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Enhancing Alzheimer's disease Classification from MRI Scans Using Deep Learning techniques

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***Abstract*:**

Identifying Alzheimer's disease early is crucial in order to slow the trajectory of cognitive decline and enhance the quality of life for those living with the condition. While brain MRI scans provide valuable structural information that may ultimately enable earlier identification, emerging and widespread artificial intelligence techniques can further enhance this process. In this study, we describe a deep-learning framework for the situated and semi-automated classification of brain MRI scans into four cognitive health levels: non-demented, very mild dementia, mild dementia, and moderate dementia. The framework is based on the EfficientNet-B3 architecture and has demonstrated the ability to reliably distinguish subtle features associated with neurodegenerative progression in brain structure. The model was trained on a large dataset of brain MRI images and achieved a validation accuracy of 99.4%, maintaining generally high precision and F1-scores across all classes. These findings suggest that the proposed method may provide a reliable approach for determining cognitive health levels and could help clinicians prioritize earlier clinical decision-making. Overall, this study demonstrates the potential of lightweight deep-learning models as validated and effective automated methods for identifying Alzheimer's disease and may represent an important next step in enhancing diagnostic screening and clinical decision-making within health systems.

***Keywords*: Alzheimer's Disease Classification, EfficientNET-B3, Medical Image Analysis, Deep Learning, OASIS-3, MRI Images.**

1. Introduction

Alzheimer's disease is the most common form of dementia, and early diagnosis is crucial for slowing cognitive decline and improving patient outcomes. Traditional diagnostic approaches rely primarily on clinical evaluations, yet emerging evidence suggests that combining neuroimaging—particularly resting-state fMRI—with deep learning can greatly enhance diagnostic accuracy by enabling automated pattern recognition and image denoising [1]. Recent research has therefore increasingly focused on leveraging MRI data and advanced learning models to support early and non-invasive detection of Alzheimer's disease. A variety of deep-learning approaches have been proposed in the literature. Several studies have applied Convolutional Neural Networks (CNNs) to classify two-dimensional MRI scans into different dementia stages, demonstrating promising performance on datasets such as OASIS [2]. Other research introduced GAN-based augmentation techniques, such as the D-BAC method, which improved classification of early Mild Cognitive Impairment (MCI) using VGG-16 and VGG-19 architectures, achieving higher accuracy and providing model explain ability through Grad-CAM visualizations [3]. Cross-modal transfer learning approaches have also been explored, using MRI-pretrained models to enhance classification on DTI data and improving multi-class differentiation across AD, MCI, and healthy controls [4]. Additional works have evaluated CNN-based models trained on OASIS-3 data, reporting an accuracy of 83.3% and outperforming traditional classifiers such as SVM and logistic regression [5]. Hybrid models combining CNNs and Capsule Networks (CapNets) have further improved feature extraction and computational efficiency, achieving classification accuracies over 92% on OASIS [6]. Attention-based strategies, such as spatial attention mechanisms applied to MRI scans, have yielded even higher performance, reaching validation accuracies of 99.69% with perfect sensitivity and specificity [7]. Other studies have explored traditional machine-learning approaches, such as Random Forest applied to MRI and cognitive features to predict Alzheimer's stages with strong interpretability

[8], while research in related domains has shown that multi-resolution segmentation and Random Forest classifiers can enhance feature discrimination beyond conventional SVM baselines [9].

While these studies demonstrate significant progress, many existing approaches remain computationally intensive or sensitive to class imbalance and variations in MRI acquisition. These limitations highlight the need for lightweight yet highly accurate deep-learning models that can generalize well across diverse MRI slices. EfficientNet-B3 offers such an advantage by providing balanced scaling of depth, width, and resolution while maintaining strong performance with fewer parameters.

The present study evaluates the performance of EfficientNet-B3 on the OASIS dataset for Alzheimer's stage classification. The objective is to demonstrate that this model can deliver high-quality predictions and achieve strong accuracy on previously unseen MRI data, supporting its potential as an efficient, scalable diagnostic tool for early Alzheimer's detection.

2. Related Work

In this section, we will review previous studies related to Alzheimer's. The detecting Alzheimer's disease (AD) early is fundamentally important. The goal of this study was to explore the OASIS and MRI data sets using convolution neural networks (CNNs) model (AlexNet, ResNet-50) and hybrid deep learning - machine learning models (AlexNet + SVM, ResNet-50 + SVM). Data preparation included balancing the data set, replacing missing values, and dimensionality reduction with t-SNE. Models performed comparably well, with Random Forest achieving 94% accuracy on OASIS data sets. In MRI data, hybrid models outperformed pure CNN models, with AlexNet + SVM achieving 94.8% accuracy and SVM models demonstrating relatively high sensitivity, specificity, and AUC [10]. Alzheimer's disease (AD), the most prevalent type of dementia, raises psychological, social, and economic considerations. This research investigates a CNN-aware model to detect AD from MRI scans, the method was enhanced with transfer learning and data generated from a GAN in hopes of raising detection accuracy. Evaluation of these methods have been conducted through three different OASIS datasets and compared to existing methods. The results of this study showed an increase detection accuracy of up to 40.1% higher than existing methods [11]. The early detection of Alzheimer's disease (AD) is important, while the use of deep learning CNN models can struggle to capture spatial and scale-invariant features. Therefore, this study developed an improved spatial attention block (I-SAB) paired with a depth-separable CNN backbone to enhance feature extraction. The model achieved an accuracy of 99.75% on OASIS, 96.20% on AD-Dataset, and 83.25% in domain adaptation tests [12]. This study provides an ROI-guided 3D ResNet with CBAM to detect Alzheimer's, while reducing the computational costs and the time needed to train the models. The model is able to achieve accuracies denoting: AD, MCI, and cognitively normal with <98.6% with OASIS and 93.33-92% with ADNI for identified targeted ROIs, indicating that targeting salient brain regions improved detection performance [13].we present a computer-assisted diagnosis tool for Alzheimer's disease based on ML models in OASIS and ADNI neuroimaging datasets. The performance using SVM, FFNN, and ViT classifiers with feature extraction and data augmentation achieved respectable accuracy, finding ViT classifiers to be most successful with sufficient amounts of data available. The results in this study offer evidence that ML models can provide assistance in early detection of AD and help clinicians treat patients early [14]. In this research, we propose a novel deep learning methodology for use in a Magnetic Resonance Imaging (MRI)-based Alzheimer's diagnosis task with the use of the OASIS dataset for validation. The approach achieved balanced accuracies of 0.93 for detection and 0.88 for disease staging, surpassing benchmark accuracies of prior approaches. Overall, the outcomes support that deep learning tools can provide a substantive and robust solution for automating Alzheimer's disease detection and diagnosis [15]. This research presents a CNN-based method for early detection and staging of Alzheimer's disease with 3D MRI images. The expressed method classifies brain scans into dementia stages (ND, VMD, MD, MoD) based on the ADNet architecture. The method exhibits a promising accuracy of 99.94%, demonstrating a reliable and affordable alternative to physician-based diagnostics [16]. This research enhances the detection of Alzheimer's disease through hybrid techniques that integrate modified deep learning models with other supervised machine learning methods using MRI data. Of the methods under evaluation, the hybrid of AlexNet-M + SVM, exhibited the highest performance among all the tested methods, accuracy, and specificity: 91.41% overall accuracy, and 100% specificity. The results of this study demonstrate the utility of hybrid models advancing the effectiveness of computer-aided diagnosis of AD [17]. In this work, we present a transfer learning model based on a modified

VGG-16 model to classify Alzheimer's disease on the OASIS MRI dataset. After fine-tuning the model while keeping the initial layers frozen, we obtained accuracy of 94.4%, precision of 90%, recall of 99.9%, and F1 score of 95%. These results confirm the effectiveness of VGG-16—based transfer learning for the early detection of AD [18]. This research implements supervised machine learning to develop and assess predictive models for early Alzheimer's disease detection, also known as preclinical Alzheimer's. The OASIS dataset was used to test several classifiers and the best performance was achieved with Naïve Bayes which yielded accuracy of 97.5%, the best accuracy of the classifiers selected. The results suggest that supervised machine learning could be an effective tool for early diagnosis and treatment of Alzheimer's disease [19]. This research introduced a 12-layer convolutional neural network (CNN) for binary classification of Alzheimer's disease (AD) using brain MRI images sourced from the OASIS dataset. The CNN model produced an accuracy of 97.75%, which is noted to exceed results produced by several pre-trained CNNs (InceptionV3, Xception, MobilenetV2, and VGG). The results of the research support the ability of the suggested CNN to demonstrate stronger results in detecting AD as compared to pre-trained CNN models [20]. This study utilized a federated learning method for the detection of Alzheimer's disease, utilizing MRI images found in OASIS and ADNI datasets, and addressing issues of data availability and patient privacy. MobileNet achieved the highest accuracy of 95.24% for OASIS, 81.94% for ADNI, and 83.97% accuracy for the merged testing data sets when compared to conventional methods. The federated learning model only shares model weights which helps protect patient privacy, while simultaneously improving robustness and sensitivity [21]. Alzheimer's disease, the leading cause of dementia, causes significant impairments in memory, cognitive capabilities, and brain function. Although the disease can be diagnosed using biomarkers based on neuroimaging devices, the majority of patients do not undergo this procedure. In this study, a CNN model using preprocessing techniques with structural MRI images trained on training and validation datasets achieved accuracy of nearly 80% for diagnosing Alzheimer's disease and mild cognitive impairment. The data suggest that the CNN model has the potential to be a useful diagnostic tool [23]. Alzheimer's disease is a progressive form of dementia and there is no current treatment available for the condition, so being able to diagnose early is necessary. This study employs an Enhanced Deep Recurrent Neural Network with feature selection on DNA methylation data in order to classify patients with AD and performed better than any models that employed CNN, RNN and DRNN [24]. The research establishes a novel deep learning process for the early assessment of Alzheimer's detection with MRI images that compares five models with and without data augmentation. The CNN-LSTM model achieved the highest accuracy of 99.92%, and has a strong promise within the potential of future DL-based AD diagnoses [25]. In this research, a model called VGG-TSwinformer is developed as an approach combining CNN and Transformer methods to perform short-term longitudinal analyses of MCI (Mild Cognitive Impairment) using sMRI (structural Magnetic Resonance Imaging) images. The VGG-TSwinformer model showed accuracy of 77.2% and 0.8153 AUC, which outperformed the other cross-sectional approaches and the proposed longitudinal approach will help facilitate early detection of individuals who are progressing towards Alzheimer's disease [26].

3. Methodology

In this section, we describe the methodology used in this study. The model was EfficientNet-B3, which we trained using the OASIS dataset to perform Alzheimer's disease detection. We outline the training methods, data preparation, and optimization procedures included in the modeling framework, emphasizing the great predictive performance and validation accuracy achieved with this model architecture. We also explain the reasons for selecting EfficientNet-B3 and describe the assessment metrics used to evaluate model performance in order to establish a broad understanding of the methodological framework.

3.1 Dataset

In this research, we utilized the OASIS MRI dataset (Marcus et al., 2007), accessed through the Kaggle platform, which provides approximately 80,000 preprocessed brain MRI images. In the Kaggle version of the dataset, the original 3D MRI scans were already converted by the dataset creators into 2D slices by extracting axial slices between positions 100 and 160 for each subject. These slices were formatted into .jpg images and organized into four classes based on the Clinical Dementia Rating (CDR): non-demented, very mild demented, mild demented, and demented. The dataset also includes the corresponding NIfTI (.nii) files generated earlier from the original .img and .hdr formats [22]. Since the 80,000 2D slices were already provided in processed form, our study directly used these images for model training and evaluation. This comprehensive dataset, totaling approximately 1.3 GB, served as a strong foundation for training the EfficientNet-B3 deep-learning model for Alzheimer's stage classification. As shown in Figure 1.

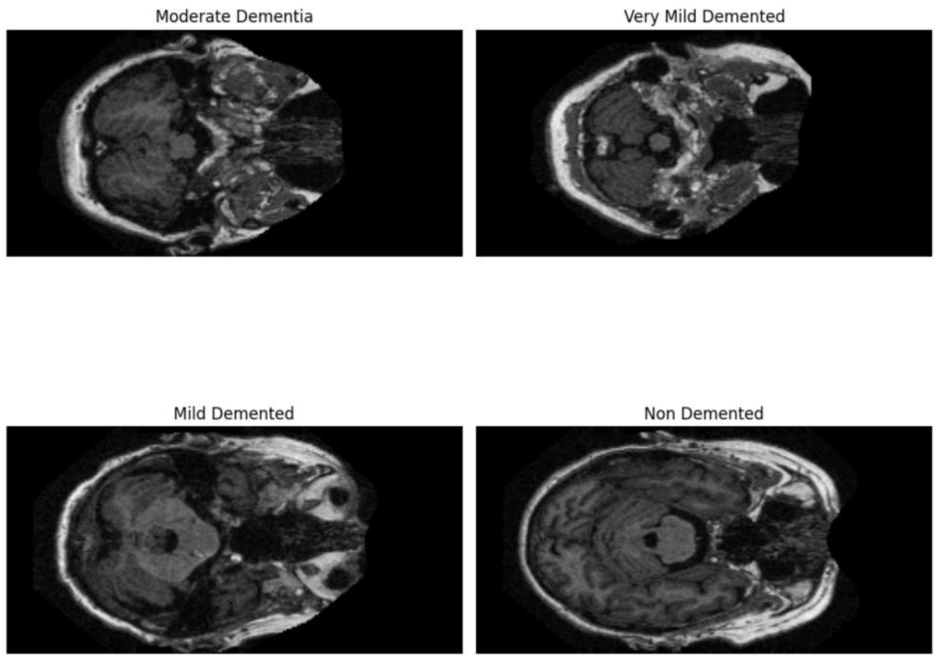

Figure 1: OASIS Alzheimer's Dataset Sample

3.2 Data Augmentation

In order to enhance model generalization and mitigate overfitting, the training images were transformed by data augmentation techniques, specifically, implementations using PyTorch transforms. The techniques are as follows: Random Rotation (±15°): Provides the model with slight invariance to orientation changes, Random Horizontal Flip: Allows the model to account for changes in image orientation, Color Jitter (brightness 0.8-1.2): Provides the model with a variability in the intensity of MRI scans, Random Affine Transformation (translation 0.1): Slightly variable images to capture spatial generalization. Overall, these transformations also serve to artificially increase the diversity of training data for the model to better capture new unseen variation in MRI images, and improve overall performance.

3.3 Data Preprocessing

All imagery was preprocessed to create the files usable by the EfficientNet-B3 model on images in all datasets. The processing that occurred includes: Resize: images were resized to a fixed size (224 × 224). Conversion to Tensor: Images were converted to PyTorch tensors. Normalization (mean - [0.485, 0.456, 0.406]; std - [0.229, 0.224, 0.225]): image pixel values were normalized (distributed around - mean/standard deviation) to standardize the input to the model. The validation dataset was only resized, converted to tensor format, and normalized. This procedure preserves the real data distribution while validating model performance.

3.4 Dataset Splitting

To ensure robust model training and evaluation, the dataset was divided into three subsets: training, validation, and testing. Specifically, 70% of the data was allocated for training, allowing the model to learn underlying patterns effectively. A further 15% was set aside for validation, which served to fine-tune model parameters and monitor performance during training, helping to prevent overfitting. The remaining 15% was reserved for testing, providing an unbiased assessment of the model's generalization ability on unseen data. Because the OASIS Kaggle dataset does not include predefined splits, the division was performed at the slice (image) level. All 2D MRI images were grouped by class, randomly shuffled, and then partitioned using a class-aware (stratified-like) 70/15/15 procedure to maintain proportional representation of the four dementia categories. This ensured that each subset reflected the original class distribution with no overlap between training, validation, and testing indices, thereby supporting reliable and reproducible evaluation. The complete distribution of the dataset is presented in Table 1.

Table 1: The splitting summary

Dataset Portion	Sample Per class	Total of Sample	Percentage
Training set	14,000	56,000	70 %
Validation Set	3,000	12,000	15 %
Testing Set	3,000	12,000	15%

3.5 EfficientNet-B3 Architecture

EfficientNet-B3 is one of the networks in the EfficientNet family that is able to scale width, depth, and resolution of the networks using a compound scaling method that increases accuracy and efficiency simultaneously. Main Features: Base Structure: Based on MBConv (Mobile Inverted Bottleneck Convolution) blocks, which use depthwise separable convolutions that minimize the computation cost in EfficientNet. Scaling: B3 scales with a much higher width and depth than B0, and has an input size of still 224×224.Feature Extractor: A series of convolutional blocks going with squeeze-and-excitation (SE) modules to perform channel-wise attention. Classifier Head: a global average pooling → fully connected layers → output layer for classification. Benefits: Efficiency for applications such as Alzheimer's detection, high accuracy with less parameters compared to traditional CNNs. The architectural details of the model are summarized in Figure 2.

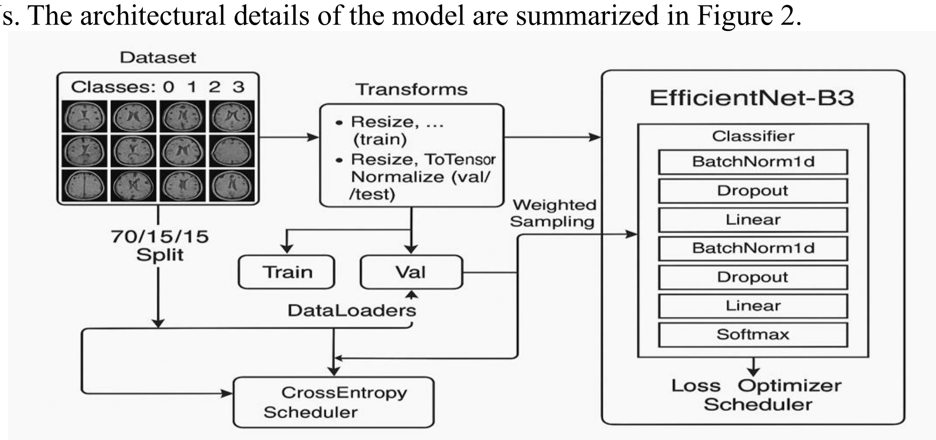

Figure 2: Alzheimer's Classification Pipeline Using EfficientNet-B3

3.6 Hyperparameters and Implementation step

We trained our model with Cross-Entropy loss, Adam optimizer, learning rate of 1e-4, batch size of 16, for 25 epochs included early stopping and ReduceLROnPlateau scheduler. We fine-tuned EfficientNet-B3 by unfrozen its last 100 layers on a custom Alzheimer MRI dataset using weighted sample for class imbalance and performed data augmentations. We ran the training on Google Colab with a T4 GPU and implemented a 70/15/15 train/val/test split while monitoring accuracy and loss.

4. Result Discussion

This section introduces and discusses the results of the study evaluating the ability of EfficientNet-B3 to detect Alzheimer's disease using the OASIS MRI dataset. The results are evaluated based on accuracy, precision, recall, F1- score, and confusion matrices. In addition, we provide comparisons among our proposed models to evaluate their performance. Lastly, we discuss implications of our findings for clinical practice, and avenues for future work.

4.1 Summary of Main Finding

This study applied deep learning techniques to the OASIS MRI dataset for Alzheimer's disease detection. Among the tested architectures, the EfficientNet-B3 model achieved the highest overall classification accuracy of 99.4%, significantly outperforming traditional and earlier deep learning baselines. The model demonstrated exceptional precision and recall across all classes, confirming its robustness in distinguishing between Normal, Very Mild Dementia, Mild Dementia, and Moderate Dementia cases. The evaluation results can be found in Table 2.

Table 2: Performance comparison of classification models on the OASIS dataset

Model	Accuracy (%)	Precision	Recall	F1-Score
MobileNetV2	81.3	0.81	0.79	0.81
CNN (baseline)	94.2	0.93	0.94	0.93
EfficientNet-B3	99.4	0.99	0.99	0.99

To ensure a fair and consistent evaluation, the baseline models (MobileNetV2 and the CNN baseline) were trained using the same training configuration as the proposed EfficientNet-B3 model. Both models were optimized using the Adam optimizer with a learning rate of 1e-4, trained for 15 epochs, and subjected to the same data preprocessing and augmentation procedures. This unified setup ensures that the performance differences reflect architectural strengths rather than variations in training settings.

4.2 Evaluation Model

The model achieves a validation accuracy of 98.4%, surpassing other models while maintaining low runtime and validation loss. The model's optimization behavior can be observed in Figure 3.

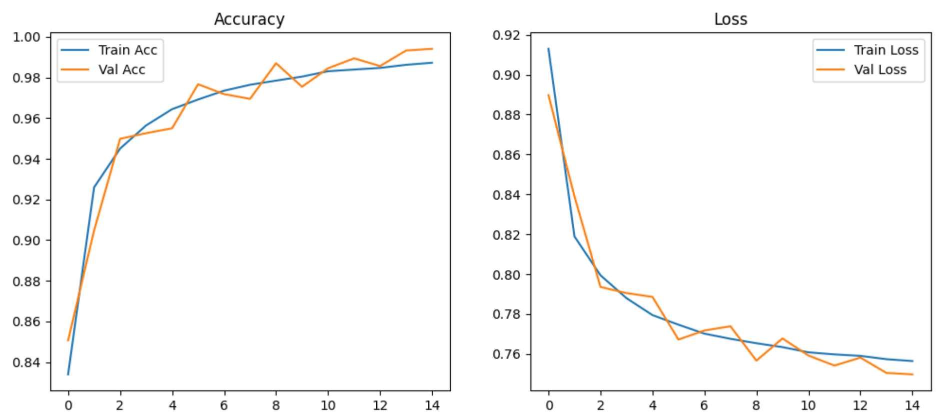

Figure 3: Training and validation loss across all epochs. The decreasing loss trend demonstrates successful optimization, while the close alignment between training and validation curves reflects minimal overfitting.

4.3 Confusion Matrix

The confusion matrix for the EfficientNet-B3 model provides a clear breakdown of the classification performance across the four neurodegenerative stages of Alzheimer's disease: Non-Demented, Very Mild Dementia, Mild Dementia, and Moderate Dementia. It illustrates how many samples were correctly classified and highlights the specific categories where misclassifications occurred. Overall, the model achieved near-perfect classification across most classes, reflecting its strong ability to learn discriminative structural patterns from the MRI slices. As expected, the majority of misclassifications occurred between the Very Mild Dementia and Mild Dementia categories. These two stages exhibit highly subtle and overlapping anatomical features, making them challenging to distinguish even for advanced deep-learning models and clinical experts. Despite this inherent difficulty, the misclassification rate between these categories remained low, indicating that the model was still able to capture fine-grained early-stage changes. In summary, the confusion matrix reinforces the strong generalization capability of EfficientNet-B3. The model achieved consistently high precision, recall, and F1-scores across all stages, demonstrating its robustness and reliability in differentiating Alzheimer's progression levels within the OASIS dataset. The confusion matrix for the EfficientNet-B3 model is provided in Figure 4.

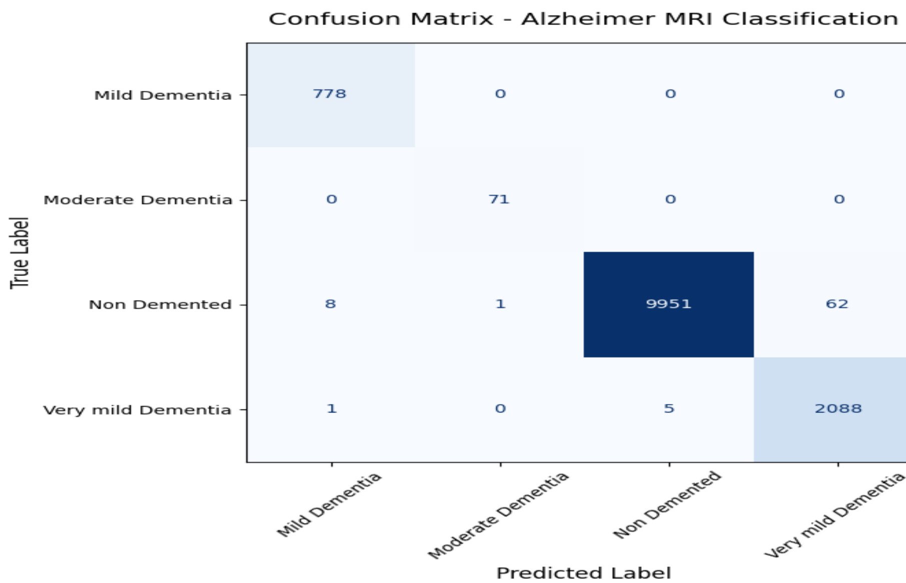

Figure 4: Confusion matrix showing the classification performance of the EfficientNet-B3 model on Alzheimer's MRI images

Although the EfficientNet-B3 model achieved excellent performance across all evaluation metrics, it is important to acknowledge several common challenges associated with MRI-based deep learning. These include limited sample sizes, variability in MRI scanners and acquisition protocols, and potential inconsistencies in image preprocessing across datasets. Such factors can introduce distribution shifts that may affect a model's ability to generalize beyond the dataset used in this study. Recognizing these limitations highlights the importance of future validation on larger, more diverse, and multi-center MRI datasets to further strengthen the model's clinical applicability.

5. Conclusion

5.1 Conclusion

The research shows that EfficientNet-B3 is highly proficient at detecting Alzheimer's disease based on the OASIS MRI dataset. The model's accuracy of 99.4% is higher than most traditional machine learning models as well as older CNN architectures. Importantly, its ability to detect subtle changes in brain structure and morphology enables alternative levels of cognitive decline to be detected in comparison to aging with high levels of precision and recall. The current results support the usefulness of compound-scale deep learning architecture in support of automated image analysis protocol of neuroimaging. EfficientNet-B3 provides accurate, rapid, and trustworthy classification that may provide the opportunity for timely diagnosis. Timely diagnosis is the most important factor in determining outcomes in conjunction with time-limited interventions.

5.2 Future Work

Even with optimal performance, there are still multiple possibilities for improvement. External validation: Validate EfficientNet-B3 on larger multisite cohorts-ADNI, UK Biobank-to ensure that it is generalizable across diverse populations and MRI scanners. Longitudinal analyses: Include longitudinal MRI scans (the same participant scanned with multiple scans) in the model for disease progression prediction, and to potentially predict preclinical stages of Alzheimer's. Multimodal analysis: Combine MRI with one or more other modalities (PET imaging, cognitive scores, or genetic data) and improve diagnostic accuracy. Explainable AI (XAI): Use interpretability approaches (e.g. Grad-CAM, attention maps) to identify which brain regions most contribute to the prediction made by EfficientNet-B3 model to increase trust in the clinical setting.Lightweight use: Consider model compression or pruning methods to apply EfficientNet-B3 in a supervised real-time capacity in a clinical setting with less computational resources.In summary, EfficientNet-B3 provides and appropriate approach to automated detection of Alzheimer's, and future research will work to expand the utility, robustness and clinical interpretability of the model.

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تعزيز تصنيف مرض الزهايمر من خلال صور الرنين المغناطيسي باستخدام تقنيات التعلّم العميق

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[١] الرياض، المملكة العربية السعودية

الملخص:

يعدّ التعرّف المبكر على مرض الزهايمر أمراً بالغ الأهمية من أجل إبطاء مسار التدهور المعرفي وتحسين جودة الحياة لدى المصابين بالمرض. ورغم أن صور الرنين المغناطيسي للدماغ توفّر معلومات بنيوية قيّمة قد تسهم في الكشف المبكر، إلا أن تقنيات الذكاء الاصطناعي الحديثة والواسعة الانتشار يمكن أن تعزّز هذه العملية بصورة أكبر. في هذه الدراسة، نقدّم إطاراً يعتمد على التعلّم العميق للتصنيف الموضعي وشبه المؤتمت لصور الرنين المغناطيسي إلى أربع درجات من الصحة المعرفية: عدم الإصابة بالخرف، الخرف بدرجة طفيفة جداً، الخرف بدرجة طفيفة، والخرف المعتدل. يقوم الإطار على معمارية EfficientNet-B3 وقد أظهر قدرة موثوقة على التمييز بين السمات الدقيقة المرتبطة بتطوّر التنكس العصبي في بنية الدماغ. تم تدريب النموذج على مجموعة بيانات كبيرة من صور الرنين المغناطيسي للدماغ وحقق دقة تحقق بلغت ٩٩,٤٪، مع حفاظه على مستويات عالية من الدقة ومعامل F1 عبر جميع الفئات. وتشير هذه النتائج إلى أن المنهجية المقترحة قد توفّر أسلوباً موثوقاً لتحديد مستويات الصحة المعرفية، وقد تساعد الأطباء في تعزيز القرارات السريرية المبكرة. وبشكل عام، تُظهر هذه الدراسة إمكانات النماذج خفيفة الوزن المعتمِدة على التعلّم العميق كأساليب تلقائية فعّالة ومُثبتة في تحديد مرض الزهايمر، بما قد يمثّل خطوة مهمة نحو تحسين فحوصات التشخيص ودعم اتخاذ القرار السريري داخل الأنظمة الصحية.

الكلمات المفتاحية: تصنيف مرض الزهايمر، EfficientNet-B3، تحليل الصور الطبية، التعلّم العميق، OASIS-3، صور الرنين المغناطيسي.