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Alzheimers and Brain Tumor Detection Using Deep Learning

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Abstract: In several industries, such as manufacturing, construction, and the Accurate detection of brain tumors and Alzheimer's disease is essential for effective treatment and disease management. With the rapid progress in deep learning technologies, the field of medical imaging—particularly the interpretation of brain scans—has seen remarkable improvements. This research focuses on utilizing two well-established convolutional neural network (CNN) architectures, VGG-19 and ResNet-50, for brain tumor classification, while employing a standard CNN model for detecting Alzheimer's disease.

VGG-19, characterized by its consistent and deep structure comprising 19 layers, is particularly effective in extracting complex features due to its sequential convolutional layers. This makes it well-suited for identifying subtle patterns in MRI images of the brain. In contrast, ResNet-50 incorporates residual connections within its 50-layer design, allowing the model to mitigate issues like vanishing gradients and improving learning efficiency by enabling the network to focus on residual mappings. This study compares both models to evaluate their accuracy, resilience, and computational efficiency in detecting brain abnormalities.

Moreover, the research examines each model's ability to generalize across various datasets and tumor types, aiming to provide insights into their clinical applicability. The results may contribute to refining current diagnostic techniques, promoting earlier detection, and assisting in the development of advanced tools for accurate brain tumor diagnosis and treatment planning. Integrating these models into healthcare systems could improve diagnostic accuracy and enhance patient care outcomes. Alzheimer's disease, the most prevalent form of dementia, leads to progressive memory loss, impaired thinking, and behavioral changes. Its symptoms typically worsen over time, eventually hindering the ability to perform everyday tasks. Dementia is a broad term describing a range of symptoms caused by cognitive decline, with Alzheimer's accounting for 60% to 80% of all cases. Vascular dementia, often following a stroke, is the second most common type, though several other reversible conditions—like thyroid imbalances and vitamin deficiencies—can produce similar symptoms.In this study, we use publicly available datasets for Alzheimer's detection. The system employs deep learning models, particularly CNN and ResNet, to analyze the data. The outcomes demonstrate the model's ability to accurately classify the disease into categories such as mild, moderate, very moderate, and dementia, based on performance metrics like prediction accuracy.

Keywords: *Deep Learning, Convolutional Neural Networks (CNN), VGG-19, ResNet-50, Brain Tumor Detection, Alzheimer's Disease, Medical Image Analysis, MRI, Classification, Transfer Learning.*

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I. INTRODUCTION

Brain tumors represent a significant challenge in the field of neurology and oncology, with their early detection being crucial for effective treatment and improved patient outcomes. The brain, being a critical organ, is highly sensitive to any pathological changes, and tumors can disrupt essential functions, leading to a range of neurological symptoms. The complexity of brain tumor detection arises from the diverse types of tumors, their varied locations, and the subtlety of early-stage symptoms. Traditionally, brain tumor detection relies on imaging techniques such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT) scans, and positron emission tomography (PET) scans. However, these methods, while effective, often depend on the subjective interpretation of radiologists, which can be influenced by

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experience and training, leading to variability in diagnostic accuracy.

ALZHEIMER's disease (AD) is the leading cause of dementia and poses a significant social and economic challenge. It is responsible for more than half of all cases of dementia. Over 50 million individuals currently suffer from dementia worldwide with a projected increase to 152 million by 2050. No cure for AD has been discovered, but there is intense effort to develop new clinical interventions that may slow or halt the disease. Such interventions are aimed at early (including preclinical and prodromal) stages of the disease prior to extensive cell damage, when it is thought treatment is more likely to be effective. Alzheimer's disease and related dementias (ADRD) have become a major public health concern in the United States. An estimated 5.6 million Americans aged 65 and older (10% of the US population) were living with ADRD in 2019, and this number is expected to grow dramatically as the population continues to age. By 2025, the number of Americans aged 65 or older with ADRD is expected to reach 7.1 million, nearly a 27% increase from 2019, and by 2050, this population is projected to be 13.8 million, with the highest growth among those in ADRD's advanced stage. Persons with ADRD require progressively extensive assistance in their daily lives, the majority of which is provided by family members, friends, and other unpaid caregivers. It is estimated that in 2018, American caregivers of persons with ADRD provided 18.5 billion hours of informal unpaid assistance, valued at $233.9 billion. Family caregivers (hereafter "caregivers") of persons with ADRD are expected to make important care decisions for their family members with ADRD on a daily basis. However, these caregivers report being unprepared for their roles and responsibilities, uninformed about care options, and unsupported by professionals in their decision making.

➢ *Role of Deep Learning in Medical Imaging*

In recent years, the field of medical imaging has been revolutionized by the advent of deep learning technologies. Deep learning, a subset of artificial intelligence (AI), utilizes neural networks with multiple layers to learn and make predictions from complex data. Convolutional Neural Networks (CNNs) have emerged as a powerful tool in image analysis due to their ability to automatically learn spatial hierarchies of features from images. CNNs have demonstrated remarkable performance in various medical imaging tasks, including tumor detection, segmentation, and classification. These networks can enhance diagnostic accuracy by identifying patterns and anomalies that might be missed by the human eye, thus providing a valuable augmentation to traditional diagnostic methods.

VGG-19 and ResNet-50: Architectures and Applications Among the various CNN architectures developed, VGG-19 and ResNet-50 are prominent due to their innovative designs and effective performance in image classification tasks. VGG-19, introduced by the Visual Geometry Group (VGG) at the University of Oxford, is a deep CNN characterized by its uniform architecture of 19 layers. Its design is notable for using small convolutional filters (3x3) and pooling layers, which contribute to its capability to learn high-level features from images. The depth and simplicity of VGG-19 allow it to capture intricate details in brain MRI scans, making it a suitable candidate for tumor detection tasks.In contrast, ResNet-50, developed by Microsoft Research, introduces the concept of residual learning through the use of residual blocks. These blocks include shortcut connections that bypass one or more layers, mitigating the vanishing gradient problem and enabling the network to learn residual mappings. ResNet-50's architecture allows it to be significantly deeper (50 layers) while maintaining efficient training and performance. This architecture has proven to be highly effective in handling complex image classification tasks, making it a strong contender for brain tumor detection.

➢ *Motivation*

Early diagnosis of brain tumors and Alzheimer's disease remains a crucial yet challenging area in medical practice due to the significant impact these conditions have on patient health. Timely identification is essential for initiating effective treatment and improving long-term outcomes. While traditional diagnostic techniques such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans are widely used to detect neurological disorders, their effectiveness often hinges on the expertise and subjective judgment of radiologists. This reliance can lead to variations in diagnosis, especially in early stages where symptoms may be subtle or difficult to detect.

This study is driven by the need to improve the accuracy and reliability of diagnostic methods for brain tumors and Alzheimer's disease. It focuses on the use of deep learning—particularly convolutional neural networks (CNNs)—to enhance medical imaging analysis. CNNs have proven highly effective in tasks involving image recognition and classification, making them suitable candidates for use in the healthcare domain.

By applying CNNs, the research aims to establish a more consistent and automated diagnostic approach. These models are capable of identifying intricate features and patterns in brain scans that might not be easily noticed by the human eye. This can help reduce the dependency on manual interpretation and lower the chances of misdiagnosis or variability between radiologists' assessments.

Furthermore, incorporating CNNs into diagnostic workflows could enable earlier detection, even before noticeable symptoms arise. This early intervention can play a pivotal role in treatment planning and patient care. An automated system based on CNNs could also act as a supportive tool for radiologists, offering a reliable second opinion and enhancing confidence in clinical decisions.

II. LITERATURE SURVEY

[1]The article "Deep Learning Approaches for Brain Tumor Detection in MRI Images: A Comprehensive Survey" provides a thorough examination of various deep learning models applied to MRI-based brain tumor detection. It explores key architectures like VGGNet, ResNet,

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EfficientNet, and AlexNet, detailing their convolutional layers, residual blocks, and attention mechanisms. The paper emphasizes image preprocessing methods such as augmentation and normalization, as well as training optimizations like transfer learning. Performance metrics like accuracy, F1-score, and computational complexity are compared to highlight model efficiency in clinical tumor diagnosis.[2] The report explores non-invasive brain tumor detection using MRI images, employing deep learning (DL) and machine learning (ML) techniques. It uses a dataset of 3264 MRI images to classify three tumor types—glioma, meningioma, and pituitary tumors—along with healthy brains. Two models were developed: a 2D Convolutional Neural Network (CNN) and a convolutional autoencoder. The 2D CNN achieved a high training accuracy of 96.47%, outperforming the autoencoder (95.63%) and traditional ML methods like K-Nearest Neighbors (KNN), which had the highest accuracy among ML models at 86%. The study demonstrates the effectiveness of the 2D CNN, highlighting its potential use in clinical settings for accurate brain tumor detection.[3] The report "MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques" focuses on the use of deep learning (DL) and machine learning (ML) for non-invasive brain tumor detection using MRI images. The study utilizes a dataset of 3264 MRI images to classify glioma, meningioma, pituitary gland tumors, and healthy brains. Two DL models were developed: a 2D Convolutional Neural Network (CNN) and a convolutional autoencoder. The 2D CNN, comprising eight convolutional and four pooling layers, achieved a training accuracy of 96.47% and a validation accuracy of 93.44%. The autoencoder also performed well with a training accuracy of 95.63% and validation accuracy of 90.93%. Both models demonstrated high recall rates and ROC curves close to 1, making them reliable for brain tumor detection.[4] Robust brain tumor classification by fusion of deep learning and channel-wise attention mode approach. The report focuses on improving brain tumor classification using deep learning, specifically the ResNet101 model combined with a Channel-wise Attention Mechanism (CWAM). This approach aims to enhance the accuracy and efficiency of diagnosing brain tumors from MRI scans, traditionally reliant on radiologists. The ResNet101-CWAM model was trained using preprocessed MRI data and achieved an impressive accuracy of 99.83%, outperforming existing methods. The attention mechanism allowed the model to focus on key features, improving classification. The study suggests integrating this model into clinical software for better decision-making in treatment planning. While the results are promising, the authors highlight the need for optimizing the model's computational complexity and recommend further research on diverse datasets to improve the system further.[5] Deep Learning in Medical Image Classification from MRI-based Brain Tumor Images. The paper investigates brain tumor classification using MRI images with four pre-trained models. MobileNetV2, ResNet-18, EfficientNet-B0, and VGG16—and introduces MobileNet-BT. This new model, built on MobileNetV2, achieved a remarkable 99.24% accuracy and F1-score, surpassing the other models in efficiency and performance. The research emphasizes how fine-tuning pre-trained models, specifically for medical imaging, can significantly improve diagnostic accuracy. MobileNet-BT's fast convergence and superior accuracy make it ideal for enhancing brain tumor diagnosis, offering a substantial improvement in clinical applications.[6] Deep Learning Approaches for Brain Tumor Detection in MRI Images: A Comprehensive Survey. The article "Deep Learning Approaches for Brain Tumor Detection in MRI Images: A Comprehensive Survey" provides a thorough examination of various deep learning models applied to MRI-based brain tumor detection. It explores key architectures like VGGNet, ResNet, EfficientNet, and AlexNet, detailing their convolutional layers, residual blocks, and attention mechanisms. The paper emphasizes image preprocessing methods such as augmentation and normalization, as well as training optimizations like transfer learning. Performance metrics like accuracy, F1-score, and computational complexity are compared to highlight model efficiency in clinical tumor diagnosis.[7] This paper discusses the application of deep learning architectures in healthcare diagnostics, focusing on disease detection from medical images such as X-rays, MRIs, and CT scans. The authors evaluate various models, including CNNs (Convolutional Neural Networks) and their derivatives like VGG-19 and ResNet-50, to determine their accuracy in diagnosing diseases such as cancer and cardiovascular issues. The research highlights improvements in prediction accuracy and discusses the potential of AI to revolutionize early-stage disease detection.[8] The paper investigates AI applications in cybersecurity, emphasizing the importance of machine learning and deep learning techniques to enhance the detection of cyber threats. By using anomaly detection methods and network traffic analysis, the authors present models capable of identifying patterns associated with malware, phishing, and DDoS attacks. They also explore the challenges in creating systems that can adapt to evolving cyber threats and discuss how AI can help automate threat detection with higher precision and efficiency than traditional systems.[9] This research focuses on the integration of AI into supply chain management, particularly in predictive modeling to forecast demand, optimize inventory, and mitigate risks such as delays and stock shortages. The authors analyze various AI-based algorithms like Random Forest, Decision Trees, and neural networks to improve the accuracy of supply chain forecasting and decision-making processes. They highlight how AI can help companies enhance their operational efficiency and adapt to changes in global supply chains, especially during disruptions such as those caused by the COVID-19 pandemic.[10] This article presents a novel solution for detecting Alzheimer's disease and brain tumors using machine learning (ML) and Convolutional Neural Networks (CNNs). It highlights the critical need for early diagnosis due to the increasing prevalence of these neurological disorders. The proposed approach integrates multi-modal data fusion (e.g., combining MRI, PET, and CT scans with clinical information such as patient demographics and genetic markers) to enhance diagnostic accuracy. Key techniques include the use of advanced CNN architectures like ResNet and DenseNet to improve feature extraction from medical images, attention mechanisms for prioritizing key features, and transfer learning to overcome limited medical datasets. The article emphasizes the potential of combining

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CNNs with Recurrent Neural Networks (RNNs) for temporal modeling, allowing for the prediction of disease progression. The framework aims for clinical applicability by improving the robustness and accuracy of automated diagnosis.[11] This paper provides a comprehensive overview of brain tumor detection and classification using computational intelligence techniques. It reviews existing methods, focusing on challenges like tumor variability in position, structure, and size. The study covers a wide range of techniques, including traditional image processing and machine learning methods, such as Leksell Gamma Knife and Radioactive beams, as well as more recent advances in deep learning (DL) and transfer learning (TL). Notable DL models discussed include 3D CNNs, DenseNet, and Mask-RNNs, which are applied for the segmentation and classification of brain tumors. The paper highlights that MRI is the primary imaging modality used for brain tumor detection and discusses the performance of various models on standard datasets, like BRATS. The use of pre-processing, feature extraction, and machine learning classifiers is covered in detail, with suggestions for future research on improving accuracy through hybrid models and advanced pre-processing techniques.[12] This article explores brain tumor and Alzheimer’s detection using deep learning models, focusing on the classification of brain tumors and the early detection of Alzheimer’s disease. The authors developed an Alzheimer’s detection model that classifies patients based on three levels of severity (very mild, mild, moderate dementia), and a brain tumor detection model that classifies three types of tumors: meningioma, pituitary, and glioma. Using MRI scans and CNN architectures, the Alzheimer’s model achieved an accuracy of 98.37%, while the brain tumor detection model reached 97.16% accuracy. The article also emphasizes segmentation techniques for localizing tumors in brain MRIs. The study concludes that deep learning models are highly effective for both detection and classification tasks, and highlights the potential for these models to be further optimized for real-time medical diagnosis applications.[13] This paper focuses on the use of AI and machine learning for improving natural language processing (NLP) tasks. The authors explore advanced NLP techniques such as BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer) for applications in text generation, sentiment analysis, and language translation. They examine the effectiveness of these models in handling large datasets, improving human-computer interaction, and developing more accurate, context-aware systems for real-world applications like chatbots and virtual assistants.[14] This research explores the integration of AI in healthcare, particularly in predicting disease outbreaks using AI-driven predictive analytics. The authors investigate how data from healthcare systems, combined with environmental and social factors, can be leveraged to build models that predict the spread of infectious diseases like COVID-19 and influenza. The paper also discusses the role of AI in resource allocation during outbreaks, highlighting the importance of real-time decision-making in managing healthcare resources and reducing the spread of diseases.[15] The paper analyzes the application of AI in the field of agriculture, specifically in precision farming. The authors discuss how AI technologies, such as machine learning models and IoT (Internet of Things) sensors, can be used to optimize crop production, monitor soil health, and reduce water usage. They highlight the potential of AI to enhance decision-making in agriculture, enabling farmers to use data-driven insights for improving yield, managing pests, and minimizing environmental impact. The paper also touches on the challenges of AI adoption in rural areas due to infrastructure limitations.

III. PROBLEM STATEMENT

The project seeks to tackle the challenges of early and accurate detection of brain tumors and Alzheimer's disease by leveraging deep learning models, including VGG-19, ResNet-50, and 2D CNN architectures, to automate MRI scan analysis, improve diagnostic precision, and overcome limitations such as manual interpretation errors and vanishing gradients in neural networks. By utilizing transfer learning techniques, the pre-trained models can effectively adapt to medical imaging tasks, reducing the need for large amounts of labeled data and enabling faster convergence. The integration of advanced image preprocessing techniques, such as gray-level co-occurrence matrix (GLCM) for texture analysis and feature extraction, ensures that the models can capture both global and local features essential for distinguishing between normal and pathological brain conditions.

IV. METHODOLOGY

➢ *Dataset Collection*

MRI images of brain tumors and Alzheimer’s disease were sourced from publicly available repositories such as Kaggle and other medical imaging databases. The datasets were selected to ensure diversity in terms of tumor types, stages, and patient demographics, providing a reliable foundation for model training and evaluation.

➢ *Image Preprocessing*

Preprocessing steps included resizing the images to a uniform resolution (e.g., 300x300 pixels) and converting them to grayscale to simplify the data and reduce computational load. Image normalization was also applied to standardize the pixel intensity distribution, thereby enhancing feature detection during model training.

- *Image Resizing:*

All input MRI and CT scan images were resized to a fixed resolution of 300x300 pixels. This standardization ensures that the convolutional neural networks (VGG-19, ResNet-50, and CNN) can process the data in batches without dimensional inconsistencies.

- *Grayscale Conversion:*

Since color information is not essential for identifying brain abnormalities, RGB images were converted to grayscale. This reduces the number of input channels from three to one, significantly decreasing memory usage and processing time, while preserving critical structural details necessary for diagnosis.

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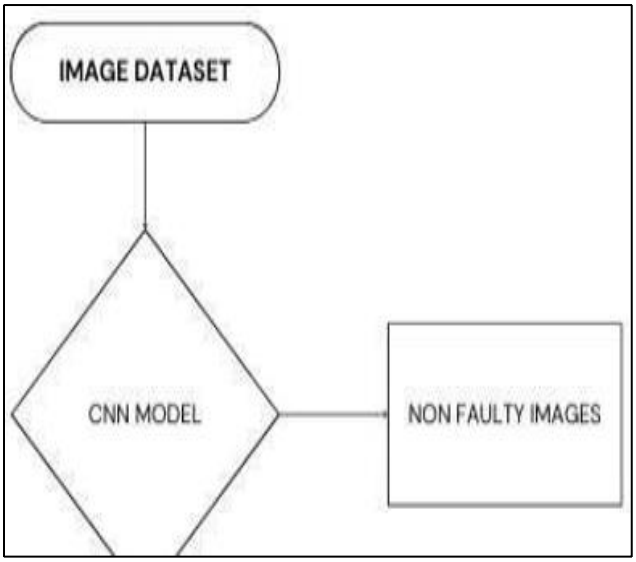

Fig 1 Workflow Diagram

➢ *Feature Extraction*

Both statistical and textural features were extracted from the preprocessed images. Techniques such as mean, median, variance, and Gray-Level Co-occurrence Matrix (GLCM) were employed to derive meaningful insights. GLCM features like contrast, correlation, energy, entropy, and homogeneity helped capture spatial texture relationships, essential for distinguishing healthy and abnormal brain regions.

In addition to GLCM, histogram-based features were analyzed to understand pixel intensity distribution, which assists in identifying abnormalities in grayscale values. Edge detection filters were also utilized to highlight boundaries of tumor-affected areas. These extracted features were then flattened into a numerical vector format suitable for feeding into the neural network models. The combination of both global statistical and local texture-based features ensured robust input representation for accurate classification and prediction.

➢ *Model Development*

To achieve accurate classification of brain tumors and Alzheimer’s disease, this study implemented three deep learning models—VGG-19, ResNet-50, and a custom-designed Convolutional Neural Network (CNN). Each model was carefully chosen or developed to exploit its strengths in medical image analysis.

VGG-19, known for its deep and uniform architecture with 19 weight layers, was employed due to its effectiveness in capturing intricate spatial hierarchies within MRI images. The use of small 3x3 convolution filters in successive layers allowed the model to focus on fine-grained features, making it particularly effective for detecting subtle anomalies in brain tissue.

ResNet-50, a 50-layer deep residual network, introduced the concept of skip connections or residual blocks, which help the network learn identity mappings. This approach effectively mitigates the vanishing gradient problem during backpropagation, thus enabling deeper networks to train efficiently without degradation in performance. ResNet-50 is especially useful for handling complex datasets with a wide variety of tumor and tissue textures.

A custom CNN model was also designed and optimized specifically for Alzheimer’s detection. This model included multiple convolutional and pooling layers followed by dense layers, using ReLU activations and softmax for final classification. While less deep than the VGG-19 and ResNet-50 models, it offered flexibility and computational efficiency for the Alzheimer's-specific dataset.

All models were trained using transfer learning, where pretrained weights from large datasets like ImageNet were adapted to the medical imaging task. Fine-tuning of upper layers was performed to tailor the models to domain-specific features, ensuring improved accuracy even with limited labeled data.

The dataset was divided into training (70%) and testing (30%) subsets using a stratified approach to preserve class distribution. The models were compiled using categorical cross-entropy as the loss function and optimized using the Adam optimizer with learning rate scheduling and dropout for regularization. Training was conducted over multiple epochs with batch normalization to stabilize and accelerate convergence.

Performance metrics such as accuracy, precision, recall, and F1-score were tracked during training, and early stopping was used to prevent overfitting. This multi-model strategy allowed for comparative analysis and identification of the most suitable architecture for medical diagnosis.

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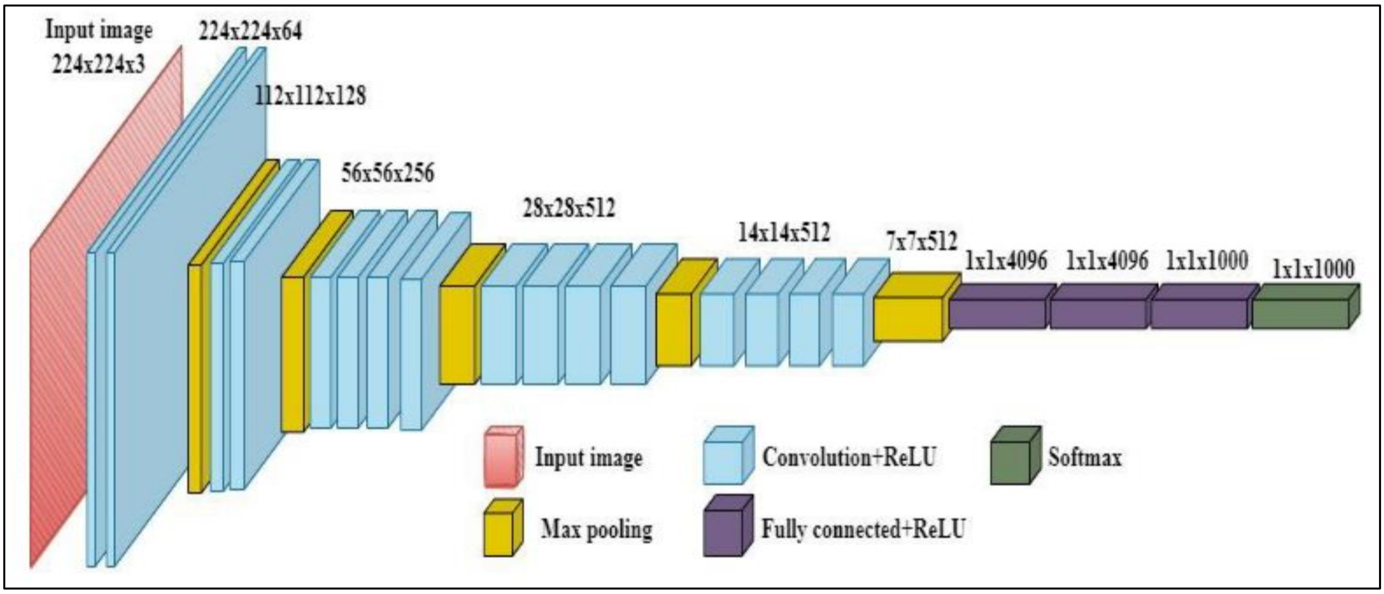

Fig 2 VGG -19

VGG-19 is a deep convolutional neural network consisting of 19 weight layers, primarily using small 3x3 convolution filters and 2x2 max-pooling layers. Its architecture follows a very uniform and simple structure, making it easier to implement and tune. The model extracts hierarchical features from images, starting from edges in the initial layers to complex patterns in deeper layers. It is widely known for its ability to handle large-scale image classification tasks. VGG-19 is effective in recognizing subtle variations in MRI scans due to its depth and fine-grained feature extraction. Despite its high accuracy, it requires significant computational resources due to the large number of parameters.

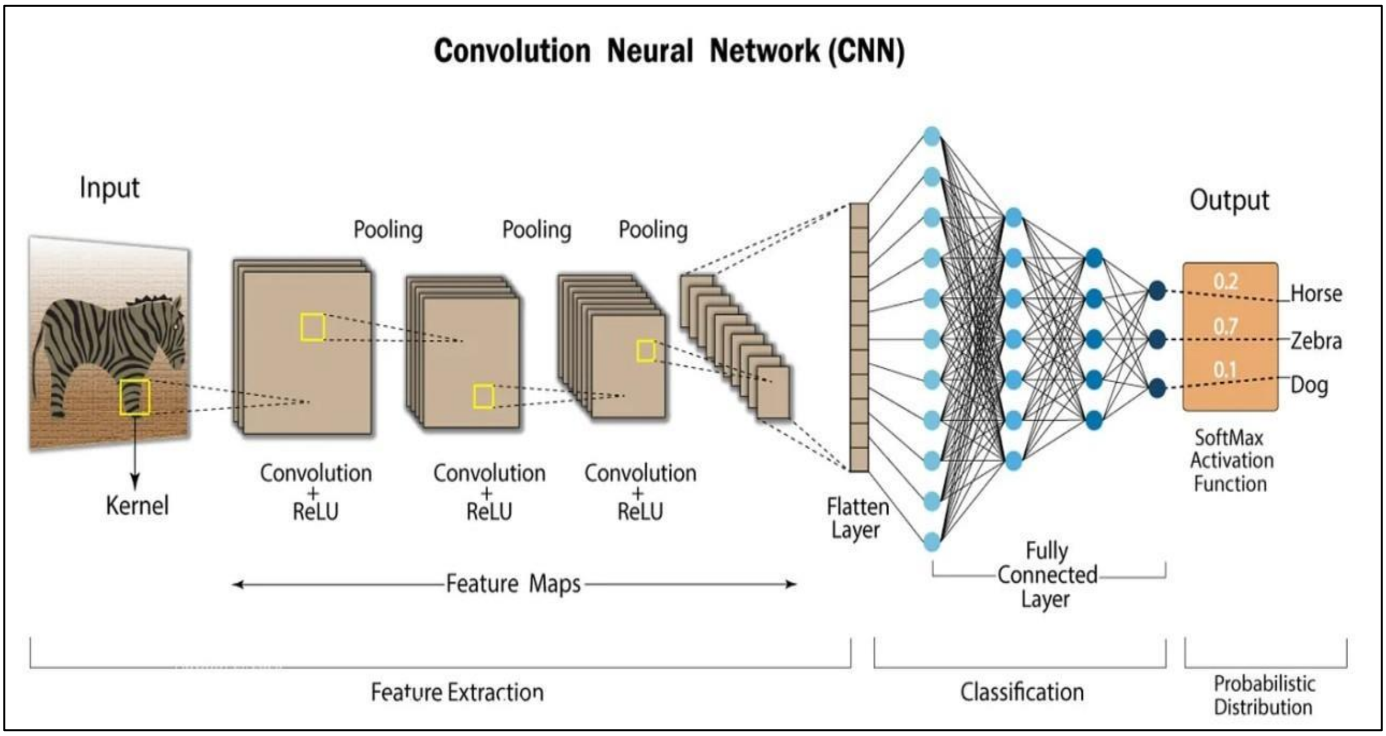

Fig 3 Convolutional Neural Network (CNN)

CNN is a class of deep learning models designed specifically for analyzing visual data. It processes input images through multiple layers of convolution, activation (usually ReLU), and pooling, which help in detecting features such as edges, textures, and shapes. These features are then passed through fully connected layers to perform classification. CNNs automatically learn to extract relevant spatial information from raw images without manual feature engineering. They are widely used in medical image analysis due to their high accuracy and adaptability. By stacking layers, CNNs can learn increasingly complex patterns to distinguish between healthy and diseased tissues.

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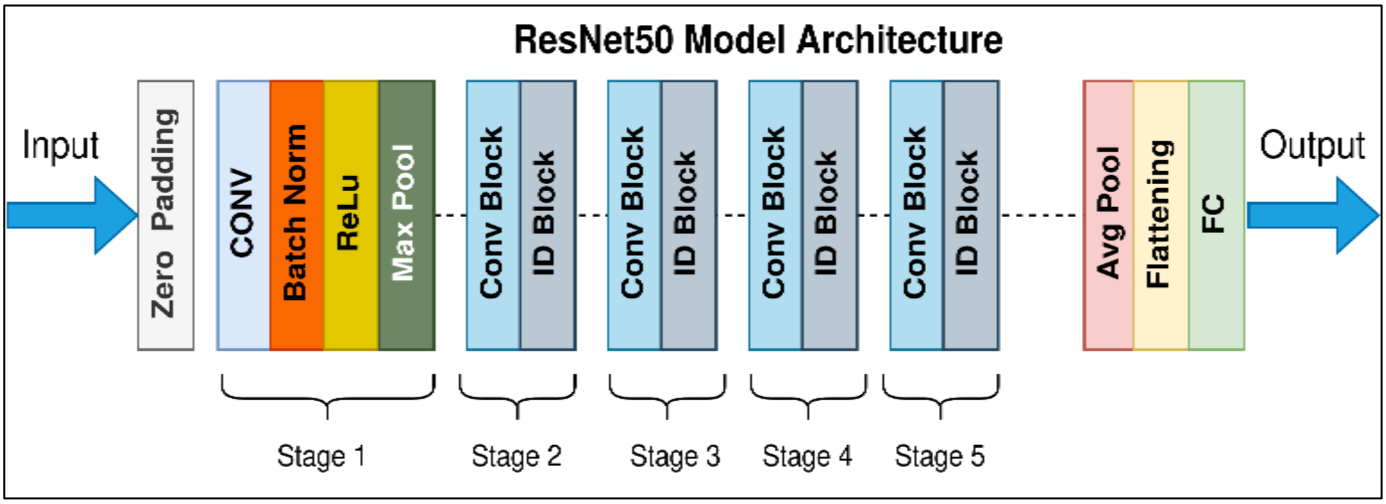

Fig 4 ResNet50 Model Architecture

ResNet-50 is a 50-layer deep neural network that incorporates residual blocks, allowing it to train much deeper architectures without performance degradation. The key innovation in ResNet is the use of shortcut or skip connections that pass the input of a layer directly to a deeper layer, helping to maintain gradient flow during backpropagation. This architecture addresses the vanishing gradient problem commonly seen in very deep networks. ResNet-50 is highly effective in complex image recognition tasks, offering improved accuracy and faster convergence. In medical imaging, it is particularly useful for identifying detailed patterns in high-resolution scans and handling diverse datasets.

V. CLASSIFICATION AND PREDICTION

After the deep learning models (VGG-19, ResNet-50, and a custom CNN) were effectively trained using the preprocessed and labeled medical images, the next important phase involved classifying new and unseen MRI scans. The main objective was to determine whether a brain MRI indicated the presence of a tumor or Alzheimer's disease and, if applicable, accurately classify the type or stage of the condition.

For brain tumor detection, the models were trained to distinguish between normal brain scans and those exhibiting tumor-affected areas. In more complex cases, the models were capable of further classifying different tumor types, such as glioma, meningioma, and pituitary tumors, depending on the dataset that was used. Similarly, for Alzheimer's disease detection, the models categorized brain images into various stages, including mild cognitive impairment, moderate Alzheimer's, severe Alzheimer's, and full dementia, allowing for more precise clinical insights.

To achieve this, each model's final output layer was constructed to perform multi-class classification through the use of the softmax activation function. Softmax transforms the model's raw output scores into a probability distribution across all possible categories. This approach allowed the model to predict the most likely class by selecting the label with the highest probability, offering a clear and confident final decision for each input image.

During the classification process, the input image passed through the network's layers where important features were automatically extracted. Convolution and pooling operations helped in reducing the image's dimensionality while preserving crucial information needed for accurate recognition. After feature extraction, the information was aggregated through fully connected layers, preparing the data for final classification. The softmax layer then generated the probabilities for each possible class, and the model selected the class with the maximum probability as the final output.

In the case of Alzheimer's detection, the system not only identified the presence of the disease but also assessed the severity of its progression. By analyzing structural brain changes, such as hippocampal shrinkage and cortical atrophy, the models could classify patients into different stages of the disease. This detailed classification was critical in helping healthcare professionals provide early diagnosis and plan effective treatment strategies tailored to each patient's condition.

After obtaining predictions, the model outputs were compared with the ground truth labels from the test dataset. To evaluate the performance and reliability of the classification results, metrics such as accuracy, precision, recall, and F1-score were calculated. Accuracy measured the overall percentage of correct predictions, while precision assessed how many of the positive predictions were actually correct. Recall determined the model's ability to detect all actual positive cases, and the F1-score provided a balanced evaluation by combining both precision and recall. Together, these performance indicators offered a comprehensive understanding of how well the models could classify brain tumors and Alzheimer's disease, highlighting their potential to support clinical decision-making and early intervention.

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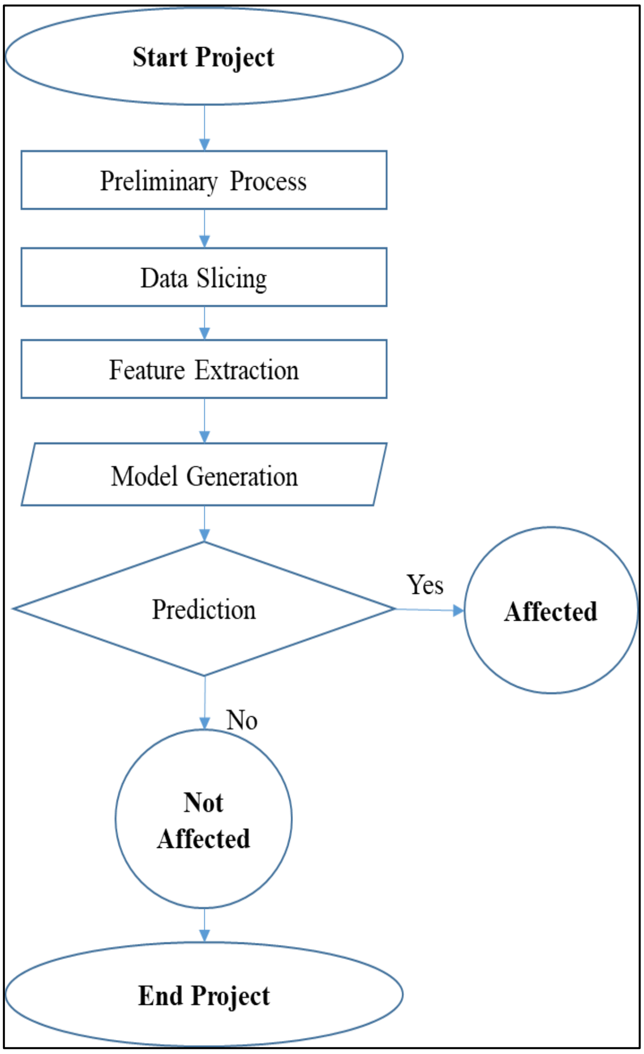

Fig 5 Flowchart of Model Generation

VI. CONCLUSION

In this study, deep learning models such as VGG-19, ResNet-50, and a custom-designed Convolutional Neural Network were successfully implemented for the classification and prediction of brain tumors and Alzheimer's disease using MRI images. The research demonstrated that these models could effectively distinguish between healthy brain scans and those exhibiting pathological changes, and could further classify tumors and Alzheimer's stages with a high degree of accuracy. The application of the softmax activation function in the final layer enabled multi-class classification, allowing the models to deliver reliable probability-based predictions.

The findings emphasized the effectiveness of deep learning architectures in extracting intricate features from complex medical images, outperforming traditional diagnostic methods that rely heavily on manual interpretation. Particularly, the VGG-19 model exhibited strength in capturing detailed spatial hierarchies, while the ResNet-50 model proved robust in training efficiency due to its residual learning technique. The custom CNN model tailored for Alzheimer's detection also provided efficient and accurate classification despite being less computationally intensive.

Performance evaluation metrics such as accuracy, precision, recall, and F1-score indicated that the proposed models maintained a strong balance between correctly identifying positive cases and minimizing misclassifications. These results support the notion that deep learning can significantly enhance early detection and diagnosis of neurological disorders, leading to better treatment planning and improved patient outcomes.

Moreover, the successful classification of Alzheimer's stages based on subtle brain structure changes highlights the potential for deep learning to assist in preclinical diagnosis, which is critical for managing progressive conditions. Integrating such automated systems into clinical workflows could serve as a valuable decision-support tool for healthcare professionals, reducing diagnostic variability and aiding in early interventions.

Overall, the research validates the potential of deep learning in revolutionizing medical imaging analysis. Future work could focus on expanding the models to handle larger, more diverse datasets, applying real-time processing techniques, and refining the architectures to further enhance clinical applicability and scalability across different healthcare environments.

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