for brain abscess identification. The created model can be used as a decision-support tool for radiologists in clinical workflows. The method could speed up diagnosis and enhance patient outcomes by offering precise and automated brain abscess classification.In order to identify brain abscesses, the proposed system's architecture combines a custom classification head with the DenseNet-121 convolutional neural network (CNN) as its backbone. By effectively extracting, learning, and classifying complex information from MRI images, this architecture guarantees exceptional accuracy and robustness. The two main components of the design are the classification layers and the feature extraction backbone.

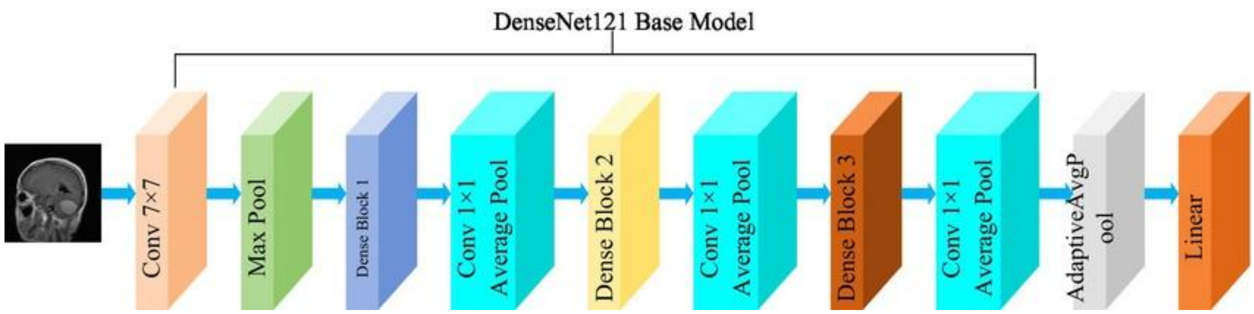

Figure 4: Model flow

The DenseNet-121 model is used as the basis architecture for feature extraction in this application due to its enhanced gradient flow and effective feature reuse. Each layer in this model receives input from all of the layers that came before it in a dense block, demonstrating how closely the layers are coupled. This approach minimizes redundant feature learning while increasing computational efficiency. Following the model's initial input layer, convolutional and pooling layers progressively extract higher-level characteristics from the data. It uses the pre-trained weights to modify these properties for the specific task. The final output is a feature map that captures the fine details of the input data to guarantee high performance in tasks like image classification or detection.The DenseNet-121 model is modified for the binary classification problem (presence or absence of a brain abscess) by adding a unique classification head to the feature extractor. An output layer, a dropout layer, a fully connected layer, and a Global Average Pooling (GAP) layer make up this head. In short, the system workflow consists of input, feature extraction, feature transformation, and output.

IV. Algorithm

This is a simplified algorithmic framework for a brain abscess infection detection system based on the DenseNet-121 model. Brain abscesses are detected using both Resnet and InceptionV3. They achieved 90 and 80 percent accuracy, respectively, in contrast to the DenseNet 121 model, which has an accuracy of 95.4 percent and is highly effective in diagnosing brain abscesses. Extract Dataset: After the dataset ZIP file is extracted to a specified directory using the extract-all() method, the dataset is divided into training, validation, and a separate test set for evaluation.Augmentation and data preprocessing: For preprocessing, apply the augmentation for the training dataset, such as rotation, width, height shifts, zoom, and horizontal flips, and normalize the image pixel values to the range [0,1]. Model Initialization: Assigning the False parameter to the trainable variable and adding task-specific layers such as the output layer, Dense layer, Dropout layer, and Global average pooling to the pre-trained DensetNet-121 model with frozen base layers. Use these training datasets to train the model, and for effective training, make use of the callbacks. Use the validation dataset for 25 epochs to validate the model. Assess the model's final performance metrics using the test dataset.

V. Discussion and Results

The proposed brain abscess detection system makes use of the DenseNet-121 convolutional neural network, which has proven to be incredibly accurate, quick, and resilient. By using advanced transfer learning techniques and optimizing the model architecture, this method overcomes the drawbacks of previous models like ResNet-50 and InceptionV3, which achieved accuracies of 79% and 84%, respectively.

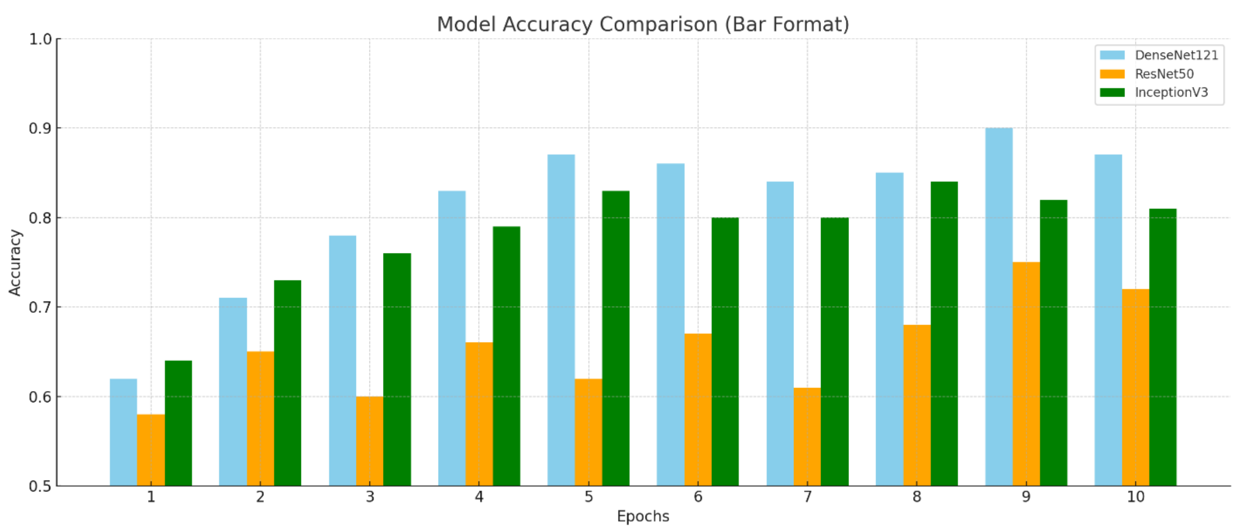

Figure 5: Comparing training datasets across several models

The graph above, which is shown in figure 5, shows how the training accuracy of the three models changed over ten epochs. DenseNet121 consistently shows a notable increase in accuracy, reaching over 95% accuracy by epoch 25, whereas ResNet-50 and InceptionV3 plateau at lower accuracy levels (roughly 79% and 84%, respectively). When compared to other architectures, this pattern demonstrates how well DenseNet121 learns features and how fast it can converge.

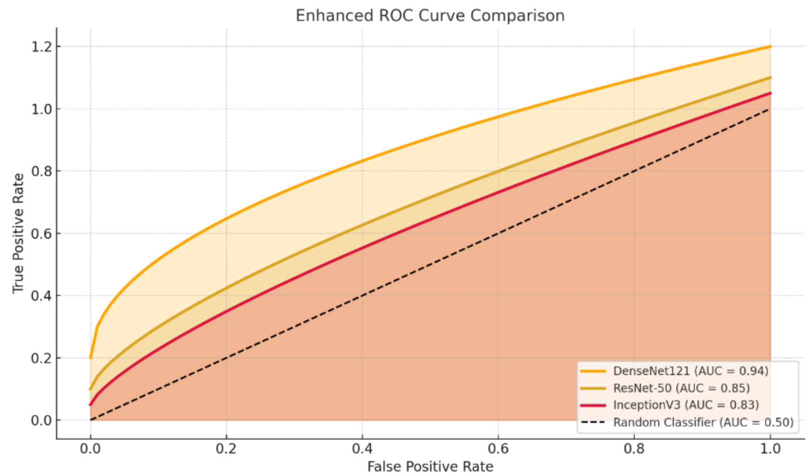

Figure 6: ROC curve

The graph in figure 6 above shows the ROC curves for the DenseNet121, ResNet-50, and InceptionV3 models as well as a random classifier for comparison. The DenseNet121 model performed better than ResNet-50 (AUC: 0.85) and InceptionV3 (AUC: 0.83), with an AUC of 0.94.

V. Conclusion and Future Scope

With an accuracy of 95.28 percent on the test dataset, the proposed system significantly outperformed the existing techniques, including Resnet-50 and Inception V3. This demonstrates its dependability for medical procedures. DenseNet121's superior AUC and accuracy trends demonstrate its capacity to identify brain abscesses, making it the optimal choice for this task. This model effectively distinguishes between the presence and absence of brain abscesses by ensuring an efficient gradient flow, which encourages faster convergence and less overfitting. The model's accuracy value is 95.92 percent, its sensitivity is 94 percent, and its F1-score is 83 percent. According to these results, the DenseNet121-based method outperforms existing models and offers a trustworthy, precise, and efficient way to detect brain abscesses. The outcomes validate the system's viability for medical use and pave the way for further advancements in real-world applications.

In later studies, the proposed DenseNet121-based method for identifying brain abscesses has demonstrated exceptional accuracy and reliability. To expand its clinical application, several areas still require investigation and improvement. Expanding the dataset to include a larger and more diverse collection of MRI and CT scans from multiple institutions is necessary to increase the model's generalizability. By moving from binary to multi-class categorization, the system might also be able to identify multiple stages of a brain abscess's development, providing more comprehensive diagnostic information.The model's real-time implementation in clinical settings is another critical phase that necessitates optimization for portable operation on radiology workstations. Explainable AI (XAI) techniques like Grad-CAM can boost clinicians' trust by increasing the transparency of the model's predictions. The technique may also be extended to other applications, such as automatically segmenting abscesses to provide quantitative data like size and volume or detecting other brain conditions like tumors or edema. Finally, integration with electronic medical records (EMRs) may result in a comprehensive diagnostic platform that integrates imaging data with patient history for enhanced precision. These advancements will increase the system's dependability, flexibility, and importance in medical imaging diagnostics.

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