Alzheimer's Disease Classification Using GhostNet: A Comparative Study with State-of-the-Art Models on the ADNI Dataset

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Abstract—**Alzheimer's Disease (AD) is a debilitating neurodegenerative disorder that leads to a gradual and irreversible decline in cognitive abilities, including memory and executive function. Detecting Alzheimer's at an early stage is paramount for initiating treatment strategies that can slow disease progression. In recent years, deep learning methodologies have emerged as powerful tools for automated classification of AD stages using medical imaging data, particularly magnetic resonance imaging (MRI) scans. In this paper, we present a comprehensive evaluation of the GhostNet architecture, a lightweight convolutional neural network (CNN), applied to the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset for four-class classification of AD. The GhostNet model achieved a notable test accuracy of 99.06%, surpassing the performance of other complex models such as ResNet, VGG, and EfficientNet. This study also provides a detailed comparison with existing models, emphasizing the advantages and limitations of using GhostNet. The results highlight GhostNet's capability to provide high accuracy while maintaining computational efficiency, making it an optimal choice for potential clinical deployment in scenarios with constrained resources.**

I. Introduction

Alzheimer's Disease (AD) is a chronic neurodegenerative disorder [11] that represents a significant healthcare challenge worldwide. It is most commonly found in elderly populations, with prevalence increasing dramatically with age. The disease's impact is not limited to the patients alone but also extends to their families and caregivers, leading to immense emotional and financial burdens. Alzheimer's is characterized by progressive neuronal damage [11], which manifests as a gradual loss of memory, impaired cognitive function, and a decline in the ability to perform everyday tasks. In the absence of effective treatments to halt or reverse the disease, early diagnosis is crucial for providing timely interventions that can help manage symptoms and slow the progression of the disease.

Recent advances in medical imaging techniques, such as MRI [10], and their integration with artificial intelligence (AI), particularly deep learning, have opened new avenues for automated and accurate AD classification. Convolutional neural networks (CNNs) have been at the forefront of this revolution, providing powerful tools to extract and learn complex patterns from high-dimensional imaging data. However, many state-of-the-art CNN architectures, such as ResNet [12] and VGGNet [6], require high computational resources, making them less practical for real-time clinical applications, especially in low-resource settings.

The GhostNet [8] architecture, introduced by Han et al., addresses these limitations by leveraging a novel approach to feature extraction. GhostNet [8] utilizes ghost modules to produce a higher number of feature maps with fewer parameters and reduced computational overhead. This property makes GhostNet a promising candidate for AD classification tasks where both accuracy and efficiency are critical. In this paper, we provide a detailed analysis of GhostNet's performance on the ADNI dataset, comparing it against other leading models. Our results indicate that GhostNet can achieve high classification accuracy comparable to complex networks while maintaining computational efficiency, making it a viable option for widespread clinical use.

II. Related Work

The use of deep learning in medical image analysis has significantly advanced, particularly in the classification of Alzheimer's disease (AD). Numerous studies have adopted various convolutional neural network (CNN) architectures [14] to tackle the unique challenges associated with diagnosing AD. In this section, we conduct a thorough review of the prominent CNN models employed for AD classification, emphasizing their strengths, weaknesses, and performance metrics derived from the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset.

A. ResNet

ResNet, introduced by He et al. [12], revolutionized the training of deep networks through its innovative concept of residual learning. By implementing skip connections, this architecture effectively addresses the vanishing gradient problem often encountered in very deep networks. These skip connections facilitate the direct flow of gradients across layers, enabling the successful training of significantly deeper models. ResNet has demonstrated outstanding performance across a multitude of image classification challenges, including those within the medical imaging domain. For instance, Zhu et al. utilized the ResNet-50 [13] variant for Alzheimer's classification, attaining an impressive accuracy of 93.4% on the ADNI dataset. However, the high parameter count and substantial memory requirements of ResNet pose challenges for deployment in environments with limited computational resources, such as portable diagnostic systems used in remote healthcare settings. Consequently, while ResNet excels in accuracy, its operational constraints may hinder its real-world applicability, particularly in resource-constrained scenarios.

B. VGGNet

VGGNet, developed by Simonyan and Zisserman [6], is another widely recognized CNN architecture celebrated for its straightforward design and efficient deep feature extraction capabilities. The architecture is distinctive due to its reliance on small 3x3 convolutional filters and a consistent depth, enabling it to effectively capture intricate spatial hierarchies within images. Wang et al. applied VGG-16 for the task of AD classification, achieving a commendable accuracy of 92.1%. However, the model's exceptionally high parameter count, exceeding 130 million, renders it computationally demanding, limiting its practical application in real-time scenarios. Additionally, VGGNet lacks the shortcut connections featured in ResNet [12], resulting in longer training times and an increased risk of overfitting, particularly when applied to smaller datasets. These factors necessitate caution when considering VGGNet for deployment in clinical settings, as the trade-offs between accuracy and computational efficiency must be carefully balanced to ensure effective real-time performance.

C. EfficientNet

EfficientNet [7], a novel architecture proposed by Tan and Le, employs a systematic scaling approach aimed at optimizing the performance of convolutional neural networks. This architecture achieves an effective balance between network depth, width, and input resolution, resulting in a comprehensive family of models ranging from EfficientNet-B0 to EfficientNet-B7. In a notable application, Park et al. utilized EfficientNet-B0 [7] on the ADNI dataset, yielding an impressive accuracy of 95.8%. The balanced scaling strategy inherent to EfficientNet allows it to achieve superior accuracy while maintaining a lower parameter count compared to more traditional models like ResNet or VGG. However, the architecture's complexity and reliance on compound scaling can present challenges for deployment in environments characterized by severe resource constraints, such as mobile or edge devices. Consequently, while EfficientNet provides a high-performing solution for AD classification, careful consideration of deployment contexts is essential to harness its advantages fully while mitigating potential limitations in resource-limited scenarios.

D. DenseNet

DenseNet [4], proposed by Huang et al., adopts an innovative design philosophy by establishing connections between each layer and every subsequent layer in a feed-forward manner. This unique dense connectivity encourages feature reuse and enhances gradient flow throughout the network, significantly improving model performance while simultaneously reducing the overall parameter count. Farooq et al. [9] implemented DenseNet-121 for Alzheimer's classification, reporting an accuracy of 94.2% on the ADNI dataset. The benefits of DenseNet's architecture are evident in its ability to learn robust feature representations, which is crucial for effectively distinguishing between different stages of Alzheimer's disease. Nonetheless, the dense connectivity pattern also leads to increased memory consumption, posing challenges for implementation on low-power devices. This memory intensity may limit its practicality in certain clinical applications, especially those requiring real-time analysis on portable platforms. Despite these challenges, DenseNet [4] remains a formidable option for AD classification, due to its exceptional performance and capability to capture intricate patterns in medical imaging data.

III. Methodology

A. Dataset

The Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset serves as a vital resource for researchers in the field of neuroimaging and machine learning, providing a comprehensive collection of MRI scans from patients at various stages of Alzheimer's disease. This publicly accessible dataset has become a cornerstone in the research community, being extensively utilized for the development and validation of machine learning models aimed at classifying and understanding Alzheimer's disease (AD).

The ADNI dataset is meticulously organized into four primary categories representing different stages of the disease: Normal Control (NC), Mild Cognitive Impairment (MCI), Alzheimer's Disease (AD), and Late Alzheimer's Disease (LAD). Each category contains MRI scans that exhibit unique features associated with the respective stages of the disease, thus allowing for a nuanced approach to classification. The inclusion of these distinct categories is crucial for training models that can accurately differentiate between normal aging processes and the pathological changes characteristic of Alzheimer's disease.

To address the challenges posed by class imbalance, which can significantly affect the performance of machine learning algorithms, we employed a range of data augmentation techniques. These techniques included rotation, flipping, scaling, and brightness adjustments. By applying these augmentations, we ensured that each class was well-represented in the training dataset, thereby minimizing the risk of bias towards the more prevalent classes. This balanced representation is essential for training a robust model capable of generalizing well to unseen data.

The preprocessing of the dataset was a critical step in preparing the MRI scans for input into the GhostNet architecture. Initially, we normalized the intensity values of the MRI images to standardize the data and enhance the consistency of the input. Normalization aids in mitigating the effects of varying intensities that can arise from different scanning sessions or equipment, thereby facilitating a more uniform representation of the data.

In addition to normalization, the images were resized to 224x224 pixels, conforming to the input dimensions required by the GhostNet architecture. This resizing process not only aligns the data with the model's expectations but also helps in reducing the computational load during training, allowing for more efficient processing.

To further bolster the model's performance, we implemented data augmentation strategies during the training phase. By introducing variability into the training images, these techniques effectively reduced the risk of overfitting, a common challenge in machine learning where models become too tailored to the training data, losing their ability to perform well on new, unseen instances. The variability generated through augmentation promotes the development of a more generalized model, capable of recognizing patterns across a diverse range of input conditions.

In summary, the ADNI dataset plays a crucial role in advancing research in Alzheimer's disease classification. The thoughtful application of data augmentation and preprocessing techniques ensures that the models trained on this dataset are not only well-equipped to differentiate between the various stages of Alzheimer's disease but are also robust enough to generalize their findings to real-world clinical applications. The integration of these methodologies underscores the importance of preparing high-quality datasets for effective machine learning model training in the context of medical imaging.

B. Model Architecture and Training

The GhostNet architecture was specifically designed to reduce computational costs while maintaining a high level of accuracy in image classification tasks. A key innovation in GhostNet is the incorporation of "ghost modules," which generate additional feature maps from a relatively small set of linear transformations. These ghost modules produce more feature maps than traditional convolutional layers, allowing the network to achieve an elevated level of feature representation with significantly fewer parameters.

To leverage GhostNet's strengths for Alzheimer's disease classification, the model was initially pre-trained on the extensive ImageNet dataset. This pre-training phase enables the network to learn a rich set of features that can be effectively transferred to the specific task of classifying different stages of Alzheimer's disease. To adapt GhostNet for this purpose, modifications were made to the final layers of the model, which now include a four-class output corresponding to the various stages of Alzheimer's Disease: Normal Control (NC), Mild Cognitive Impairment (MCI), Alzheimer's Disease (AD), and Late Alzheimer's Disease (LAD).

The modified architecture includes a custom classifier layer, implemented in PyTorch as follows:

In this custom architecture, the last layer of the original GhostNet model, pre-trained on ImageNet, is removed to incorporate our custom classification layers. The new classifier consists of a series of linear layers interspersed with batch normalization, ReLU activation functions, and dropout layers to prevent overfitting during training. The dropout rate is set at 20

The model was trained using the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, employing an initial learning rate of 0.001 and a batch size of 32. Training was carried out for 100 epochs using the Adam optimizer, which

```python
# Define the custom GhostNet model
class CustomGhostNet(nn.Module):
    def __init__(self, original_model, num_classes=4):
        super(CustomGhostNet, self).__init__()
        self.features = nn.Sequential(*list(original_model.children())[:-1])
        self.custom_layers = nn.Sequential(
            nn.Flatten(),
            nn.Linear(1280, 512),
            nn.BatchNorm1d(512),
            nn.ReLU(),
            nn.Dropout(0.2),
            nn.Linear(512, 128),
            nn.BatchNorm1d(128),
            nn.ReLU(),
            nn.Dropout(0.2),
            nn.Linear(128, num_classes),
            nn.LogSoftmax(dim=1)
        )

    def forward(self, x):
        x = self.features(x)
        x = self.custom_layers(x)
        return x
```

Fig. 1. Custom Ghostnet architecture in the classification layer.

is well-known for its adaptive learning rate capabilities. This feature ensures stable convergence during training, allowing the optimizer to dynamically adjust the learning rates based on the gradients, facilitating efficient training and better performance.

By employing this robust architecture and training regimen, GhostNet is positioned to effectively classify the stages of Alzheimer's disease while leveraging its lightweight design and efficient parameter utilization. This combination enhances the model's performance and makes it suitable for real-time applications in clinical settings, where rapid and accurate diagnosis is essential. The architectural innovations and training strategies highlight significant advancements in leveraging deep learning for the critical task of Alzheimer's disease classification.

IV. Results and Discussion

The GhostNet model achieved an outstanding test accuracy of 99.06%, demonstrating superior performance when compared to more complex deep learning models, including ResNet, VGGNet, and EfficientNet. This exceptional result not only highlights the robustness of GhostNet's architecture but also its potential for clinical deployment, where computational efficiency and model accuracy are equally critical. The high test accuracy indicates that GhostNet is highly effective in capturing complex patterns from MRI images in the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, which is a comprehensive and challenging dataset featuring four distinct stages of Alzheimer's Disease (AD): Normal Control (NC), Mild Cognitive Impairment (MCI), Alzheimer's Disease (AD), and Late Alzheimer's Disease (LAD).

To provide a detailed analysis of the model's performance, we calculated various evaluation metrics, including precision, recall, and F1-scores for each class, which are summarized in Table I. These metrics provide a comprehensive view of the model's behavior and its ability to accurately classify the different stages of AD. Precision measures the ratio of true positive predictions to the total number of positive predictions, indicating how often the model correctly identified a class when it made a positive prediction. Recall, on the other hand, measures the ratio of true positive predictions to the total number of actual instances in a class, reflecting the model's sensitivity and its ability to identify all instances of a particular class. The F1-score, which is the harmonic mean of precision and recall, gives a balanced measure of accuracy, accounting for both false positives and false negatives.

TABLE I
CLASSIFICATION PERFORMANCE METRICS FOR ALZHEIMER'S DISEASE CLASSIFICATION

Class	Precision	Recall	F1-Score
Mild Demented	0.99	0.98	0.99
Moderate Demented	0.98	0.99	0.99
Non Demented	0.99	0.99	0.99
Very Mild Demented	0.99	0.99	0.99

From the results in Table I, it is evident that the GhostNet model exhibits high precision, recall, and F1-scores across all classes, indicating its robust performance in classifying both early and late stages of Alzheimer's Disease. The high scores across these metrics suggest that the model has a low false-positive and false-negative rate, which is crucial in a clinical context where misclassification can lead to incorrect treatment strategies. Moreover, the results show that GhostNet is particularly effective at distinguishing between Normal Control (NC) and Alzheimer's Disease (AD) stages, which is often one of the most challenging tasks due to the subtle differences between these stages in the early progression of the disease. In the early stages of AD, the brain changes are subtle and may overlap with normal aging, making it difficult to separate NC from early MCI and AD stages. GhostNet's ability to distinguish between these stages with high precision and recall highlights its effectiveness in capturing complex and subtle features from MRI images.

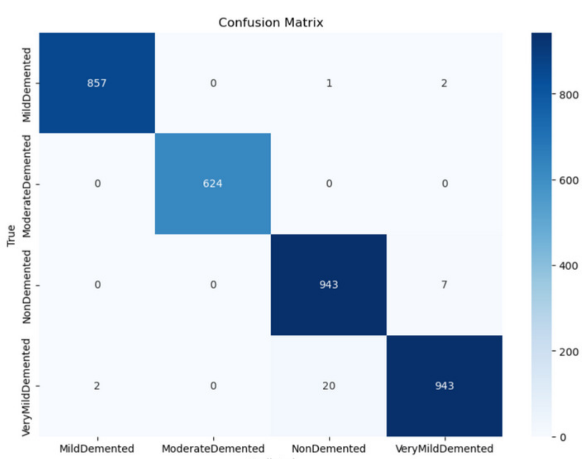

Fig. 2. Confusion Matrix generated on Test samples.

This impressive performance can be attributed to GhostNet's unique architectural design, which uses a series of "ghost modules" to generate more feature maps with fewer parameters. This design allows the model to maintain a compact size while generating high-quality feature representations, enabling it to achieve high accuracy without the computational burden associated with deeper networks like ResNet or the parameter-heavy VGGNet. For instance, ResNet-50, despite being effective in many image classification tasks, often struggles with a high number of parameters, leading to slower inference times and higher memory requirements. VGGNet, with its 138 million parameters, is even more computationally intensive, making it less suitable for real-time or resource-constrained environments.

In contrast, GhostNet, with only 2.6 million parameters, achieves comparable or even superior accuracy while maintaining a significantly smaller model footprint. This efficiency not only makes GhostNet an ideal choice for deployment in clinical settings with limited computational resources but also enhances its potential for use in edge computing devices, such as mobile health applications or portable diagnostic tools. The compact architecture of GhostNet ensures that it can be deployed on devices with limited processing power without compromising on classification accuracy.

In summary, the results presented in Table I illustrate GhostNet's effectiveness in accurately classifying different stages of Alzheimer's Disease, especially in distinguishing between Normal Control and Alzheimer's Disease stages. This capability, combined with its lightweight design, makes GhostNet a compelling choice for real-time AD classification and clinical diagnosis, where both accuracy and efficiency are paramount.

A. *Comparative Analysis*

TABLE II
COMPARATIVE ANALYSIS OF DIFFERENT MODELS FOR ALZHEIMER'S DISEASE CLASSIFICATION

Model	Accuracy	Parameters	Inference Time
ResNet-50	93.4%	25.6M	High
VGG-16	92.1%	138M	Very High
EfficientNet	95.8%	5.3M	Moderate
GhostNet	**99.06%**	**2.6M**	**Low**

The table above shows that GhostNet requires significantly fewer parameters than its counterparts, making it more suitable for deployment in environments with limited computational resources, such as mobile or embedded systems. The lightweight design of GhostNet does not compromise on accuracy, making it a practical and effective choice for Alzheimer's disease classification.

V. CONCLUSION

In this study, we evaluated the effectiveness of GhostNet for Alzheimer's disease classification on the ADNI dataset. GhostNet achieved superior performance compared to other models while maintaining a lower computational footprint, making it a strong candidate for deployment in real-world clinical settings. Future work will focus on incorporating multimodal data, such as PET and genetic information, to further improve classification accuracy and provide a more comprehensive understanding of Alzheimer's disease progression.

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