Brain Tumour Detection Using Deep Learning

Mrs. Manjula Devi P*, Abdullah**, Abrar Pasha***, Ameer Ul Haq****,Mirza Wasi Abbas*****
*(Faculty of ISE, AMC Engineering College,Bengaluru, Karnataka
Email: manjuladevi.pari@gmail.com)
**(Student of ISE, AMC Engineering College,Bengaluru, Karnataka
Email: abdullahabdullah08280@gmail.com)
***(Student of ISE, AMC Engineering College,Bengaluru, Karnataka
Email: abrarpashapasha47@gmail.com)
****(Student of ISE, AMC Engineering College,Bengaluru, Karnataka
Email: ameerulhaq081@gmail.com)
*****(Student of ISE, AMC Engineering College,Bengaluru, Karnataka
Email: mirzawasi.2001@gmail.com)

--************************---------------------------------

Abstract:

Brain tumors are among the deadliest diseases affecting humans, often leading to rapid fatality if not identified and treated at an early stage. However, relying solely on visual examination can sometimes result in inaccuracies, and seeking expert assistance may be expensive or inaccessible. In this context, deep learning (DL) has emerged as a transformative approach for detecting tumors in medical images. This work proposes a modified DL-based model leveraging EfficientNet-B0, a variant of the EfficientNet (EN) family, to classify MRI scans as tumorous or non-tumorous. The model incorporates multiple deep layers and employs the Soft Max classifier for image classification. A substantial dataset of MRI images was utilized to train and evaluate the model, addressing a limitation in prior studies, which often used smaller datasets. Notably, few studies have explored the application of the EfficientNet architecture for brain tumor detection. Our model achieved a detection accuracy of 99.97%, with a precision of 91.63%, an F1-score of 86.94%, and a recall of 85.49%. These results indicate that our model outperforms previous EfficientNet-based approaches in terms of detection accuracy.

Keywords- EfficientNet, EfficientNet-B0, deep learning, CNN

--************************---------------------------------

I. INTRODUCTION

A tumor is a rounded growth that can develop under the skin in any part of the body. Among the various types, brain tumors (BT) are the most life-threatening, causing significant fatalities annually. BTs are categorized into benign and malignant types, with malignant tumors posing a higher risk due to their ability to spread and produce carcinogenic cells. In 2016, brain tumors were a leading cause of cancer-related deaths among children (ages 0-14) and the third most common cause among adolescents (ages 15-39) in the USA. Early detection is essential for effective treatment and reducing complications.

This study focuses on developing a deep learning (DL)- based model to detect brain tumors in MRI images. MRI scans, being more precise than CT scans for identifying tumors, often require expert interpretation, which may be unavailable in underserved areas. DL models, especially Convolutional Neural Networks (CNN), offer a powerful solution by learning from datasets to make accurate predictions. Transfer learning using pre-trained models like EfficientNet (EN) further enhances performance, addressing the limitation of insufficient training data. Our model demonstrated exceptional performance, achieving a detection accuracy of 99.97%, precision.

Leveraging the publicly available BD_Brain_Tumor dataset containing 20,000 CT images. Using data augmentation techniques (zooming, rotating, flipping) to enrich the dataset.Implementing pre-processing steps to crop and focus on the tumor's central region, reducing irrelevant data analysis.

II. LITERATURE SURVEY

1). Vikash K. Singh et al: Vendor Managed Inventory (VMI) is a replenishment strategy that allows vendors to respond directly to demand without the distortions caused by purchasing decisions. Traditional VMI implementations rely on EDIFACT reports in systems like SAP R/3, which are too expensive for SMEs at the lower end of the supply chain. To address this, a cost-effective framework using composite Web Services is proposed, enabling SMEs to implement VMI.

2). Utkarsha Mendhel et al:This study examines inventory management and customer satisfaction in the paper production industry using survey data from various management. Following this, stages two through eight include Model Architecture: The proposed model is built upon the EfficientNet-B0.

the highlights inefficiencies in inventory control and bill generation. A proposed system introduces alerts for stock updates and bill generation using PDF formats, helping shopkeepers track remaining items.

3). K. Ohmori et al: The paper describes an Internet-based accounting system with a three-tier structure (Web, 1 2 application, database) that enables on-the-spot transaction entry and data distribution. The system supports multi-user, multi-currency, and multi-language operations, offering functions such as inventory management, CRM, supply chain management, and performance analysis, critical for global businesses

.4). Friedrich Wiemer et al: Password authentication remains widely used but vulnerable to database attacks. To mitigate this, servers store password hashes generated by functions like PBKDF2, bcrypt, and scrypt. This study presents a high-speed bcrypt password search system with 40 parallel cores at 100 MHz, achieving 6,511 passwords/second and outperforming existing implementations by 42%.

5). Ravi Kishore Kodali et al: Manual attendance marking is time-consuming and prone to errors like proxies. While biometric systems have been used, they are vulnerable to spoofing. This study proposes a facial recognition-based attendance system using a deeply supervised network for accuracy in dynamic classroom settings. The solution, integrated with a web application, performs analytics on Amazon EC2, ensuring efficiency and reliability.

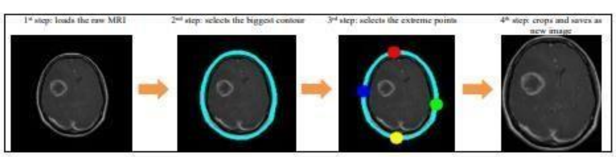
III. METHODOLOGY AND PROPOSED SOLUTION:

Proposed Model Overview: Our proposed model processes MRI images through multiple stages. First, input images undergo pre-processing, including resizing to 224x224 resolution and cropping to focus on the brain region. These images are then passed through EfficientNet-B0 (EN-B0) blocks for analysis via convolutional layers, with the final layer classifying them as tumorous or non-tumorous.

Data Source: The ―BD_Brain-Tumor‖ dataset from Kaggle, consisting of 20,000 images, was used. Images were split into training (13,547), testing (2,064), and validation (4,356) sets. Formats included jpg, png, and jpeg, with 34 blurry images excluded. All images were resized to 224x224 resolution for model compatibility. The dataset was further divided into 80% training and 20% testing data.

Data Resizing and Cropping: MRI images with varying resolutions were resized to 224x224. To optimize processing, pixels outside the brain's central region were removed by cropping the main contour, reducing computational complexity and irrelevant pixel analysis.

Data Augmentation: To enhance the dataset, augmentation techniques such as 10° rotation, 10x zoom, and width shifting were applied using Python libraries, increasing the model's robustness.



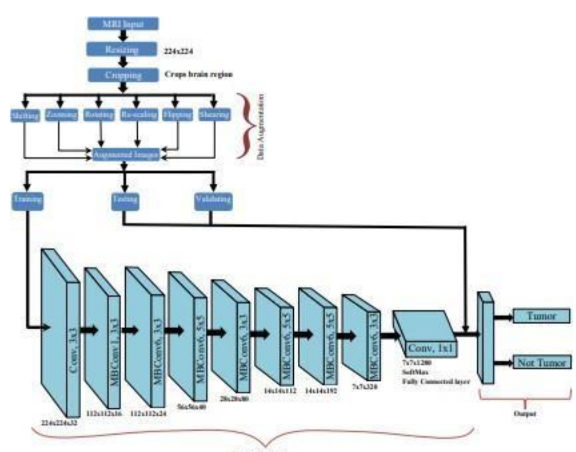
Deep Network: EfficientNet: Developed by Google Research in 2019, EfficientNet (EN) achieves better performance through compound scaling of depth, width, and resolution. EN-B0, the base version, utilizes convolutional layers and Mobile Inverted Bottleneck (MBConv) blocks, making it effective for transfer learning

Model Architecture: The proposed model is built upon the EfficientNet-B0 (EN-B0) architecture, consisting of a total of nine stages. The first stage features a convolutional layer with a kernel size of 3x3, designed to extract essential low-level features from the input MRI images. Following this, stages two through eight include seven Mobile Inverted Bottleneck (MBConv) blocks, which utilize 3x3 or 5x5 kernels. These blocks are specifically designed to balance depth, width, and resolution, ensuring efficient feature extraction and minimizing computational complexity.

The final stage of the model incorporates a combination of convolutional, pooling, and fully connected layers. The convolutional layers continue to refine feature maps, while the average pooling layer is employed to downsample the spatial dimensions and aggregate critical information. For classification, the SoftMax activation function is used in the final fully connected layer, enabling the model to output probabilities for the two categories: tumorous and nontumorous.

This design leverages the compound scaling capability of EfficientNet, which optimizes depth, width, and resolution scaling through the use of a compound coefficient. This approach enhances the model's performance and adaptability to the dataset. Extensive experimentation demonstrated that the proposed EN-B0-based model consistently outperforms other EfficientNet variants, achieving superior accuracy and reliability in classifying MRI images for brain tumor detection.

Furthermore, the EN-B0-based model's lightweight architecture ensures computational efficiency, making it highly suitable for deployment in real-time clinical environments and resource-constrained settings. Its ability to maintain a balance between accuracy and computational cost offers a scalable solution for brain tumor detection, addressing the growing need for advanced AI-driven diagnostic tools that can seamlessly adapt to diverse hardware configurations and healthcare applications. Additionally, the model's robustness in handling complex variations within MRI datasets, such as noise, intensity variations, and structural abnormalities, underscores its adaptability and generalization capabilities.



IV. RESULTS:

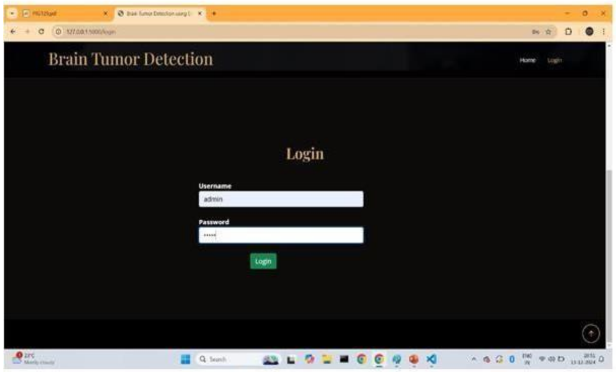


Fig 4.1 Login Page

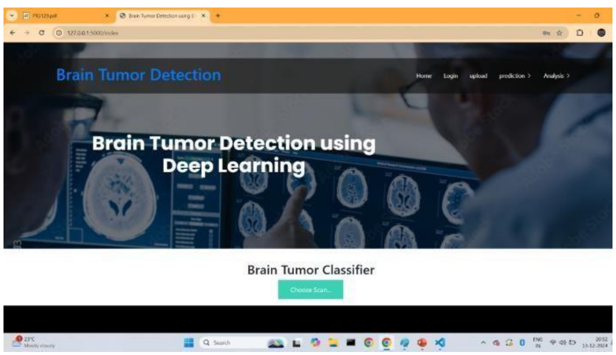


Fig 4.2 Dashboard Page

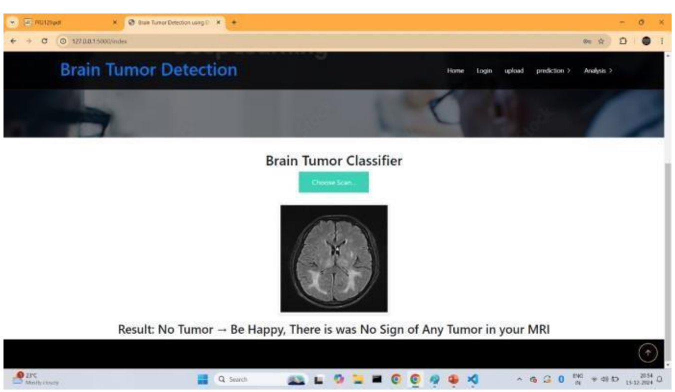


Fig 4.3 Result Page(1)

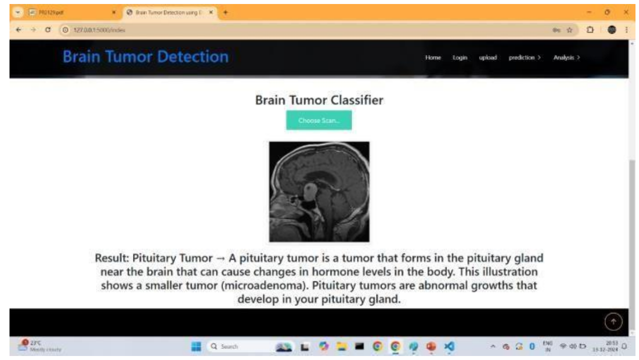


Fig 4.4 Result Page(2)

V. CONCLUSION

Numerous researchers have attempted to develop deep learning (DL) models to address brain tumor detection. While many of these models have utilized small datasets and achieved commendable accuracies, it is well-established that deep networks require substantial data to make accurate predictions. Moreover, a model's accuracy does not solely depend on its structural complexity. Efficient Net (EN) models have demonstrated that properly scaling the model's depth, width, and resolution is crucial for achieving superior performance. Despite its relatively simple design, EfficientNet's compound scaling approach optimizes these factors effectively, enhancing its predictive capability. In our study, we trained the proposed model over 50 epochs using the SoftMax activation function. The model achieved an accuracy of 99.97%, a precision of 91.63%, and an F1-score of 86.94%. These results highlight the efficiency and accuracy of our model compared to other similar approaches.

Our model was specifically designed to classify MRI images as either tumorous or non-tumorous. However, its ability to distinguish between different types of brain tumors—such as Meningioma, Glioma, Pituitary, Glioblastoma, and Sarcoma—remains unexplored. Future research could extend this work by adapting the proposed model for multi-class tumor detection.

Acknowledgment: I express my deepest gratitude to my creator for granting me the patience and ability to carry out this study. I also extend my sincere thanks to Professor Md. Abdur Rahman for his invaluable mentorship. Finally, I am profoundly grateful to my wife for her unwavering mental support and encouragement throughout this journey.

VI. FUTURE WORK

Focusing on Improved Model Architectures, particularly 3D Convolutional Neural Networks (3D-CNNs), stands out as a promising future direction for brain tumor detection using deep learning. 3D-CNNs can leverage the volumetric data from MRI and CT scans to better capture spatial relationships within brain structures, leading to more accurate tumor detection, segmentation, and characterization. By processing images in three dimensions rather than two, these models can provide more detailed insights into the size, shape, and location of tumors, which is crucial for accurate diagnosis and treatment planning.

An exciting and transformative direction for advancing brain tumor detection through deep learning is the adoption of enhanced model architectures, with 3D Convolutional Neural Networks (3D-CNNs) emerging as a particularly promising solution. Unlike traditional 2D models, 3D-CNNs are designed to fully exploit the rich volumetric data provided by MRI and CT scans, enabling a deeper understanding of complex spatial relationships within brain structures. By processing images in three dimensions, these models can achieve superior performance in tumor detection, segmentation, and characterization. This comprehensive approach allows for a more detailed analysis of key tumor attributes, such as size, shape, boundary irregularities, and precise spatial localization. As a result, 3D-CNNs offer immense potential for significantly enhancing diagnostic accuracy, improving treatment planning, and ultimately contributing to better clinical outcomes for patients with brain tumors.

VII. REFERENCES

[1] Mohammadi, F., & Rastgar-Jazi, M. (2017). Analytical and Experimental Solution for Heat Source Located Under Skin: Modeling Chest Tumor Detection in Male Subjects by Infrared Thermography. Journal of Medical and Biological Engineering, 38(2), 316–324.

[2] Rehman, A., Naz, S., Razzak, M. I., Akram, F., & Imran, M. (2019). A Deep Learning-Based Framework for Automatic Brain Tumors Classification Using Transfer Learning. Circuits, Systems, and Signal Processing.

[3] Varade, A. A., Ingle, K. S. (2017). Brain MRI Classification Using PNN and Segmentation Using K Means Clustering, International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 6(5), 6181–6188.

[4] N. Abiwinanda,M. Hanif, S.T. Hesaputra, A. Handayani, T.R.Mengko, Brain tumor classification using convolutional neural network. In World Congress on Medical Physics and Biomedical Engineering, pp. 183–189. Springer (2019)

[5] Song, Yadong, et al. "Association of GSTP1 Ile105Val Polymorphism with the Risk of Coronary Heart Disease: An Updated Meta-Analysis." PLoS One, vol. 16, no. 7, Public Library of Science, July 2021, p. e0254738.

[6] Cho, Kyunghyun, et al. "Learning phrase representations using RNN encoderdecoder for statistical machine translation." arXiv preprint arXiv:1406.1078 (2014).

[7] Sirichotedumrong, Warit, and Hitoshi Kiya. "A GAN- based image transformation scheme for privacy-preserving deep neural networks." 2020 28th European Signal Processing Conference (EUSIPCO). IEEE, 2021.

[8] Karlik, Bekir, and A. Vehbi Olgac. "Performance analysis of various activation functions in generalized MLP architectures of neural networks." International Journal of Artificial Intelligence and Expert Systems 1.4 (2011): 111-122.

[9] Schmah, Tanya, et al. "Generative versus discriminative training of RBMs for classification of fMRI images." NIPS. 2008.