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Multi Feature-Based Alzheimer's Disease Detection from MRI Images

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Abstract: The early and correct diagnosis of Alzheimer disease (AD) is a major challenge since brain changes occurring at the early stages of AD are mild and overlap with one another. MRI is a non-invasive way to pick up the anatomical distribution of brain degeneration and structural MRI allows us to pick up anatomical patterns of brain degeneration, but what tends to be missing is the complexity of what is happening in AD with the single feature set based models. This paper suggests a multi feature-based deep learning framework combining deep features learned with a proprietary CNN and pretrained ResNet50 and handcrafted descriptors such as GLCM (Shape, Texture, Intensity). MRI images consisted of four categories of AD, namely, MildDemented, Moderate Demented, VeryMildDemented, and NonDemented. The hybrid model outperformed the rest by displ aying 99.70% accuracy, 98.21% precision, 95.14% recall, 96.59% F1-score, 95.14% sensitivity, and 98.84% specificity. The outcomes demonstrate the optionality of joining several forms of features to increase the precision and stability of the diagnosis. The method serves an encouraging means of detecting and diagnosing AD as early as possible and helps clinicians make decisions based on AI-enhanced neuroimaging.

Keywords: Alzheimer's Disease; Magnetic Resonance Imaging; Transfer Learning; Handcrafted Features; Feature Fusion; Deep Learning; Neuroimaging

1. Introduction

The most common type of dementia is Alzheimer disease (AD), a progressive neurodegenerative disorder that influences memory, cognition and behaviors. It comes in so gradually and sometimes it starts with slight memory problems and then becomes worse into what is known as cognitive decline. As the world population continues to age, AD represents a serious health challenge with currently more than 50 million individuals in the world affected by AD and imposing a serious economic strain on the healthcare system. Although there is continuous development in neurosciences, a cure has yet to be found and therefore to be able to find an effective cure and treatment an early and correct diagnosis proves to be decisive. The non-invasive and highly accessible neuroimaging technique, known as Magnetic Resonance Imaging (MRI), provides high resolution images of brain structures, which enables clinicians to appreciate the three significant features of AD" cortical atrophy, enlarged ventricles, and reduced hippocampal sizes". Nonetheless, manual review of these images is time consuming, subjective and prone to inter-observer inconsistency. In order to work out these difficulties, the use of machine learning (ML) and deep learning (DL) methods has become an extremely effective means of analyzing MRI scans with the help of the automatization.

Early algorithms based on manually extracted features e.g. texture, shape and volumetric measures on selected brain structures. Although these features are explainable and biological meaningful, they frequently lack higher order spatial dependencies in the brain. In their turn, Convolutional Neural Networks (CNNs) have proven themselves very well in learning very deep hierarchical features in raw MRI data, resulting in the possibility of correctly classifying AD stages. CNNs have previously been well-utilized in various forms, including plant disease identification [1], proving it to be capable of learning discriminating features on image data. However, most of these methods rely on single-feature pipelines, which might not be adequate in explaining the multi-faceted aspect of AD-related brain alteration. To close this gap, we suggest a hybrid multi-feature-based framework, the combination of the deep learning-based features and handcrafted descriptors. The two permit us to tap into both global and localized structural changes in MRI scans. The presented methodology combines use of custom designed CNN and pre-trained ResNet50 as a part of transfer learning scheme, as well as engineered features of Gray Level Co-occurrence Matrix (GLCM).

The training and validation are done using an MRI dataset, which is sorted into four classes: NonDemented, VeryMildDemented, MildDemented, and ModerateDemented. As experiment results reveal, this integrated feature method brings the improvement of a significant degree of high performance of the classification scheme compared to single feature set-based-schemes. The suggested system attains the top figures in terms of precision, sensitivity, specificity and accuracy, and it points to its legitimacy in terms of practical clinical applications in early AD detection. This study provides a hybrid deep learning architecture that combines the handcrafted descriptors obtained through GLCM (texture, shape and intensity features) with deep features obtained by custom CNN and the ResNet50 architecture from MRI images in the context of the Alzheimer disease, an experimental evaluation of a variety of fusion strategies, which proves that feature level concatenation is more effective, and a critical evaluation of the available literature, illustrating the excellent accuracy of the method.

2. Related Work

The earliest methods of machine learning for the detection of AD through MRI were based on manually configured features, such as cortical thickness, hippocampal volume and texture statistics, to differentiate between disease states. According to a study conducted by Maity et al., the accuracy of using support vector machines (SVMs) using segmented hippocampal ventricular features was over 93% [2]. Although interpretable, these methods often did not capture the complex geometry in the brain that existed between the different spatial structures. CNNs and DL methods have shown better performance during AD classification tasks. Oraby et al. used a CNN with a super resolution generative adversarial network (GAN) to achieve 99.2% accuracy [3]. Similarly, Khalid et al. combined DenseNet-121 and GoogLeNet representations with handcrafted descriptors, such as Local Binary Patterns (LBP) and Discrete Wavelet Transform (DWT), up to 99.7% accuracy [4]. These results support the fact that multimodal feature fusion tends to be superior to single stream deep architectures.

Classification using MRI has been further optimized with transfer learning techniques using pretrained networks, e.g., ResNet, VGG, and EfficientNet. Nasir et al. combined EfficientNet-B0 and MobileNet-V2 with an accuracy of 94.7% [5], and Khan et al. proved the effectiveness of transfer learning to stratify AD stages [6]. The pretrained models also reduce convergence and enhance generalization especially when data is limited. Modern researches explored multimodal and hybrid architecture. Akan et al. used a combination of vision transformer and bidirectional LSTM (Bi-LSTM) networks to analyze three-dimensional MRI and Kim et al. proposed a multimodal scheme, which combines MRI and PET modalities to support the early detection of AD [7] [8]. Alayba et al. combined CNN-derived features with handcrafted descriptors GLCM, DWT, and LBP) in an XGBoost classifier, achieving 98.8% accuracy and 99.5% specificity [9]. Similarly, Ali et al. used canonical correlation analysis (CCA) with Whale Optimization Algorithm (WOA) to identify salient features effectively [10], and Zia et al. combined the representations of several pretrained CNNs, which increased the overall classification accuracy [11]. Also, image enhancement with the use of GAN has increased diagnostic fidelity in low-resolution MRI images [12]. A recent study by Bano et al. emphasized the importance of context-aware deep learning architectures to improve the feature detection and recognition tasks that could also be applied in the neuroimaging field [13]. Although the prior studies apply the convolutional neural networks, transfer learning methods or handcrafted features, they often did not apply a systematic combination of deep and handcrafted features in a single model. Moreover, there are limited studies on the effects of feature level fusion on interpretability or robustness hence the necessity of the hybrid design presented in this paper. Besides that, based on previous studies in the field of pattern recognition and feature engineering, the effectiveness of multi-descriptor representations, statistical feature modeling, and hybrid learning systems to improve the performance of classification in heterogeneous tasks has been empirically validated, thus supporting the factual basis of our multi-feature fusion approach [14]–[19].

3. Methodology

3.1. Dataset

The dataset used in this research is the publicly available Alzheimer Dataset (4-Class of Images) in Kaggle, in which there are a total of 6,400 brain MRI slices that are divided into four types of diagnosis, NonDemented (3,200), VeryMildDemented (2,240), MildDemented (896), and ModerateDemented (64) [20]. Every category is associated with the clinically defined stage of the severity of the Alzheimer disease. The dataset consists of about 200 different subjects, each with an average of 32 horizontal MRI slices. All the images are in the JPEG format and have the average resolution of 176x 208 pixel and depict axial brain sections [21]. However, it is restricted to one source (Kaggle) and lacks cross-institutional or multi-center samples. Subject identifiers are not provided in the Kaggle dataset therefore all experiments are conducted at slice level. The dataset was split into 70% training and 30% testing using a stratified strategy based on class labels to preserve class distributions across the splits. Fig. 1 shows the different categories of the Alzheimer's disease.

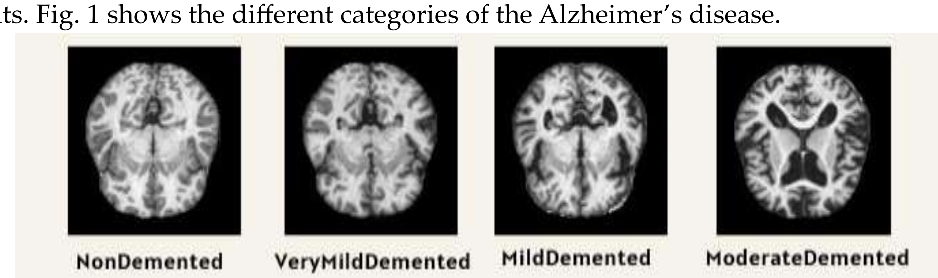

Figure 1. Sample MRI scans showing four Alzheimer's diagnostic categories.

3.2. Preprocessing

Preprocessing is an essential part to get the dataset into the desired input shape while maintaining the images quality. Sparse based super resolution methods have proved useful in reconstruction of high-resolution medical images [22]. Interventions in other super-resolution sources such as OCT have shown improvement in their image quality via sparse super resolution [23]. Structural details can be strengthened in all biomedical images through relative smoothness and Laplacian filtering [24]. It is well known that restoration and enhancement frameworks are widely used in order to enhance clinical imaging pipelines [25]. Brightness inconsistencies and specular reflection have been addressed by techniques based on intrinsic layers [26].

To prepare dataset for training the model several preprocessing steps were done, which included resizing, normalization, and augmentation. To normalize the dataset the pixel intensities of images were brought to range [0,1] through division by 255 hence ensuring uniform brightness and maximizing gradient stability in the optimization procedure. All the images were resized to 224x224 pixels to align with the size input of architectures of CNN. Data augmentation was utilized to increase variability as well as reduce overfitting. The augmentation processes included random image rotations in a 15° window, image translations up to 10% and zoom factors of 10-20% as well as horizontal flipping, brightness and contrast adjustments, and Gaussian noise. These transformations simulate a variety of acquisition protocols and patient positioning conditions, which improves the strength and generalization power of the model. All data augmentation operations were applied exclusively to the training set after the train-test split to avoid introducing augmented variants of test images into the training data. Fig. 2 shows the different augmentation techniques used in this study.

3.3. Feature Extraction

This paper focuses on a hybrid approach of the feature extraction that uses a combination of deep learning generated features and hand created features:

3.3.1. Custom CNN Architecture

A lightweight custom CNN was designed specifically for 2D slices of MRI data (grayscale). It includes three convolutional layers with increasing filters depth (32, 64, 128) each employing 3x3 kernels, followed by 2x2 max-pooling, ReLU activations, batch normalization, and dropout layers (rate=0.2) to prevent overfitting. The resulting feature maps are flattened and passed through a fully connected layer of 128 units with ReLU activation. This branch outputs a 128-dimensional deep feature vector used for feature fusion. Roy et al. demonstrated that using sequential convolutional blocks helps extract useful features needed to find AD [27].

3.3.2. Pretrained Model (ResNet50)

In order to make use of the transfer learning, ResNet50 architecture previously trained on ImageNet was modified [28]. As ResNet50 expects a three-channel input, the grayscale MRI images are converted to RGB using channel replication. The pretrained convolutional layers are frozen during the training to mitigate overfitting on the limited dataset. The output feature maps from the final convolutional block are flattened and passed through a fully connected layer of 256-units with ReLU activation, followed by batch normalization and dropout (rate=0.5) producing a 256-dimensional feature representation. The last set of fully connected layers were removed as well as replaced by more dense layers containing task-specific ones. The convolutional layers were frozen and only the higher layers of it were fine-tuned. Islam et al. demonstrated that a pre-trained ResNet50 can be a powerful automatic feature extractor for Alzheimer's classification [29].

3.3.3. Handcrafted Features

Handcrafted features were obtained from every MRI slice, using GLCM based texture descriptors (contrast, dissimilarity, homogeneity, energy, correlation, and ASM), shape and morphological features (area, perimeter, eccentricity, and solidity) and intensity histograms. GLCM features were extracted using four angular offsets (0°, 60°, 90°, 135°) resulting in 24 texture features, shape features and 32-bin global intensity histograms were computed per slice yielding a 60 dimensions handcrafted feature vector. The handcrafted feature vector is provided as a separate input and is projected through a fully connected layer of 64 units with ReLU activation, followed by batch normalization and dropout (rate=0.3). This transformed handcrafted feature representation is then concatenated with the fused deep deep feature vector to form the final hybrid feature representation. These handcrafted attributes were normalized using standard scaling before being merged with deep features derived using CNN and ResNet50 [30].

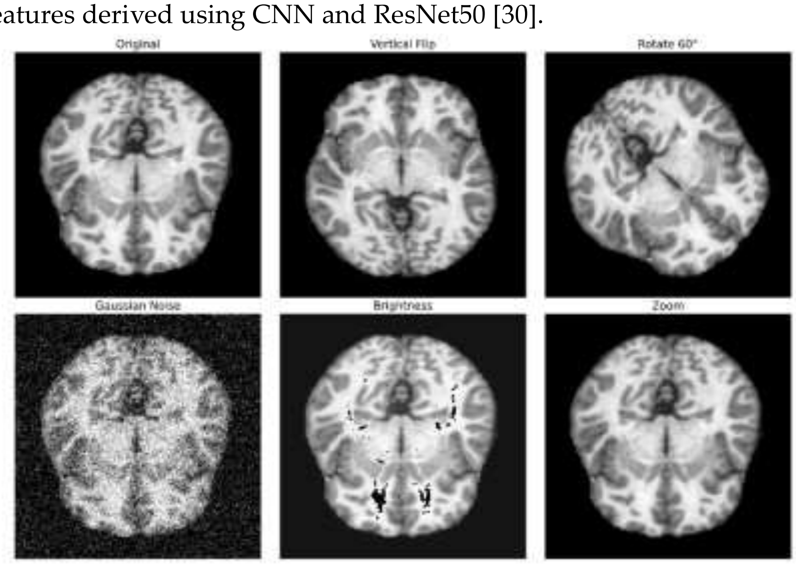

Figure 2. Examples of data augmentation applied to MRI scans.

A lightweight custom CNN and ResNet50 have been chosen because they complement each other in the feature representation. ResNet50 which is pre-trained on ImageNet, extracts global structural and contextual information of MRI scans, whereas the custom CNN concentrates on domain specific spatial and textural features. GLCM based texture descriptors, shape metrics, and intensity histograms were handcrafted features that were incorporated to retain localized structural features that deep models tend to ignore. This is a balanced mix that improves the discriminative ability of the model in detecting Alzheimer at its initial stages.

3.4. Feature Fusion

In order to integrate the best abilities of deep features and handcrafted features, we took advantage of feature level fusion through straightforward concatenation approach, it was chosen due to its simplicity, low computational costs, and proven effectiveness in maintaining complementary information [31]. The CNN and ResNet50 were jointly used for obtaining deep features to perform similarity matching. Prior to concatenation, all deep and handcrafted feature vector were normalized to ensure scale compatibility during feature level fusion. The deep feature vectors extracted from ResNet50 branch (256 dimensions) and the custom CNN branch (128 dimensions) are concatenated to form a unified 388-dimensional representation. This fused vector is further transformed using a fully connected layer of 128-units with ReLU activation, followed by batch normalization and dropout (rate=0.5) yielding a compact deep representation for subsequent fusion with handcrafted features. Their outputs were concatenated with handcrafted descriptors to get a complete feature vector, otherwise they could have been used individually too and that process was repeated to get a comprehensive feature vector and it was used in feeding a classifier to obtain the results.

3.5. Classification and Evaluation Metrics

The combined features generated were run through fully connected neural network classifier. To minimize overfitting dropout layers were implemented. Adam optimizer and cross-entropy as a loss function were applied to the model in training. The following are the measures that were used to measure the performance: Accuracy, Precision, Recall (Sensitivity), Specificity, F1-Score. Fig. 3 shows the accuracy and loss graph of the proposed model where training and validations accuracy is increasing gradually and training and validation loss is decreasing gradually.

4. Results And Discussion

In ensuring the viability of multi-feature framework, five experimental set-ups have been considered. The effectiveness of various kinds of features (handcrafted, deep learning-based, or fused) is tested in each configuration with the same dataset and protocol of evaluation. The metrics applied to the performance were: Accuracy, Precision, Recall (Sensitivity), Specificity and F1-Score.

The overall Accuracy is calculated as:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively. This measures the overall correct classification rate.

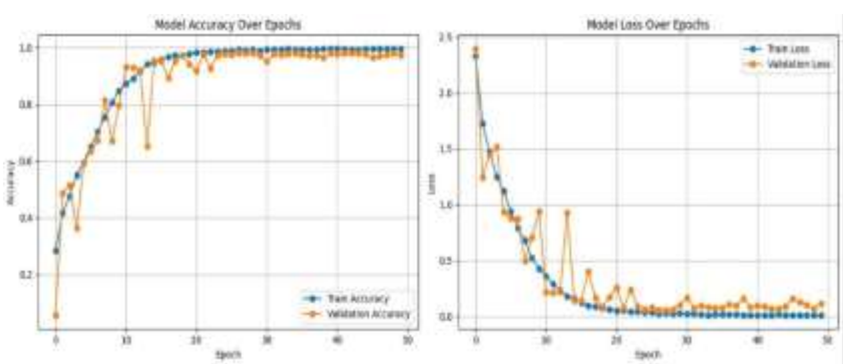

Figure 3. Training and validation accuracy/loss curves for the proposed hybrid model.

For each class i, the Precision and Recall (Sensitivity) are given by:

$$\text{Precision}_i = \frac{TP_i}{TP_i + FP_i},$$

$$\text{Recall}_i = \frac{TP_i}{TP_i+FN_i} \quad (2)$$

Precision indicates the proportion of correctly predicted positive observations, while Recall (Sensitivity) reflects the proportion of actual positives correctly identified.

The F1-score for each class is the harmonic mean of Precision and Recall:

$$\mathrm{F1}_i = 2 \cdot \frac{\mathrm{Precision}_i \cdot \mathrm{Recall}_i}{\mathrm{Precision}_i + \mathrm{Recall}_i} \quad (3)$$

We report both per-class and average metrics. For an overall F1-score, the macro-average is computed as the mean of all class-wise F1-scores:

$$\mathrm{F1}_{\mathrm{macro}} = \frac{1}{C}\sum_{i=1}^{C} \mathrm{F1}_i \quad (4)$$

where C is the total number of classes. This ensures equal weight is given to each class regardless of class imbalance.

The Specificity (true negative rate) for each class i is calculated as:

$$\mathrm{Specificity}_i = \frac{TN_i}{TN_i + FP_i} \quad (5)$$

4.1 Handcrafted Features

Classification in this experiment was done by use of only handcrafted features (such as GLCM, LBP, DWT, and volumetric measures). A fully connected neural network was fed with such features. Although logical, the model was weak in terms of accounting small differences among classes, especially during early stages of AD shown by the performance metrics as seen in Table 1.

Table 1. Performance Metrics using Handcrafted Features

Metric	Value (%)
Accuracy	72.79
Precision	70.70
Recall	52.61
F1 Score	55.84
Sensitivity	52.61
Specificity	88.31

4.2. Custom CNN

In this experiment a CNN designed specifically has been trained on preprocessed slices of MRI by training it completely. CNN performed better and this illustrates that it can learn spatial patterns. Nevertheless, the model with the help of only that could still not identify all structural abnormalities that were identifiable with the help of handcrafted features. The performance of the custom CNN can be seen in Table 2.

4.3. Custom CNN + Handcrafted Features

In this experiment, the deep features of the CNN were concatenated with the hand crafted features to another feature vector. The fusion enhanced the performance in every metrics and particularly in specificity and recall, which serves as evidence that both handcrafted descriptors and CNN features are complementary as it can be seen in Table 3.

Table 2. Performance metrics using the custom CNN model

Metric	Value (%)
Accuracy	93.03
Precision	95.33
Recall	90.84
F1 Score	92.93
Sensitivity	90.84
Specificity	96.88

Table 3. Performance metrics combining CNN and handcrafted features

Metric	Value (%)
Accuracy	96.99
Precision	98.10
Recall	96.11
F1 Score	97.08
Sensitivity	96.11
Specificity	98.80

4.4. Custom CNN + ResNet50

In this experiment, we used the hybrid approach that combined features of a custom CNN and pre-trained ResNet50. Using two deep architectures together made the feature representation even better and advanced the classification. The results of this hybrid approach classification is shown in Table 4 below.

Table 4. Performance metrics combining custom CNN and pretrained ResNet50

Metric	Value (%)
Accuracy	98.00
Precision (Macro Avg)	99.00
Recall (Macro Avg)	97.00
F1 Score (Macro Avg)	98.00
Sensitivity (Avg)	97.00
Specificity (Avg)	98.00

4.5. Custom CNN + ResNet50 + Handcrafted Features

The proposed hybrid model used all three types of features: handcrafted features, CNN-based features and ResNet50 based features. The given model demonstrated the best accuracy, which proves the hypothesis according to which multi-feature fusion is more efficient than single methods. The results of the final hybrid model can be seen in Table 5.

Table 5. Performance metrics of the final hybrid model integrating CNN, ResNet50, and handcrafted features.

Metric	Value (%)
Accuracy	99.70
Precision (Macro Avg)	98.21
Recall (Macro Avg)	95.14
F1 Score (Macro Avg)	96.59
Sensitivity (Avg)	95.14
Specificity (Avg)	98.84

4.6. Comparative Analysis

Table 6 outlines the ablation analysis which was done to determine the performance of different feature set combinations. The continuous enhancement in successive configuration is an indication of the complementary nature of handcrafted and deep learning derived features, where the final hybrid model achieved an accuracy of 99.70%, a precision of 98.10%, and an F1-score of 97.08%.

Table 6. Comparative analysis of all tested configurations in the proposed framework.

Model Configuration	Accuracy	Precision	Recall	F1-Score	Specificity
Handcrafted Only	72.79	70.70	52.61	55.84	88.31
CNN Only	93.03	95.33	90.84	92.93	96.88

CNN+ Handcrafted	96.99	98.10	96.11	97.08	98.80
CNN+ ResNet50	98.00	99.00	97.00	98.00	98.00
CNN+ResNet50 + Handcrafted (Final)	99.70	98.21	95.14	96.59	98.84

As the results show in Table 7, the approach in this study performs better than other recent methods, by using ResNet50, a Custom CNN and extra handcrafted features. The difference between the handcrafted and deep features confirms how joining the two enhances the precision and strength of classification methods in MRI-based Alzheimer's detection.

4.7. Clinical and Ethical Considerations

The proposed hybrid model has a strong diagnostic performance on the Kaggle Alzheimer data, but to implement it in clinical practice, it is necessary to consider a number of methodological issues. In a working healthcare case, this model may be used as a computer-aided diagnostic (CAD) system, which will help radiologists by pre-screening MRI scans and pointing out the places where degeneration due to Alzheimer may be present. This potential can make radiologists workload less and encourage early diagnosis, especially in resource-restrictive environments. Ethically, the implementation of such systems must follow the strict rules of data privacy, bias mitigation, and clinical validation procedures.

Table 7. Comparative analysis of Alzheimer's disease classification models based on standard performance metrics

Reference/ Author	Accuracy	Precision	Recall	F1-Score	Sensitivity	Specificity
Murugan et al. [32]	95.23	96.00	95.00	95.27	–	–
Ahmed et al. [33]	90.00	91.34	87.34	88.09	–	–
Sharma et al. [34]	90.40	90.50	90.40	90.40	–	–
Balasundaram et al. [35]	94.10	96.50	94.75	95.50	–	–
Hazarika et al. [36]	88.00	92.00	90.00	91.00	–	–
Balaji et al. [37]	98.50	94.80	98.00	–	–	–
Sethuraman et al. [38]	96.61	–	–	–	94.34	94.96
El-Latif et al. [39]	95.93	95.93	95.98	95.90	–	–
Chabib et al. [40]	98.62	–	99.05	99.21	–	98.50
Prasanna et al. [41]	98.99	99.11	99.31	98.71	–	–
Al-Rawashdeh et al. [42]	98.90	96.60	100.00	98.30	97.30	–
Alruily et al. [43]	97.93	95.94	95.89	87.50	95.89	98.04

Proposed Model	99.70	98.21	95.14	96.59	95.14	98.84

5. Conclusion and Future Work

5.1. Conclusion

In this study, the early diagnosis and classification of AD using the grayscale MRI images was presented with a strong, multi-feature based approach. Using features incorporated based on handcrafted descriptors, as well as representations provided by a custom CNN and pretrained ResNet50 model using deep learning, we were able to achieve an extensive increase in classification performance using all the metrics. The results of the experiments indicated that combination of feature types always gave better results compared to single methods. The last proposed hybrid model attained an accuracy of 99.70%, precision of 98.21%, recall of 95.14%, F1-score of 96.59% and a specificity of 98.84%. These results reveal the idea that a combination of the traditional and data-driven features provides a more thorough model of structural alterations in the brain associated with the AD. Furthermore, this system was able to classify four levels of cognitive impairment: NonDemented, VeryMildDemented, MildDemented, and ModerateDemented, thus it could be very much applicable in clinical practice and screening a population. The piece of work is an addition to the literature that promotes hybrid, interpretable, and precise diagnostic models in neuroimaging. It also supports the importance of handcrafted features in the age of deep learning as well as when combined with hierarchical CNN representation. The code and dataset used is publicly available at the following link "https://github.com/wah33dilahi/Alzheimer-s-DiseaseDetection".

5.2. Future Work and Limitations

Although this hybrid model has outstanding performance on the Kaggle Alzheimer dataset, it has some shortcomings that are worthy of consideration. The accuracy is almost perfect (99.7%), which implies a possible probability of overfitting as there is a risk that the dataset does not capture the heterogeneity of clinical populations entirely. To avoid this risk the data augmentation methods were used and dropout layers were added to both CNN and ResNet50 branches to improve the generalization. However, the model needs to eventually be tested on independent, clinically verified data sets including ADNI and OASIS to determine its externalizable and strength across different sources of imaging and diverse demographic groups. The dataset is limited that causes class imbalance, the future work will apply methods of synthetic data generation, such as SMOTE and GAN-based augmentation, in order to balance the number of classes better. Because subject identifiers are unavailable, the evaluation is performed at the slice level which may overestimate performance due to inter-slice similarity. Future work will include subject wise and multi-center validation. Also, the present study used the 2D MRI slices, which are not the natural development of the Alzheimer disease, which is a structural process that needs to be three-dimensional. Future research will conduct a study based on 3D CNNs and volumetric feature extraction schemes to better represent the spatial distributions of neurodegeneration.

Regarding model interpretability, explainable AI (XAI) methods (e.g. Grad-CAM and SHAP visualizations) will be integrated in order to determine important brain regions contributing to predictions. This attempt should help raise transparency and create clinical acceptance. Lastly, clinical implementation will require the use of cross-dataset validation, prospective testing, and working closely with medical practitioners to assess the reliability of diagnostic, usability, and ethical requirements. To sum up, the study in question helps to emphasize that hybrid AI systems have a huge potential of transforming the Alzheimer disease diagnostics and in particular at its earliest and most treatable stages.

Conflicts of Interest

The authors declare no conflict of interest.

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