Hybrid Feature Extraction Technique-based Alzheimer’s Disease Detection Model Using MRI Images

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ABSTRACT

Detecting Alzheimer’s disease (AD) using magnetic resonance imaging (MRI) is essential for early diagnosis and management. This study introduces a new method for detecting AD by combining three robust models: DenseNet201, EfficientNet B7, and extremely randomized trees (ERT). We improve the ability to extract features in DenseNet201 by including a self-attention mechanism. Additionally, we use early stopping techniques on EfficientNet B7 to address the issue of overfitting. In addition, Bayesian Optimization and Hyperband optimization techniques are used to adjust the hyperparameters of extra-trees to differentiate normal and abnormal MRI images. In addition, the authors used SHapley Additive exPlanations to understand the model’s decision. With minimal computer resources, the proposed model achieved a remarkable accuracy of 98.9% in detecting AD. The findings highlight the effectiveness of recommended feature extraction and ERT models and optimization methods to accurately identify AD using MRI images.

KEYWORDS

feature extraction, pre-trained model, machine learning, deep learning, gradient boosting, degenerative condition

INTRODUCTION

Alzheimer’s disease (AD) is a degenerative condition of the nervous system that gradually causes a deterioration in cognitive abilities, memory loss, and difficulties in performing everyday activities (Yadav and Sutar, 2021). AD is the prevailing kind of dementia, impacting a large number of individuals globally and presenting substantial obstacles to healthcare systems and society at large (Hag et al., 2020; Sudha and Srinivasan, 2020). The earliest identification of AD is essential for prompt intervention, effective disease management, and enhancing the quality of life for persons afflicted by the condition. Medical imaging methods, including magnetic resonance imaging (MRI), have become more important in recent years for aiding in diagnosing and predicting AD (Hazarika et al., 2021). These imaging techniques provide comprehensive and precise data on the structure and function of the brain, allowing medical professionals to identify tiny alterations linked to AD pathology (AlSaeed and Omar, 2022).

MRI is widely applied for AD detection due to its non-invasive nature, high-resolution imaging capabilities, and ability to provide detailed insights into brain structure and function (AlSaeed and Omar, 2022). By offering precise visualization of key brain regions affected by AD, such as the hippocampus and cortex, MRI enables the identification of subtle atrophy and structural changes indicative of the disease (AlSaeed and Omar, 2022). Its non-invasive nature ensures patient safety and allows for repeated imaging, crucial for monitoring disease progression over time. Moreover, MRI’s ability to detect early signs of AD before significant cognitive symptoms manifest is invaluable for early diagnosis and intervention (Abunadi, 2022). Quantitative biomarkers extracted from MRI images, such as brain volume and cortical thickness, provide quantitative measures of neurodegeneration, aiding in disease staging and tracking progression. Additionally, functional MRI offers insights into
brain activity patterns associated with AD-related cognitive decline.

Although there have been significant improvements in medical imaging technology, accurately interpreting MRI images for the diagnosis of AD still poses a difficult challenge (Abunadi, 2022). Human professionals often encounter challenges when differentiating between typical age-related changes and pathological changes linked to AD, resulting in inconsistency and subjectivity in diagnosis (ElZawawi et al., 2022). Machine learning (ML) and deep learning (DL) approaches have shown potential in automating the processing of MRI images and enhancing the precision of AD identification (Vidhya et al., 2023).

Nevertheless, effectively diagnosing AD is a complex and formidable undertaking. ML techniques mainly depend on subjective clinical data, which may lack sensitivity, especially during the initial phases of the illness (Zia et al., 2022). Medical imaging methods, such as MRI, allow for examining brain structure and function without intrusive procedures (Abuhmed et al., 2021). These techniques provide significant information on the degenerative changes linked to AD.

In recent years, there has been an increasing interest in using ML and DL methods to automate MRI processing to identify AD. These methods have shown potential in extracting meaningful characteristics from imaging data and enhancing the precision of AD diagnosis. Nevertheless, notable obstacles must be addressed, such as the need for solid feature extraction techniques, fine-tuning model hyperparameters, and effective exploitation of computing resources.

The purpose of this work is to tackle these problems and make progress in the field of AD identification using MRI imaging. Our objective is to enhance the accuracy and efficiency of AD diagnosis by offering a complete strategy that includes advanced DL architectures, optimization techniques, and unique feature extraction and model development tactics. In essence, our objective is to make a valuable contribution to the development of early diagnosis and intervention methods for AD, resulting in enhanced patient outcomes and more effective treatment of this incapacitating condition. The detailed contributions of this study are as follows:

1. Utilization of DL architectures
   - We propose to leverage three robust DL architectures: DenseNet201, EfficientNet B7, and extremely randomized trees (ERT).
   - DenseNet201 is chosen for its dense connectivity pattern, which facilitates feature reuse and enhances feature representation, while EfficientNet B7 is selected for its superior efficiency and scalability across different model scales.
   - Additionally, extra-trees, a variant of ensemble learning, is employed to leverage the diversity of individual decision trees for improved generalization performance.

2. Incorporation of self-attention mechanism
   - To enhance the feature extraction capabilities of DenseNet201, we introduce a self-attention mechanism. This mechanism allows the model to focus on relevant regions of the input data, effectively capturing spatial dependencies and enhancing feature discriminability.
   - We employ early stopping strategies in the training of EfficientNet B7 to prevent overfitting and improve generalization performance. Early stopping monitors the model’s performance on a validation set during training. It halts the training process when the performance starts to degrade, thus preventing the model from memorizing noise in the training data.

3. Optimization techniques
   - Bayesian Optimization and Hyperband (BOHB) optimization are utilized to tune the hyperparameters of the extra-trees model. BOHB combines the benefits of Bayesian Optimization with the efficiency of Hyperband, allowing for the simultaneous exploration of multiple hyperparameter configurations and efficient resource allocation.

4. Performance evaluation
   - The proposed approach is evaluated on a benchmark dataset consisting of MRI images of subjects with and without AD.
   - We assess the performance of our method in terms of accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve, comparing it with existing state-of-the-art approaches.

5. Resource-constrained environment
   - Notably, our research is conducted in a resource-constrained environment with limited computational resources. Despite these constraints, we demonstrate the effectiveness of our approach in achieving high accuracy in AD detection, highlighting its practical applicability in real-world settings.

The novelty of this research is encapsulated in its sophisticated integration of the state-of-the-art models and optimization techniques, enhanced feature extraction through self-attention, model interpretability using SHapley Additive exPlanations (SHAP), and the achievement of high diagnostic accuracy with minimal resource utilization. These contributions collectively push the boundaries of current AD detection methods, offering a robust and efficient solution for the early diagnosis and management of AD.

LITERATURE REVIEW

Traditional ML approaches, such as support vector machines, random forests, and logistic regression, have been extensively applied to AD detection using MRI data (Bhatele and Bhadauria, 2020; EL-Geneedy et al., 2023; Sindhu et al., 2024). These methods often rely on handcrafted features extracted from MRI scans, such as voxel-based morphometry and regional volumetric measurements. While these approaches have shown promising results, they are limited by their reliance on predefined features and may struggle to capture subtle patterns indicative of early-stage AD.

Despite attempts to develop interpretable DL models, including attention processes or saliency maps, attaining complete explainability still poses a significant challenge (Mahendran et al., 2021). DL models with millions of parameters can capture intricate correlations within the data.
(Balaji and Suresh, 2023). Explainable DL approaches are crucial for obtaining a better understanding of AD’s molecular foundations and establishing confidence in DL-driven diagnostic tools (Ismael, 2018).

Different MRIs may reveal different brain structures within and across subjects and different acquisition parameters (Xiao et al., 2017). DL models trained on diverse MRI data may face challenges in generalizing across varying imaging methods or demographic cohorts. It is crucial to have strong DL models that can effectively handle the differences in MRI data gathering and patient characteristics in order to be used in real-world clinical applications (Altaf et al., 2017).

Interpretability offers medical professionals a deeper understanding of the elements that drive diagnostic choices by providing insights into the rationale behind a model’s predictions (Savita and Sabharwal, 2021). To make well-informed clinical choices about patient care and treatment plans, clinicians should have confidence in and comprehend the rationale behind a model’s predictions. Interpretability allows researchers and doctors to assess the dependability and credibility of ML models (Savita and Sabharwal, 2021). Researchers may evaluate the alignment between the model’s predictions and current medical knowledge and clinical skills by identifying the specific aspects or areas of MRI scans that contribute to the diagnosis of AD. Interpretable models aid in identifying relevant biomarkers or imaging characteristics linked to AD pathogenesis (Khan and Zubair, 2022). Gaining knowledge about the biological foundation of AD and the modifications in brain structure observed by MRI scans is essential for developing diagnostically significant indicators and targets for therapy. Interpretable models aid in error analysis by pinpointing instances when the model may have produced inaccurate predictions or misread imaging characteristics (Orouskhani et al., 2022). This iterative method enables researchers to detect any flaws in the model and enhance its architecture, training data, or preprocessing processes in order to improve its performance and dependability.

Timely identification of AD is essential for promptly implementing therapies to decelerate the advancement of the illness. Utilizing longitudinal analysis of MRI data allows for the observation of structural changes in the brain over a period of time, which may possibly detect first signs of AD prior to the manifestation of clinical symptoms. Longitudinal studies have distinct obstacles, such as obtaining and preparing data, registering longitudinal data, and modeling longitudinal patterns. It is crucial to overcome these hurdles and create robust longitudinal analytic tools in order to facilitate early identification and intervention in AD.

**RESEARCH METHODOLOGY**

The suggested approach for detecting AD using MRI scans includes numerous essential elements, including choosing DL architectures, incorporating novel processes for extracting features, optimization strategies, and evaluation metrics. The technique utilizes three robust DL architectures: DenseNet201, EfficientNet B7, and extra-trees. The DenseNet201 model is selected because its dense connection design promotes feature reuse and improves feature representation. The selection of EfficientNet B7 is based on its exceptional efficiency and scalability across several model sizes, rendering it highly appropriate for processing high-resolution MRI data. As an ensemble learning approach, extra-trees enhance resilience and generalization performance by amalgamating several decision trees.

DenseNet201 and EfficientNet B7 are state-of-the-art DL architectures known for their effectiveness in image classification tasks. DenseNet201 employs densely connected layers to facilitate feature reuse and gradient flow throughout the network. This architecture is particularly well-suited for extracting informative features from MRI scans with high spatial resolution. On the other hand, EfficientNet B7 achieves better accuracy and efficiency by scaling network depth, width, and resolution in a principled manner. These architectures serve as the backbone for feature extraction in AD detection models.

The Alzheimer’s dataset (Kaggle, n.d.), accessible on Kaggle, offers researchers a useful tool for developing and evaluating DL models for MRI imaging-based AD diagnosis and detection. Researchers may use this dataset to make significant contributions to the field of understanding AD pathology, enhancing early detection techniques, and creating diagnostic tools that are more precise and dependable for clinical use. MRI images are frequently available in standard medical imaging formats, such as DICOM (Digital Imaging and Communications in Medicine) or NIfTI (Neuroimaging Informatics Technology Initiative). These formats maintain the spatial and anatomical data of the MRI images, allowing researchers to do thorough analysis and processing.

**Feature extraction**

Feature extraction methods aid in limiting the number of dimensions in MRI data while retaining crucial information pertaining to the diagnosis of AD. Dimensionality reduction enables the training of ML models and enhances their efficiency and performance by choosing a subset of informative characteristics. Utilizing significant information from MRI data may improve the capacity of AD detection algorithms to generalize. By prioritizing pertinent imaging biomarkers, models that are trained on varied datasets demonstrate an improved ability to identify typical patterns linked to AD pathology and apply this knowledge to new data from distinct patient groups or imaging procedures. The extracted variables often align with clinically significant elements of AD disease, such as alterations in specific brain areas or neuroanatomical structures. These characteristics are easily understood and consistent with current medical understanding, enhancing their usefulness for healthcare practitioners’ clinical analysis and decision-making.

Feature extraction enhances the diagnostic accuracy of AD detection models by detecting minor anatomical changes in the brain that are linked with AD. Extracted characteristics
function as distinctive indicators that differentiate between individuals with AD and normal individuals, resulting in more precise and dependable diagnostic predictions. Figure 1 presents the proposed feature extraction using DenseNet201 and EfficientNet B7 models.

**DenseNet201**

The suggested technique uses DenseNet201 as its base architecture to extract features from MRI scans. DenseNet201 is composed of densely linked convolutional blocks, which enable the effective transmission of gradients and the extraction of distinguishing characteristics at various levels of abstraction. The pre-trained weights obtained from ImageNet are adjusted using a substantial dataset of MRI images in order to customize DenseNet201 for the specific task of AD identification. Transfer learning methods are used to use the acquired knowledge from ImageNet to extract features in the context of AD detection. The MRI scans undergo preprocessing to standardize intensity levels, normalize spatial dimensions, and increase picture contrast. The DenseNet201 architecture takes the preprocessed images and uses several convolutional layers to extract features. A classification model is trained and evaluated using the collected characteristics to differentiate between healthy controls and AD patients.

**EfficientNet B7**

The suggested technique utilizes EfficientNet B7 as the primary framework for extracting features in order to diagnose AD from MRI images. EfficientNet B7 employs compound scaling to optimize the network’s depth, breadth, and resolution, leading to enhanced feature extraction skills. Transfer learning is used to refine the EfficientNet B7 model using a vast collection of MRI images. This enables the model to be adjusted specifically for the categorization of AD. The network weights are initialized, and the training process is accelerated by using pre-trained weights from ImageNet.

**Early stopping strategies**

Overfitting is a common challenge in DL models, wherein the model learns to memorize training data rather than generalize to unseen data. Early stopping techniques mitigate overfitting by monitoring the model’s performance on a validation set and halting training when performance deteriorates. By applying early stopping techniques to EfficientNet B7, the proposed method aims to improve the generalization ability of the model and prevent overfitting, thereby enhancing its performance in AD detection tasks.

Early stopping criteria were employed to mitigate overfitting in the EfficientNet B7 model. This technique involves monitoring the model’s performance on a separate validation dataset during training and halting the training process when the validation performance starts deteriorating. Specifically, we monitored the validation loss, which measures the discrepancy between the model’s predictions and the ground truth labels on the validation set. When the validation loss began to increase consistently over a certain number of epochs, the training was halted to prevent the model from memorizing noise in the training data, which is indicative of overfitting. By terminating the training at this point, we ensured that the model did not continue to learn from noisy or irrelevant patterns in the training data, thereby improving its ability to generalize to unseen data. This approach effectively addressed overfitting by promoting a balance between the model’s ability to capture underlying patterns in the data while avoiding the fitting of noise or outliers, ultimately enhancing the model’s robustness and performance in AD detection.
Extra-tree-based AD detection

Extra-trees is a decision tree algorithm ensemble learning approach. The algorithm constructs several decision trees using random subsets of the training data and aggregates their predictions using a voting process to get the final predictions. Multiple decision trees are constructed using random subsets of the training data during the training process. Extra-trees differ from standard decision trees in that they produce splits at random thresholds within the range of each feature, rather than selecting splits based on optimal criteria such as Gini impurity or information gain. The use of randomization in this context enhances the variety among the trees, thus mitigating overfitting and enhancing the resilience of the model. Although extra-trees are ensemble models that lack interpretability compared to individual decision trees, approaches such as feature importance analysis might provide insights into the relative significance of various retrieved features in AD detection. The authors established SHAP values as a means to quantify the importance of biomarkers in predicting AD. This research facilitates comprehension of the specific anatomical attributes of the brain that are most significant in differentiating between individuals with AD and those who are in good condition. Figure 2 highlights the proposed AD model.

Hyperparameter optimization

Optimizing hyperparameters is essential for achieving optimal performance in DL models. Bayesian Optimization and Hyperband are two popular techniques used for hyperparameter optimization in ML. Bayesian Optimization constructs a probabilistic model of the objective function and iteratively selects hyperparameters to evaluate based on their expected improvement. On the other hand, Hyperband adaptively allocates computational resources to different hyperparameter configurations based on their performance, allowing for efficient exploration of the hyperparameter space. By leveraging BOHB, the proposed method aims to quickly adjust the hyperparameters of the ensemble model, leading to improved accuracy and efficiency in AD detection.

In hyperparameter tuning for the ERT model, BOHB works together to search the hyperparameter space and efficiently identify the optimal configuration. Bayesian Optimization explores the space by intelligently selecting hyperparameter values based on the surrogate model’s predictions, while Hyperband allocates resources dynamically to focus on promising configurations, accelerating the search process. This combination of techniques maximizes the chances of finding the best hyperparameter settings for the ERT model, ultimately improving its performance in AD detection.

RESULTS AND DISCUSSIONS

The authors constructed the proposed model using Windows 10, Intel i7, 16 GB RAM, and NVIDIA 350X (NVIDIA Corporation, Santa Clara, CA, USA). Fivefold cross-validation was used to train the proposed model. The DenseNet201 and EfficientNet B7 models were built using the GitHub repository. Table 1 shows the outcomes of the fivefold cross-validation. Figure 3 shows the finding of the fivefold cross-validation.

In Table 1 and Figure 3, the fivefold cross-validation results underscore the proposed model’s exceptional performance. This rigorous validation method, which divides the dataset into five subsets and iteratively trains and tests the model, demonstrates the model’s robustness and reliability. Each fold consistently shows high accuracy, precision, and recall, indicating that the model effectively generalizes across different data partitions. The minimal variance in performance metrics across the folds highlights the model’s

![Figure 2: The recommended AD detection. Abbreviations: AD, Alzheimer’s disease; BOHB, Bayesian Optimization and Hyperband.](image)

<table>
<thead>
<tr>
<th>Folds</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1-score</th>
<th>Specificity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
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<tr>
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<td>97.1</td>
<td>96.8</td>
<td>96.9</td>
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</tr>
<tr>
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<td>98.1</td>
<td>97.3</td>
<td>97.5</td>
<td>97.1</td>
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</tr>
<tr>
<td>5</td>
<td>99.2</td>
<td>98.7</td>
<td>98.6</td>
<td>98.5</td>
<td>98.1</td>
</tr>
</tbody>
</table>

Table 1: Findings of fivefold cross-validation.
stability and efficiency in resource optimization and yield maximization. These findings validate the model’s potential as a reliable tool for agricultural management, ensuring consistent and high-quality outcomes.

Table 2 presents the performance validation outcomes, showcasing the impressive efficacy of the proposed AD model. The metrics, including accuracy, precision, recall, and F1-score, consistently demonstrate high performance across various validation sets. This uniformity indicates the model’s robustness and reliability in accurately diagnosing AD.

The confusion matrix shown in Figure 4 further supports these findings by detailing the model’s classification capabilities. The high number of true positives and true negatives, coupled with minimal false positives and false negatives, underscores the model’s exceptional accuracy and precision. These results collectively validate the proposed AD model as a powerful tool for early and accurate diagnosis of AD, offering significant potential for clinical application and improving patient outcomes.

Table 3 presents the comparative analysis outcomes, highlighting the superior performance of the proposed AD model against existing models. The table includes key metrics such as accuracy, precision, recall, and F1-score, each showcasing the AD model’s enhanced diagnostic capabilities. Compared to other models, the proposed AD model consistently achieves higher accuracy, indicating its effectiveness in correctly identifying both AD and non-AD cases. The precision metric demonstrates the model’s ability to minimize false positives, while the high recall value reflects its proficiency in detecting true-positive cases. The F1-score, balancing precision and recall, further underscores the model’s robust and reliable performance. These comparative results validate the exceptional efficacy of the proposed AD model, confirming its potential as a leading tool for AD diagnosis and management.

Table 4 presents the computational complexities of the proposed AD model compared to existing models. The table evaluates critical factors such as training time, inference time, and resource utilization, comprehensively assessing the computational demands. The proposed AD model demonstrates efficient computational performance with significantly reduced training and inference times. This efficiency is attributed to the model’s optimized architecture, which leverages advanced DL techniques to minimize computational overhead. Additionally, the model’s resource utilization, including memory and processing power, is lower than that of traditional models, making it suitable for deployment on various hardware platforms, including those with limited resources. These findings highlight the proposed AD model’s capability to deliver high diagnostic accuracy and reliability while maintaining computational efficiency. This balance between performance and complexity ensures that the model is effective and practical for real-world applications, facilitating widespread adoption in clinical settings.

The findings of this study hold significant implications for clinical practice, offering a promising approach to enhance the early detection and management of AD. With a remarkable accuracy of 98.9% achieved in detecting AD from MRI images, the proposed model presents a reliable and efficient tool for clinicians. Early and accurate diagnosis facilitated by this model can enable timely interventions, leading to better patient outcomes and improved quality of life. Additionally, the model’s ability to operate with minimal computational resources enhances its accessibility and practicality in diverse clinical settings, offering a valuable asset in the fight against AD.

The proposed method demonstrates exceptional accuracy in diagnosing AD using MRI images and minimum computing resources. The approach achieves high accuracy in AD detection tasks by integrating DenseNet201, EfficientNet B7, and extra-trees in an ensemble architecture. It additionally incorporates optimization methods such

**Table 2: Performance validation outcomes.**

<table>
<thead>
<tr>
<th>Folds</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1-score</th>
<th>Specificity</th>
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</thead>
<tbody>
<tr>
<td>Normal</td>
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<td>100</td>
<td>98.4</td>
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<tr>
<td>Abnormal</td>
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<td>96.9</td>
<td>100</td>
<td>98.3</td>
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<tr>
<td>Average</td>
<td>98.9</td>
<td>96.6</td>
<td>100</td>
<td>98.3</td>
<td>97.3</td>
</tr>
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</table>
In conclusion, this study introduces an innovative approach to AD detection using MRI images by integrating DenseNet201, EfficientNet B7, and ERT. The enhanced feature extraction capabilities of DenseNet201, augmented by a self-attention mechanism, significantly improve the model’s performance. By employing early stopping techniques, EfficientNet B7 addresses the issue of overfitting, ensuring robust model generalization. Additionally, applying BOHB optimization techniques to adjust the hyperparameters of the ERT model enhances its ability to distinguish between normal and abnormal MRI images. The integration of these advanced techniques and models has resulted in an impressive accuracy of 98.9% in detecting AD, demonstrating the potential of combining state-of-the-art DL models with sophisticated optimization techniques to achieve high performance in medical image analysis. The proposed method’s efficiency in using minimal computational resources makes it a practical solution for real-world clinical settings, facilitating early detection and management of AD. These promising results pave the way for further research and development, aiming to refine and validate the approach across diverse datasets and clinical environments.

CONCLUSION

In conclusion, this study introduces an innovative approach to AD detection using MRI images by integrating as BOHB, showing its efficiency. The suggested technique has been validated using benchmark datasets, demonstrating its higher performance compared to current methodologies. These results emphasize the potential of the technology for clinical applications.

Despite its success, this study has limitations. First, the model’s performance was evaluated on a specific dataset, potentially limiting its generalizability to different populations or imaging protocols. Additionally, the interpretability of the model’s decisions, enhanced with SHAP, could be further improved. Future research could focus on validating the model on larger and more diverse datasets, incorporating multi-modal imaging data for improved diagnostic accuracy, and refining interpretability techniques. Furthermore, exploring the model’s performance in longitudinal studies and clinical trials could provide valuable insights into its real-world utility and effectiveness in aiding clinical decision-making.

Though ML and DL approaches have made progress, several constraints and obstacles remain in AD detection. The lack of standardized datasets and assessment measures impedes comparing and replicating various methods. Furthermore, the widespread application of AD detection models across various populations and imaging methods continues to be a significant limitation since differences in demographics and image collection settings might affect the efficacy of these models.

**Table 3**: Comparative analysis outcomes.

<table>
<thead>
<tr>
<th>Models</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1-score</th>
<th>Specificity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed model</td>
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<td>96.6</td>
<td>100</td>
<td>98.3</td>
<td>97.3</td>
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<tr>
<td>DenseNet201</td>
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<td>93.7</td>
<td>93.7</td>
<td>95.5</td>
</tr>
<tr>
<td>EfficientNet B7</td>
<td>95.8</td>
<td>94.8</td>
<td>94.9</td>
<td>94.7</td>
<td>95.1</td>
</tr>
<tr>
<td>Khan and Zubair (2022)</td>
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<td>96.8</td>
<td>95.7</td>
<td>95.2</td>
<td>94.1</td>
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<td>95.1</td>
<td>94.9</td>
<td>94.8</td>
</tr>
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</table>

**Table 4**: Computational complexities.

<table>
<thead>
<tr>
<th>Models</th>
<th>Parameters (in millions)</th>
<th>FLOPs (in giga)</th>
<th>Testing time (seconds)</th>
<th>Learning rate</th>
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<tbody>
<tr>
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<td>105</td>
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FLOPs, floating point operations.

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