

Comparison Between U-Net and Googlenet for Alzheimer's Disease Detection and Analysis Using MRI Images

Lead Author

Yetunde Otun

Affiliation:

Department of
Computer
Science
Redeemer's
University
Ede, Osun
State



Abstract

Alzheimer's disease (AD) is a brain disorder that causes gradual memory loss and cognitive decline. Early detection is important because it helps doctors manage the disease better. MRI scans are often used to find early signs of Alzheimer's, and deep learning models, like Convolutional Neural Networks (CNNs), have become useful tools for analyzing these images. This paper focuses on a comparative analysis of two prominent deep learning architectures, U-Net and GoogLeNet, in the context of Alzheimer's disease research using MRI images. U-Net, known for its encoder-decoder architecture with skip connections, is widely used for biomedical image segmentation, such as hippocampal segmentation in Alzheimer's disease. It excels in tasks requiring precise localization of brain structures. Conversely, GoogLeNet, designed for image classification, employs Inception modules for multi-scale feature extraction, making it suitable for distinguishing between Alzheimer's and healthy brain images. The authors developed a Convolutional Neural Network (CNN) to classify MRI images into four categories: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The model was trained on a dataset comprising 6,400 images gotten from Kaggle, and was split into 70% for training, 24% for validation and 6% for testing. The training process involved several data preprocessing techniques such as, normalization, and data splitting. U-Net and GoogLeNet, a pre-trained model, served as the foundation for the network, which was fine-tuned for the task of Alzheimer's stage classification. The model was optimized using the Adam optimizer and trained for 20 epochs with categorical crossentropy as the loss function.



Co-Authors: Bosede Oguntunde; Olufade Onifade Department of Computer Science Redeemer's University Ede, Osun State

The results indicated a training accuracy of 85% for U-Net while GoogLeNet indicated a training accuracy of 93.50%. Despite moderate success, the gap between training and testing performance suggests room for improvement, particularly in addressing class imbalance and fine-tuning the model. The study concludes that while the deep learning approach shows promise in aiding Alzheimer's diagnosis, further enhancements such as advanced data augmentation, model refinement, and expanded clinical application are needed to fully realize its potential.

Keywords: U-Net, Googlenet, Alzheimer's Disease, Mri Images

1. Introduction

Alzheimer's disease (AD) is a progressive brain disorder that causes damage to brain cells over time, leading to the loss of thinking and memory abilities. It is a growing concern for public health worldwide and is a widely spreading neurodegenerative disorder. Unfortunately, there is no cure for AD because current methods of diagnosis and treatment cannot stop or prevent the disease's progression. On average, people diagnosed with AD are estimated to live only 3.1 years, especially when the diagnosis is made at an early stage [1, 15]. Nigeria faces a growing burden of Alzheimer's disease, with an estimated prevalence of 2% among the elderly population. This represents a significant portion of the dementia cases in the country, highlighting an urgent need for enhanced awareness, diagnosis, and care services [2].

Advances in Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), and computer vision have greatly enhanced early disease diagnosis. These technologies offer innovative research possibilities for more accurate and precise detection, exceeding the diagnostic accuracy of conventional methods. By leveraging AI and ML, healthcare professionals can now identify diseases at earlier stages with greater accuracy [13]. Traditional diagnostic methods, such as manual analysis of medical images or the evaluation of visible symptoms, often face challenges due to their reliance on subjective interpretation, making them vulnerable to human error. These approaches can also be time-intensive and may struggle to accurately identify small or early-stage diseases. Deep Learning (DL) algorithms, on the other hand, excel at rapidly processing large



volumes of data and detecting subtle patterns that could indicate the onset of disease. This capability enhances diagnostic accuracy by enabling earlier detection and intervention, ultimately improving patient outcomes. By leveraging diverse datasets, DL models enhance their ability to generalize across different individuals and conditions, facilitating the identification of nuanced patterns for more timely and accurate diagnoses [10]. Techniques like Convolutional Neural Networks (CNNs) and sophisticated image recognition algorithms, including Recurrent Neural Networks (RNNs) [16], play a crucial role in advancing disease detection through deep learning and computer vision.

Various advanced imaging techniques are being utilized for detecting Alzheimer's Disease (AD), powered by the implementation of deep learning methodologies. These imaging modalities include Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Single-Photon Emission Computed Tomography (SPECT), Computed Tomography (CT), Functional MRI (fMRI), and Diffusion Tensor Imaging (DTI). Each technique provides a unique view of the complex mechanisms driving AD pathology. MRI [6], in particular, is noteworthy for its capability to offer an in-depth examination of the pathological changes linked to AD. The combination of neuroimaging data with AI technologies is revolutionizing AD detection, opening the door to personalized diagnoses and improved tracking of disease progression. **U-Net** is a Convolutional Neural Network (CNN) architecture designed primarily for biomedical image segmentation. It was introduced in 2015 by Ronneberger et al. [12] and it has since become a standard tool for medical image analysis.

U-Net is particularly known for its ability to generate precise segmentation maps of medical images by capturing both global and local features. U-Net follows an encoder-decoder structure with symmetric paths. The encoder extracts high-level features through successive convolution and pooling layers, while the decoder reconstructs the image by up sampling. The key feature of U-Net is its **skip connections** between corresponding layers of the encoder and decoder, which allow for fine-grained spatial information to be retained during reconstruction. U-Net is widely used for **segmentation tasks**, such as hippocampal segmentation in MRI images for Alzheimer's disease research. Segmentation is critical in isolating important brain regions, such as the hippocampus, which is a known biomarker for Alzheimer's progression while **GoogLeNet** (also known as Inception-v1) was developed by Szegedy et al. [17] and introduced a novel approach to deep CNN architecture by integrating **Inception modules**. These modules allow for multi-scale feature extraction within

a single layer, enhancing its classification capabilities without a drastic increase in computational costs. GoogLeNet's Inception modules apply multiple filters (1x1, 3x3, 5x5) and pooling operations in parallel, enabling the network to capture both fine and coarse details. Its deep architecture, coupled with the use of 1x1 convolutions, reduces the dimensionality of the feature maps, ensuring efficient computation. GoogLeNet excels in **classification** tasks. In Alzheimer's disease studies, it has been applied to distinguish between normal and Alzheimer's-affected subjects based on MRI data, leveraging its robust multi-scale feature extraction [11]. The main aim of this paper is to provide a comparative analysis between U-Net and GoogLeNet, focusing on their applications in medical imaging, particularly in the context of Alzheimer's disease research.

2. Literature Review

Deep learning (DL) models, a subset of machine learning, are designed to extract deeper, more complex features from the provided training data. Typically, these models consist of multiple layers, each comprising a fixed number of neurons, which serve as the fundamental processing units for feature extraction. Unlike traditional machine learning techniques, where features are manually derived from the data using mathematical models, DL models automatically extract features through their hidden layers. This capability makes DL models highly effective in various applications. One such application is computer-aided diagnosis (CAD), which has gained significant attention recently. In the following sections, we will explore DL models specifically designed to tackle the challenge of diagnosing Alzheimer's disease (AD). While traditional models rely heavily on manual feature tuning, making data preprocessing a critical step, DL models, although still benefiting from preprocessing, can significantly enhance performance by automating feature extraction [5]. In this regard, Salehi et al. [14] developed a CNN to classify and diagnose Alzheimer's disease in its early stages using MRI images. The model was implemented using TensorFlow on a system with an Intel HD 6000 1536 MB graphics card and 8GB RAM, achieving an accuracy of 99%. To enhance performance, the model combines two image datasets, increasing the quantity of images used for training. However, the model does not account for the moderate dementia class, limiting its scope. Hussain et al. [7] developed a 12-layer CNN model for binary classification and Alzheimer's disease detection using brain MRI data. They employed image scaling and image denoising as pre-processing techniques. The model achieved an accuracy of 97.75%, outperforming four pre-trained models: Xception with 84.37%, InceptionV3 with 90.62%, VGG19 with 50%, and MobileNetV2 with

81.24%. However, the model does not incorporate a multi-class classification approach. Murugan et al. [9] developed a model called DEMentia NETWORK (DEMNET) for detecting various stages of dementia. The model uses a CNN to identify specific Alzheimer's disease traits from MRI images. It accounts for the four phases of dementia and provides precise diagnoses by generating high-quality disease probability maps based on regional brain structures. The model achieved an accuracy of 95.23% and effectively identifies brain areas associated with Alzheimer's disease, serving as a useful decision-support tool in diagnosis. However, challenges such as an imbalanced dataset and pre-processing steps like intensity normalization and skull stripping limited its potential for even better performance. Liu et al. [8] developed a technique using a 3D Deep Convolutional Neural Network (DCNN) to accurately distinguish patients with mild Alzheimer's dementia from those with mild cognitive impairment (MCI) and cognitively normal (CN) individuals using structural MRI (sMRI). The model is built based on the dimensions and thickness of brain regions known to be affected by the disease. The simulation is performed on the NVIDIA CUDA parallel computing platform, and the model provides a forecast of disease progression. Due to computational limitations, a batch size of four is used, resulting in a low learning rate and a time-consuming process. Basavaraj et al. [4] implemented a deep learning model using the DenseNet-169 Convolutional Neural Network (CNN) to detect dementia from MRI brain images.

The dataset, containing over 5,000 images, was divided into four classes: non-demented, mild dementia, moderate dementia, and severe dementia. The model was trained using Python and TensorFlow, with image pre-processing techniques like resizing to 224x224 pixels. The model achieved a high classification accuracy of 98%, successfully distinguishing between different stages of dementia. The author stated that the model demonstrated an improvement in accuracy compared to other models, such as VGG16 and ResNet. The study identified challenges related to the imbalance of classes, particularly the limited number of severe dementia cases, which impacted the model's ability to generalize across all classes. Archana and Prasanna [3] proposed an AD-TL framework utilizing transfer learning for early Alzheimer's disease prediction. The MRI dataset was preprocessed using a Multi-Layer Perceptron (MLP) combined with Convolutional Neural Networks (CNN) to reduce noise, followed by image enhancement using the CLAHE technique and segmentation via watershed image segmentation. The model was trained using ResNet50 with AlexNet architecture, and classification was performed using a Deep Convolutional Neural Network (DCNN). The model achieved a classification accuracy of 98.99% in identifying Alzheimer's



stages. The author stated that the model demonstrated high precision, recall, and F-measure scores, outperforming other existing methods such as CNN and DNN in Alzheimer's disease prediction. Although the model attained impressive accuracy, the authors noted that the approach requires further enhancements to improve performance with real-world MRI images and integration with mobile applications for broader accessibility.

3. Methodology

a. Dataset

The dataset used consists of MRI images categorized into the four Alzheimer stages which are: 'Non Demented', 'Very Mild Demented', 'Mild Demented' and 'Moderate Demented'. Our purpose is to preprocess the images and utilize them to train a Convolutional Neural Network (CNN) for precise classification of Alzheimer's disease stages. The dataset was split into 70% for training, 24% for validation and 6% for testing.

b. Data Preprocessing

- Resizing: Each image with the original size of 128x128 pixels is resized to 150x150 pixels matching the new target dimensions.
- Normalization: After resizing, each pixel value is rescaled (normalized) from the original range of 0 to 255 to the range of 0 to 1 by dividing each pixel by 255.

c. Model Architecture

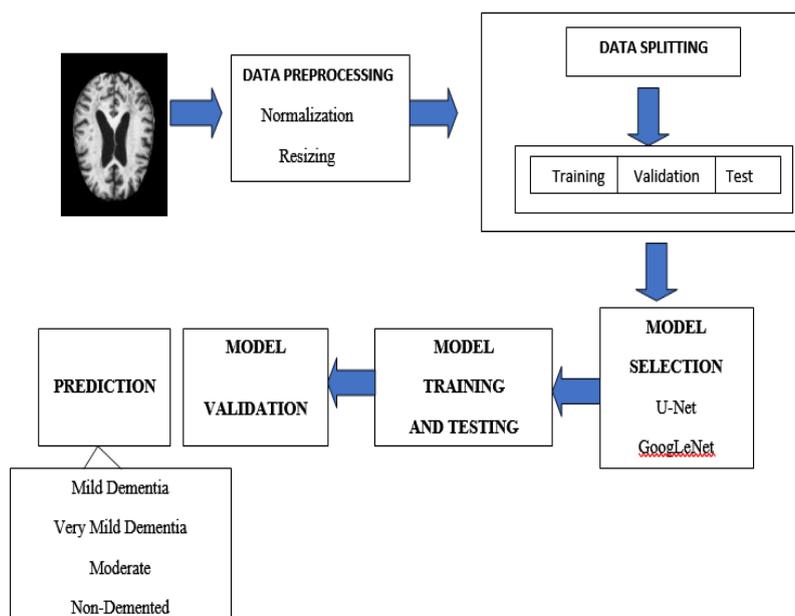
A pre-trained U-Net and GoogLeNet architecture was employed, fine-tuned for Alzheimer's disease classification. The following below include the key layers:

Base Model: U-Net and GoogLeNet (pre-trained on ImageNet), excluding its top layers.

Optimizer: Adam optimizer was used to improve the performance.

Loss Function: Categorical Crossentropy for multi-class classification.

Metrics: Accuracy was used to evaluate the model's performance.



4. Results

The two models U-Net and GoogLeNet can help detect Alzheimer's disease at an early stage. Python is used in the development of the models. Jupyter lab is chosen as the tool for executing this work. The model classified the images as Non-dementia, Mild dementia, Moderate dementia and Very Mild dementia. The models training come step by step. At each step, it iterates 6400 batches in forward and backward propagation to calculate the validation loss and training loss. As we go on evaluating the steps the validation loss decreases relatively with an increase in the accuracy rate. The model was trained for a maximum of 20 epochs, but **EarlyStopping** was included to halt the training process earlier if the validation loss stopped improving. The performance metrics of the CNN model are summarized in the table below:

	Training Accuracy
U-Net	85%
Google Net	93.50%

The U-Net model achieved a training accuracy of 85% while GoogLeNet achieved 93.50%. When evaluated on the test dataset, the model's accuracy was 58.8% for GoogLeNet and 65% for U-Net. These results indicate that while the model performed well during training, there is room for improvement in generalization.

5. Conclusion

Alzheimer's disease is a progressive neurodegenerative disorder that affects memory and cognitive function, making early diagnosis crucial for effective treatment. In this study, two deep learning models were developed to classify Alzheimer's disease from brain MRI images. The models demonstrated moderate accuracy, showing promise as diagnostic tools. However, the performance gap between the training and test datasets suggests that further fine-tuning and additional data are needed to improve generalization.

6. Future Works

Future improvements could include: Expanding the dataset through additional augmentation techniques to improve the model's robustness. Unfreezing more layers of the pre-trained model for fine-tuning could help extract more relevant features. Addressing class imbalance through techniques like oversampling or using class-weighted loss functions and exploring other pre-trained architectures like ResNet or InceptionNet to enhance model performance. This approach lays the groundwork for more refined models capable of achieving higher diagnostic accuracy, paving the way for practical applications in healthcare diagnostics.

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