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Research Article

Optimized Alzheimer's Detection from Brain Scans using CNN-Based Approach

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ABSTRACT

A progressive neurological disease, Alzheimer's disease affects millions of individuals globally. For Alzheimer's disease to be effectively treated and managed, early detection and stage classification are essential. Our proposal in this paper is to use brain MRI scans to classify Alzheimer's disease stages using a Convolutional Neural Network (CNN) based method. Using Bayesian and Grid Search approaches, we optimize the models and investigate both simple and complex CNN architectures, including transfer learning with VGG16. Notably, the Grid Search Advanced CNN model has a validation accuracy of 0.5269, the Bayesian Basic CNN model has a validation accuracy of 0.5044, and the Grid Search Basic CNN model has a validation accuracy of 0.4203. The most accurate validation, 54.84%, is obtained by the sophisticated CNN model with Bayesian optimization, according to our data. Based on validation accuracy, this data is useful for choosing the best model for a particular task.

We also go over the implications of our findings for early Alzheimer's disease detection and present a thorough comparison of the models.

Keywords: Deep Learning, Alzheimer Disease, Concolutional Neural Network(CNN),VGG16,Bayesian and Grid Search network.

INTRODUCTION

Alzheimer's disease (AD) is a degenerative neurological condition that mainly affects the elderly, affecting 60–70% of people worldwide. Because the disease develops before clinical symptoms appear, early detection is crucial for improving patient outcomes and allowing participation in clinical trials for potential treatments[1]. The limitations of conventional methods, such as clinical evaluation, cognitive testing, and imaging techniques like MRI and PET scans, include the inability to identify the illness until significant brain damage has occurred, as well as the fact that they are expensive, time-consuming, and difficult to obtain[2]. When beta-amyloid or tau proteins are detected in CSF, for example, patients find biomarker analysis to be invasive and painful. Because these diagnostic methods often require highly specialized equipment and personnel, they are less feasible for mass screening.

Deep learning, a new topic in medical diagnostics, has the latent to completely transform this profession. Deep learning is a subdivision of machine learning that uses artificial neural networks to handle vast volumes of data in a manner similar to how the human brain functions. When it comes to Alzheimer's detection, deep learning can examine genetic information, clinical records, and medical imaging to find minute patterns linked to the illness, frequently before symptoms appear[3].Deep learning algorithms for Alzheimer's detection are being developed to predict the disease's progression and identify risk factors. These models are capable of analyzing data from electronic health records, imaging, and genetics. Furthermore, different phases of AD have been categorized using deep learning models, potentially enabling more customized treatment plans[4].

In order to identify risk factors and forecast the course of the disease, deep learning models for Alzheimer's detection are being created. These models can evaluate genetic, imaging, and electronic health record data. Additionally, deep learning models have been used to categorize various AD phases, which may allow for more individualized treatment regimens. With advancements in computational influence and the availability of large-scale datasets, deep learning is becoming a viable solution for overcoming the limitations of traditional diagnostic techniques.

Early identification of Alzheimer's disease, a advanced neurological disease marked by memory loss, cognitive decline, and behavioral changes, may be made easier with deep learning. Conventional diagnostic techniques are either overly intrusive, costly, or dependent on clinical symptoms that don't show up until after serious brain damage. By evaluating vast amounts of medical data, finding patterns that might not be apparent to the naked eye, and learning from a variety of data sources, including genetic information, medical histories, and imaging scans, deep learning might overcome these difficulties.

This study investigates how deep learning models might be enhanced for Alzheimer's disease early detection, which could revolutionize the diagnosis and treatment of the condition. If effective, this strategy could lessen dependency on costly and intrusive diagnostic techniques, give clinicians early detection tools for more prompt intervention, and increase accessibility to Alzheimer's screening in low-resource environments.

Alzheimer's disease classification relies heavily on brain imaging method Magnetic Resonance Imaging (MRI), which have become essential for identifying these early symptoms. Significant advancements in AD detection and classification have resulted from the revolution in medical image analysis brought about by the introduction of artificial intelligence (AI) and intense learning approaches. This study examines the classification of Alzheimer's disease using brain imaging, the function of deep learning in this process, and the present and potential future directions of the field.

OBJECTIVES

The primary objective of this research is to develop a strong and reliable deep learning framework for early disease diagnosis in medical diagnostics. This comprises:

Methodical Data Gathering: A range of extensive datasets, such as structured patient data (such as clinical history, and laboratory results) and medical images (such as MRI, and X-rays), should be curated to ensure that the model is proficient on representative and high-quality data. Efficient Preprocessing Sophisticated preprocessing methods including normalization, data augmentation, and scaling are used to prepare raw data for model training in order to guarantee consistency and enhance model performance.

Optimized Model Development: To increase feature extraction and predictive accuracy, hybrid architectures and transfer learning are used in the design and optimization of Convolutional Neural Networks (CNNs) and other deep learning models. Rigorous optimization refers to the use of advanced optimization techniques, such as learning rate scheduling, regularization (e.g., dropout, L2 regularization), and hyperparameter tweaking (e.g., grid search, Bayesian optimization), to enhance model performance and generalization[5][6].

Extensive evaluation: A variety of assessment metrics, including precision, recall, F1 score, and AUC-ROC, are employed to extensively analyze model performance in order to guarantee reliability and applicability in real-world clinical scenarios[7]. Aiding in the Diagnostics of Medicine: Providing helpful guidance and a systematic approach to deep learning implementation in healthcare, which will ultimately improve patient outcomes, diagnostic accuracy, and the adoption of AI in clinical setting[8].

METHOD

Systematic approach to developing deep learning models for medical diagnostics, emphasizing data collection, preprocessing, model development, optimization, and evaluation. The methodology is designed to ensure reliability, validation, and robustness in disease detection, with a focus on improving patient outcomes through artificial intellignece[9].

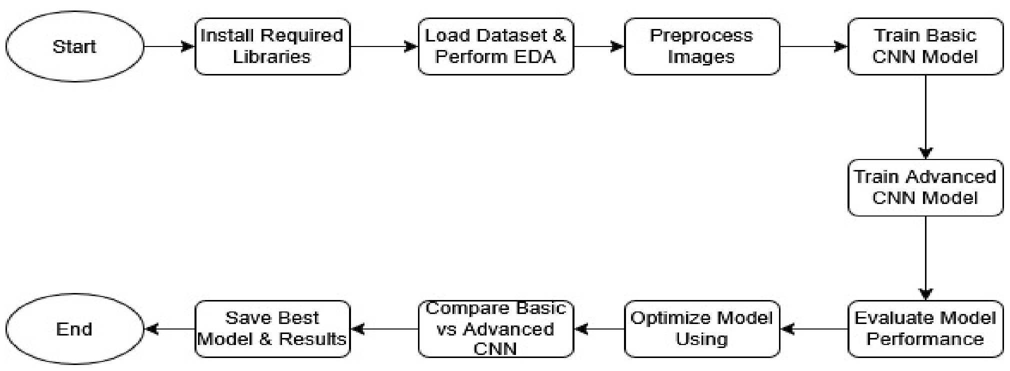

Figure 1: Block Diagram for the Proposed Alzhiermer Disease Detection Methodology

1. Data Collection

Data collection is the foundational step in building effective machine learning models. The research utilizes diverse datasets, including medical images and structured patient data, to ensure comprehensive training and evaluation.

1.1 Medical Images

Types of Images: MRI scans, CT scans, X-rays, and histopathological slides.

MRI Scans: Used for visualizing soft tissues, such as brain tumors[11].

CT Scans: Provide detailed cross-sectional images for diagnosing conditions like lung cancer.

X-rays: Commonly used for respiratory disease detection (e.g., pneumonia).

Histopathological Slides: Used for identifying cancerous tissues.

Datasets: Public repositories like Kaggle (e.g., Chest X-ray dataset) and LIDC-IDRI (lung CT images) are employed.

1.2 Structured Patient Data

Types of Data: Demographics, clinical history, and laboratory results.

Demographics: Age, gender, ethnicity, etc., help understand disease risk factors.

Clinical History: Previous diseases, treatments, and hospital admissions (e.g., MIMIC-III database).

Laboratory Results: Blood tests and biomarkers provide quantitative health indicators.

2. Preprocessing

Preprocessing transforms raw data into a format suitable for model training, ensuring consistency and improving model performance.

2.1 Normalization

Scales pixel values to a uniform range (e.g., [0, 1]) to stabilize training.

Techniques include grayscale conversion and mean/standard deviation normalization.

2.2 Data Augmentation

Increases dataset size artificially by applying transformations (e.g., rotation, flipping, scaling, adding noise).

Enhances model generalization and reduces overfitting.

2.3 Resizing

Standardizes image dimensions (e.g., 224x224 pixels) to match neural network input requirements.

2.4 Dataset Splitting

separates data into three categories: testing (15%), validation (15%), and training (70%) sets to ensure unbiased evaluation.

3. Model Development

The research employs Convolutional Neural Networks (CNNs) for medical scan analysis due to their effectiveness in feature removal and spatial shape acknowledgment.

3.1 CNN Architecture

Convolutional Layers: Use filters to extract features.

Non-linearity is introduced by activation functions (ReLU).

Pooling Layers: To simplify, downsample feature maps.

Fully Connected Layers: Integrate characteristics to arrive at the ultimate classification.

3.2 Transfer Learning

Utilizes pre-trained models (e.g., VGG16) to leverage existing knowledge[13].

Fine-Tuning: Adjusts pre-trained models to specific medical tasks, improving performance with limited data.

4. Model Optimization

Optimization techniques enhance model performance and generalization.

4.1 Hyperparameter Tuning

Grid Search: Exhaustively searches predefined hyperparameter groupings.

Bayesian Optimization: Uses probabilistic models to efficiently find optimal hyperparameters.

4.2 Learning Rate Scheduling

Dynamically adjusts the learning rate (e.g., ReduceLROnPlateau, step decay, cosine annealing) to improve convergence.

5. Evaluation Metrics

The research employs a suite of metrics to assess model performance, ensuring reliability in disease detection.

5.1 Key Metrics

Accuracy: Overall prediction accuracy.

Precision: Amount of correct confident estimates.

Recall (Sensitivity): percentage of true positives that were accurately identified.

F1 Score: precision and recall harmonic mean.

AUC-ROC: Deal model performance across different classification thresholds.

5.2 Justification for Metrics

Precision: Critical for minimizing false positives, especially in low-prevalence diseases.

Recall: Essential for identifying all positive cases, particularly in life-threatening conditions.

AUC-ROC: Provides a inclusive evaluation of model presentation across thresholds, making it ideal for imbalanced datasets.

The methodology outlined in this research ensures a rigorous and systematic approach to developing deep learning models for medical diagnostics. By meticulously addressing each phase—data collection, preprocessing, model development, optimization, and evaluation—the study aims to contribute valuable insights to the field. The structured framework enhances the reliability of results and provides a foundation for future research, promoting the adoption of AI technologies in healthcare to improve patient outcomes.

RESULTS

The project involves creating and refining a Convolutional Neural Network (CNN) model for brain scan scan-based Alzheimer's disease identification. Utilizing cutting-edge methods like transfer learning, Bayesian optimization, and grid search, the code is organized to manage data preprocessing, model training, evaluation, and optimization[10].

1. Key Libraries and Tools

The implementation of the study utilizes a comprehensive set of libraries for data handling, visualization, machine learning, deep learning, and optimization. The libraries used include os, numpy, pandas, cv2, and PIL for data handling. For visualization, matplotlib, seaborn, and plotly are employed. Machine learning techniques, including evaluation metrics such as classification reports and confusion matrices, are implemented using scikit-learn. Deep learning models are developed using tensorflow and keras, particularly leveraging pre-trained architectures like

VGG16 . For optimization, Optuna is used for Bayesian optimization, while GridSearchCV is applied for exhaustive hyperparameter tuning.Each of these libraries plays a significant role in handling images, generating visual insights, optimizing hyperparameters, and implementing deep learning models effectively.

2. Dataset Overview

The dataset contains 11,679 brain scan images categorized into four dementia severity levels:Moderate Demented, Non-Demented, Mild Demented ,Very Mild Demented. A training set of 9,123 photos and a testing set of 2,556 images make up the dataset. Each image has uniform dimensions of 176x208 pixels. However, variations in brightness and contrast are observed across different categories, which may impact model learning.The distribution of images within each category for training and testing purposes is shown in the table below.

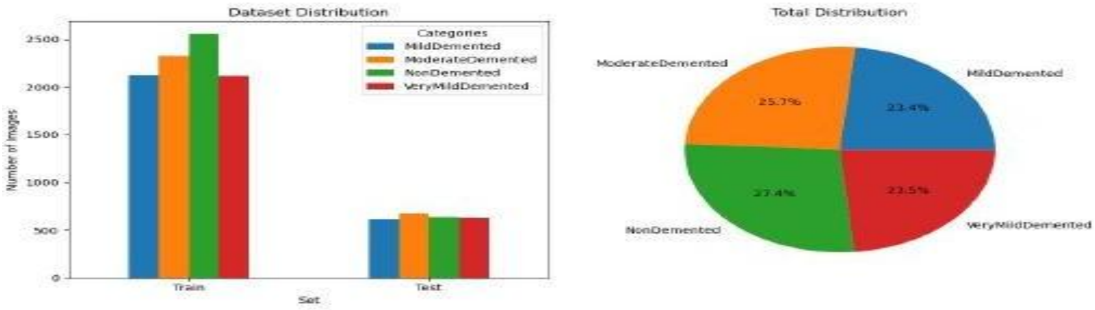

Figure 2: Dataset categorization

Table no. 1 Total Image Classification

Class	Training Images	Testing Images	Total
Non-Demented	2,560	640	3,200
Very Mild Demented	2,113	632	2,745
Mild Demented	2,122	612	2,734
Moderate Demented	2,328	672	3,000
Total	9,123	2,556	11,679

The dataset follows a structured split, where training uses 70% of the data, validation uses 15%, and testing uses 15%.The images are uniformly sized at 176×208 pixels, ensuring consistency in processing. However, variations in brightness and contrast are observed across categories, which could impact model performance.

3. Data Preprocessing

Several methods are used in the preparation pipeline to get the data ready for deep learning models. These In order to guarantee consistency and improve model learning, preprocessing is an essential step. To increase numerical stability, the pixel values are standardized to the interval [0,1]. To reduce overfitting, data augmentation methods like rotation, flipping, scaling, and noise addition are used. To comply with CNN architectures' input requirements, the photos are scaled to 224x224 pixels. To guarantee balanced learning and assessment, The dataset is split into three categories: testing, validation, and training[11].

4. Model Development

CNN architectures are used to classify images. The model consists of pooling layers to decrease dimensionality while maintaining key structures, convolutional layers that use filters to extract spatial data, and ReLU activation to add non-linearity. Dropout layers avoid overfitting by randomly deactivating neurons during training, whereas fully connected layers aggregate retrieved characteristics for classification. VGG16 models that have already been trained are refined to add transfer learning.

5. Model Optimization

Hyperparameter optimization plays a crucial role in improving model performance. Grid Search conducts an exhaustive search over a predefined set of hyperparameters, while Bayesian Optimization employs probabilistic models to efficiently identify optimal hyperparameters[12][14].

Table No. 2 : Optimization Technique

Class	Accuracy
Non-Demented	79.69%
Very Mild Demented	5.85%
Mild Demented	5.23%
Moderate Demented	11.46%

Table no. 3 : Accuracy of Classes

Technique	Description
Grid Search	This method performs an exhaustive search over a predefined set of hyperparameters to identify the best combination.
Bayesian Optimization	Unlike Grid Search, Bayesian Optimization efficiently finds optimal hyperparameters using probabilistic models, reducing computational cost.

6. Evaluation Metrics

AUC-ROC, accuracy, F1 score, precision, and recall are used to measure the model's presentation. Precision determines the percentage of accurately predicted positive cases, whereas accuracy quantifies the percentage of correctly recognized photos. The F1 score offers a harmonic mean of recall and precision, whereas recall quantifies the percentage of true optimistic cases that are accurately identified. Classification performance is assessed using AUC-ROC over a range of threshold values. These metrics offer a thorough comprehension of the model's capacity to differentiate between various stages of dementia.

The mathematical formulations for these metrics are as follows:

Precision: How many of the anticipated positive cases turn out to be positive is measured by precision.

$$Precision = \frac{TP}{TP + FP} \quad \text{Eq (1)}$$

$$Recall = \frac{TP}{TP + FN} \quad \text{Eq(2)}$$

Recall quantifies the skill of the model to classify actual optimistic cases.

7. Results and Insights

7.1 Model Performance

The complete accuracy of the top model is 25.67%, demonstrating significant room for improvement. Class-wise accuracy reveals disparities in the model's skill to distinguish between dementia steps.

Struggle of the model is significantly with the Very Mild Demented and Mild Demented classes, likely due to feature similarities among these stages.

7.2 Optimization Results:

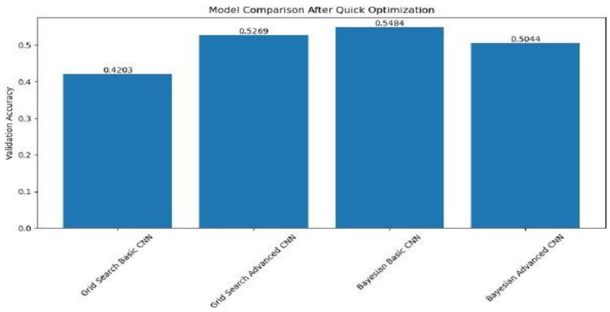

Figure 3: Model Comparison

Table no. 4: Bayesian and Grid Search Optimization Comparision

Model	Validation Accuracy
Grid Search Basic CNN	42.03%
Grid Search Advanced CNN	52.69%
Bayesian Basic CNN	54.84% (Best Model)
Bayesian Advanced CNN	50.44%

The Bayesian Basic CNN model achieves the highest validation accuracy of 54.84%. Interestingly, advanced CNN models perform worse, possibly due to overfitting or excessive complexity given the dataset size.

DISCUSSION

This study offers a thorough process for creating a deep learning model that uses brain scan data to identify Alzheimer's disease. The study illustrates the promise of AI in medical diagnostics by utilizing cutting-edge methods including transfer learning, data augmentation, and hyperparameter optimization (Bayesian and grid search). The Bayesian Basic CNN performs best with a validation accuracy of 54.84%, while the model attains a moderate level of accuracy. High misclassification rates, especially between the Non-Demented and Very Mild Demented categories, show that there are still difficulties differentiating between dementia phases that are similar. By highlighting areas for improvement, performance measure such as recall, AUC-ROC, precision, offer important insights into model performance. To increase classification accuracy, future research should concentrate on improving feature extraction, balancing datasets, and investigating hybrid architectures.

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