

Deep Learning for Neuroimaging-Based Brain Disorder Detection: Advancements and Future Perspectives

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Abstract

This review focuses on the recent advancements in neuroimaging enabled by deep learning techniques, specifically highlighting their applications in brain disorder detection and diagnosis. The integration of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) has significantly improved feature extraction, pattern recognition, and predictive modeling, leading to enhanced accuracy, sensitivity, and specificity in diagnosing Alzheimer's, Parkinson's, schizophrenia, and brain tumors across MRI, fMRI, and PET scans. Despite these advancements, current challenges persist, including limitations in interpretability, data scarcity, and ethical concerns. To address these issues, future perspectives involve leveraging transfer learning, federated learning, and multimodal data sources. This review aims to provide a comprehensive overview of the current state of deep learning in neuroimaging, highlight the existing challenges, and discuss potential solutions for future innovation. By addressing the current limitations and exploring innovative techniques, deep learning can unlock new possibilities in neuroimaging, ultimately leading to improved diagnosis, treatment, and patient outcomes.

Keywords

Deep Learning, Brain Disorder Detection, Neuroimaging Data

1. Introduction

In recent years, an increase of Brain disorders has significantly impacted the lives of many people worldwide [1]. With the latest advancements in medical imaging technologies, diagnosis has been simplified which has resulted into a non-invasive assessment of the brain's structure and function [2]. Despite the advancement in

medical imaging technologies like Magnetic Resonance Imaging (MRI) and Computed Tomography (CT), early diagnosis and precision remain a big challenge [3]. The over reliance to the knowledge and experience of radiologists and neurological specialists affects accuracy and reliability of the diagnosis and as such affects the critical role played by the human expertise [4].

The [4] [5] has highlighted that accurate and timely detection of Alzheimer's Disease amongst several other brain disorders like epilepsy, and others, remains a critical challenge amongst the medical community. Early diagnosis of these disorders is essential for initiating targeted interventions, monitoring disease progression, and improving patient outcomes. Traditional neuroimaging analysis methods often rely on manually engineered features and heuristic algorithms, which are limited in their ability to capture subtle and non-linear patterns inherent in neuroimaging data [4].

The advancement of deep learning techniques has brought a dynamic change in the field of neuroimaging analysis, bringing significant progress in the early detection and diagnosis of various brain disorders. With the exponential growth in the Neuroimaging datasets, which include amongst others functional magnetic resonance imaging (fMRI), positron emission tomography (PET), and diffusion tensor imaging (DTI), provide crucial insights in studies related to the brain's normal performance [5]. Deep learning models have demonstrated remarkable capabilities in extracting intricate patterns and representations from these complex data, contributing to the understanding and diagnosis of brain disorders.

Deep learning methods have shown promise in automating the analysis of neuroimaging data, offering data centric informed decision making to feature extraction, training, and detection of abnormalities in the brain tissues [5] [6]. Several Architectures have been adopted for brain disorder detection which include amongst others Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based architectures and they have exhibited excellent performance compared to the normal machine learning methods [6] [7].

The process of training deep learning models wouldn't be possible if the data collection was poorly done. With the advancements of MRI machines, neurodegenerative studies have been simplified [7] [8] whose impact as made early detection of brain disorders possible to even the new bones [9].

This paper presents a comprehensive analysis of current deep learning models applied to brain disorder detection using neuroimaging data. We aim to explore the various methodologies employed in the literature and provide valuable insights into the strengths and limitations of these approaches by critically examining various literatures for the past 10 years as well as identifying opportunities for further improvements and proposing potential avenues for future research. To answer this, the following research questions have guided this study.

- 1) What are the current advancements and limitations of deep learning techniques in neuroimaging-based brain disorder detection?
- 2) How do current challenges, such as interpretability, data scarcity, and ethical

concerns, impact the development and deployment of deep learning models in neuroimaging?

3) What are the potential solutions and future perspectives for addressing current challenges and advancing deep learning in neuroimaging-based brain disorder detection?

This paper follows a systematic literature approach where Section 2.0 gives a background and discusses the significance, as well as outlining the guiding research questions of the study, Section 3.0 looks at deep learning and its applications in relation to brain disorder detection with subsections of deep learning for brain disorder detection, pre-training, and transfer learning as applied in deep learning, the concept of interpretability and explainability a major challenge in deep learning. Section 4.0 explores preprocessing and feature extraction reviewing through skull stripping, image registration and bias correction with the individual applications and algorithms used in each case. Section 5.0 looks at the considerations for preprocessing and feature extraction and finally a discussion and conclusion section.

This study contributes to the growing body of applied deep learning research where techniques to neuroimaging data and brain disorders are gaining an increased attention in detection. By comprehensively evaluating the current landscape of deep learning models, we aim to foster advancements in this critical area of neuroscience and ultimately aid in the early diagnosis and management of brain disorders.

2. Background on Brain Disorders and Their Significance

Neurological conditions encompass a broad spectrum of disorders that significantly influence the regular functioning and growth of brain cells. These conditions have profound implications for individuals, families, and societies at large. Among these, Alzheimer's disease (AD) stands out, presenting a particularly pressing public health concern due to its widespread prevalence, profound impact on cognitive function, and the absence of a definitive treatment [8] [9]. AD, characterized by a progressive degeneration of brain function, leads to manifestations like memory loss, cognitive decline, and behavioral alterations. This imposes a substantial burden on individuals, caregivers, and healthcare systems on a global scale. Brain disorders are pervasive and globally affect millions of people. The World Health Organization (WHO) has highlighted that neurological disorders contribute to a substantial proportion of the global disease burden, accounting for approximately 13% of all deaths worldwide [8]. The effects of brain disorders significantly affect the lives of individuals which in the end hampers their day-to-day activities and individuals' participation in society.

With the challenges that this comes with, it's prudent that these brain disorders need to be accurately detected in a timely manner for an effective intervention, treatment, and progressive monitoring of these diseases to be done. Relying on traditional diagnostic methods which rely on clinical examination where specialistic

doctors/personnel physically examine the brain scan MRI or PET images. These methods end up being time wasting and more reliant on the expert professionals whose decisions may not be consistent and are prone to errors.

The recent emergence of deep learning a sub field of artificial intelligence is a big promise in the analysis of complex medical data which will improve on the accuracy of diagnosis [9]-[11].

These deep learning models with their unique capabilities to study raw data and draw insights from them have changed the space of medical image analysis. With its capabilities to accurately detect tumors and lesions [9] with high performance deep learning models like CNN [12], show a great future to the more complex discoveries in the medical image diagnosis.

Using large datasets of brain MRI and CT scans, deep learning models have demonstrated capabilities of learning making it be able to identify underlying variations in different scans [10] to make decision that exposes some image to have a given complication at an early stage [11] which helps to improve on the treatment of such conditions at an early stage.

Outside the brain tumors and other associated cancerous growth detection in the brain, a research by [13] has deployed deep learning specifically when analyzing EEG Signals in detecting conditions such as epilepsy and other associated sleep disorders and has showed a significantly higher level of performance.

In relation to Alzheimer's disease and dementia, very key biomarkers have been identified using feature engineering techniques as a result from the analysis of multiple brain scan images [14] with variations which can be distinguished from the normal brain functionality, AD can be accurately detected at various levels of progression.

Overall, deep learning's contributions extend to predictive models that estimate disease progression and treatment outcomes based on patient data [15]. This assists medical professionals in devising personalized treatment plans for patients with brain disorders.

The potential of deep learning also extends to drug development for brain disorders by analyzing biological data, predicting drug interactions, and identifying potential therapeutic targets [16].

3. Applied Deep Learning and Its Application in Brain Disorder Detection

3.1. Deep Learning for Brain Disorder Detection

With the promise of deep learning in the analysis of brain imagery data significantly aiding in the detection, diagnosis, and potential solution to the treatment of brain disorders all relying on the power of deep learning, researchers, and clinicians with a great intent in enhancing the accuracy, efficiency, and objectivity of brain disorder detection [17]. Deep learning models excel at processing large volumes of brain scan image data, extracting meaningful features that a human eye may not ordinarily be able to identify.

Various architectures have been deployed to detect brain disorder, each with its own advantages and suitability for specific tasks. [18] deployed Convolutional Neural Networks (CNNs) in analyzing neurological imagery data in form of magnetic resonance imaging (MRI) and or positron emission tomography (PET) to uniquely detect brain disorders. Great success has been attained when capturing spatial patterns and has demonstrated impressive performance while detecting and segmenting brain tumors [19]. For brain disorders manifesting in 3D volumetric data, such as 3D MRI scans, 3D CNNs are used to learn spatial features and patterns, aiding in the detection of abnormalities [20].

On the contrary, Recurrent Neural Networks (RNNs) have shown their effectiveness at modeling temporal dependencies, making them suitable for tasks that involve sequential data, such as time series analysis of brain signals [21]. With its ability in capturing temporal dependencies in brain signals, RNN's have been applied for epilepsy detection and prediction of neurological disorders [22]. LSTMs are a type of RNN that can capture long-range dependencies in sequential data and have been used in brain disorder detection tasks like in the detection of Alzheimer's disease (AD) using time-series datasets [23].

Attention Mechanisms and Transformer models have shown relevance in capturing unique features from neuroimaging data and have been applied to tasks like detecting lesion and classification of diseases [24] [25]. They help in focusing on specific regions of brain images that are most relevant for detection, reducing the influence of irrelevant information and improving model accuracy [26].

Autoencoders have been employed for feature extraction and dimensional reduction in brain imaging data, aiding in the identification of relevant features and anomalies [27].

3.2. Pretraining and Transfer Learning in Deep Learning

Using large scale datasets like such as ImageNet in pretraining deep learning models and then fine-tuning them for specific brain disorder detection tasks has become a common practice [28]. This approach, known as transfer learning, leverages the learned features from pretrained models, which can accelerate training and improve performance, especially when the labeled data is limited [29] [30]. By adapting pretrained models to brain imaging data, transfer learning facilitates the development of robust and accurate deep learning models for brain disorder detection.

Whereas transfer learning helps in scenarios of data paucity, other techniques like data augmentation have been adopted where data is artificially expanded on the training dataset to increase its diversity. Data Augmentation has found a vital role in brain disorder detection as it has been used in cases where data may be imbalanced and as such has limited labeled data. Common data augmentation techniques include rotations, translations, flips, and elastic deformations [31] [32]. These techniques help to enhance the generalization ability of deep learning models and improve their performance on brain imaging datasets.

3.3. Interpretability and Explainability in Deep Learning for Brain Disorder Detection

Whereas deep learning models are known to have issues with Interpretability and explainability, it's important to understand the processes that originate when deep learning models are making decisions if clinicians' trust must be obtained to facilitate a smooth clinical adoption. Various methods, such as saliency maps, gradient-based attribution, and attention mechanisms, have been proposed to interpret and explain deep learning models predictive decisions.

4. Preprocessing and Feature Extraction

4.1. Preprocessing

Preprocessing is a core step that initiates data analysis and machine learning. It transforms raw data into information which can be used in developing predictive algorithms based on extracted features from these datasets. If a systematic process is followed to clean, transform, and select relevant feature domains from this data, hidden patterns in this data can be explored for an informative decision-making process. Various image preprocessing and feature extraction techniques and methods will be explored during this study. Several preprocessing techniques have been adopted and continue to play a critical role in accurately detecting other brain disorders. This study explores the common techniques used in preprocessing and feature extraction.

4.1.1. Skull Stripping

Skull stripping, also known as brain extraction, is a fundamental neuroimaging data preprocessing stage. It involves separating brain tissue from non-brain tissues for a given MRI scans. Non-brain tissue can be the skull, scalp, extracranial tissues, and other brain tissues with intent of isolating and focusing on the brain region of interest. Accurate skull stripping is crucial for subsequent analyses, such as brain segmentation, registration, and volumetric measurements.

Amongst the common skull stripping techniques used are Brain Extraction Tool (BET) which is a widely used and popular algorithm for skull stripping in neuroimaging. Being part of the FSL software suite, BET estimates brain tissue boundary and models out the actual brain tissue excluding other non-brain regions. [33] describes the BET as one that employs a principle of deformable surface modelling on an iterative deformed 3D surface mesh to properly fit the brain edges.

Other applications which perform the same role include FreeSurfer, a software used for structural MRI analysis. [34] describes FreeSurfer software as one that uses both intensity thresholding and surface-based modelling to separate non-brain tissue in each image generating a resultant high quality brain mask. Other notable applications like ROBEX (Robust Brain Extraction) [35], ANTs herein as Advanced Normalization Tools [36] have found a wide applicability in skull stripping.

4.1.2. Image Registration

The act of image registration is a technique of wrapping some images to align their features in a perfect reference plane. This is usually done to ensure spatial correspondence amongst the images being preprocessed for group level analysis and comparisons to be done. Several methods have been used. Among the popular ones are FSL (FMRIB Software Library) FLIRT which according to [37], FSL uses a transformed model to align a given image to a central reference plane for structural and functional neuroimages.

ANTs (herein as Advanced Normalization Tool) performs both skull stripping and image registrations tasks with a reach library with embedded algorithms like symmetric diffeomorphic registration. Because of its highly advanced image registration capabilities, ANTs has found itself widely taken as an image normalization tool of choice in image registration [38]. Other notable applications like SPM (Statistical Parametric Mapping) which according to [39] is used for analyzing brain imaging, Elastix being a command line based software contains a wide range of transformation techniques like rigid, affine, and non-rigid enabling maximum customization of its features thus making it a dynamic tool for image registration [40] and finally ITK (Insight Segmentation and Registration Toolkit) an open source software package has found itself being widely adopted for medical image analysis by most of the research communities. This versatile nature according to [41] makes ITK a software package of choice in research.

4.1.3. Bias Field Correction

The data collection process is prone to bring bias which can affect the overall quality of the data. The bias field correction technique is deployed to eliminate varying biases in the datasets specifically neuroimaging datasets, these inconsistencies often corrected by shading off artifacts originate because of the imaging techniques used which can be biased by the pre-imaging clinical examinations miss directing the image acquisition process. Several methods have been deployed to correct these biases which include amongst others N3 (Non-parametric Non-uniform Normalization) Algorithm which according to use for bias correction in cases where the field is represented as a smooth spatial function. According to [42], this bias correction technique has found a huge adoption rate in circumstances where images have features which may have inconsistencies that make them not clear for analysis. Other normalization techniques used in this area include algorithms like Polynomial Approximation with Linear Combinations of Exponentials (PALM) and non-parametric methods with specific algorithms like the GradWarp algorithm. Depending on the imaging data used and the study objectives, researchers can opt for a specific bias technique.

4.1.4. Intensity Normalization

Intensity normalization is a preprocessing technique used to scale the image intensities of medical images, such as neuroimaging data from MRI (Magnetic Resonance Imaging) scans. The purpose of intensity normalization is to bring the

image intensities into a standardized range, making the images comparable across different subjects or imaging sessions. This is particularly important in neuroimaging studies, where consistent intensity scaling is essential for accurate and reliable quantitative analyses.

To normalize images in such a manner that their mean and standard deviation give a zero, normalization technique of z-score has been widely adopted. [43] explains that as opposed to other normalization techniques like mini max and percentile normalization techniques, z-score transforms image pixels intensities to achieve a z-score with a mean and standard deviation of zero which method may become a method of choice depending on the characteristics an image possesses, and the requirements of a given research. Other techniques like Motion Correction, Spatial Smoothing, Voxel-based Morphometry (VBM), Standard Space Normalization, and Independent Component Analysis (ICA) amongst others have been widely chosen for processing neuroimaging datasets. A summary of the key references has been outlined in **Table 1**.

Table 1. Summary of feature extraction techniques.

Method	Summary	References
Principle Component Analysis (PCA)	PCA is a dimensional reduction technique used to identify key features from a dataset, achieving significant performance improvements in various studies cited.	[44]-[48]
Linear Discriminant Analysis (LDA)	LDA a dimensional reduction technique often used for classification problems was combined with PCA for preprocessing ECG data enhancing classification performance. Neural Networks were integrated for further improvements.	[47]
Convolutional Neural Networks (CNN)	CNNs are used in computer vision to automatically learn hierarchical features from images, with activations of intermediate layers serving as meaningful features for various tasks. These methods are part of the broader set of feature extraction techniques, with the choice depending on the data type and specific analysis of the model tasks.	[48]-[51]

4.2. Feature Extraction Methods

Several studies have deployed various feature extraction methods in classifying brain tissue.

4.2.1. Principal Component Analysis (PCA)

PCA is a technique in dimensionality reduction that identifies key features (principal components) from a dataset and narrows down the data onto a lower-dimensional space while preserving as much variance as possible.

Studies [44]-[48] have deployed PCA feature extraction techniques and have achieved a significant performance.

4.2.2. Linear Discriminant Analysis (LDA)

LDA like PCA is a technique in dimensionality reduction, but it is often used in the context of classification problems. It targets projections with maximum separation amongst different class bounds.

[47] combined PCA and LDA to preprocess electroencephalography (EEG) data for brain activity classification. Neural Networks were added into PCA and LDA techniques for improved performance of the classification.

4.3. Convolutional Neural Networks (CNN) Features

Table 2. Shows various categories of feature extraction with corresponding details.

Category	Technique	Description	Mathematical Representation
Convolutional Layers	Convolution	Apply filters to scan data in spatial and temporal dimensions.	$*(x) = \sum(w \times x) + b$ $*(x) = \sum(w \times x) + b$ $*(x) = \sum(w \times x) + b$
	Activation Functions (ReLU)	Introduce non-linearity.	$f(x) = \max(0, x)$ $f(x) = \max(0, x)$ $f(x) = \max(0, x)$
	Activation Functions (Sigmoid)	Output probabilities between 0 and 1.	$f(x) = 1 / (1 + e^{-x})$ $f(x) = 1 / (1 + e^{-x})$
	Activation Functions (Tanh)	Scale outputs between -1 and 1.	$f(x) = 2 / (1 + e^{-2x}) - 1$ $f(x) = 2 / (1 + e^{-2x}) - 1$ $f(x) = 2 / (1 + e^{-2x}) - 1$
	Batch Normalization	Stabilize training by normalizing layer outputs.	$BN(x) = \gamma x - \mu\sigma + \beta$ $BN(x) = \gamma\{x - \mu\} / \{\sigma + \beta\}$ $BN(x) = \gamma\sigma x - \mu + \beta$
Recurrent Layers	Pooling	Down sample feature maps while retaining essential information.	$P(x) = \max(x)$ $P(x) = \max(x)$ $P(x) = \max(x)$
	RNN's	Handle sequential data by maintaining an internal state.	$H_t = f(h_{t-1}, x_t)$ $h_t = f(h_{t-1}, x_t)$ $h_t = f(h_{t-1}, x_t)$
Data Augmentation	LSTM	Control information flow using gates and memory cells.	$C_t = f_t \cdot c_t - 1 + i_t \cdot g_t$ $c_t = f_t \cdot c_{t-1} + i_t \cdot g_t$ $c_t = f_t \cdot c_t - 1 + i_t \cdot g_t$
	Random Rotation	Simulate orientation variations by rotating images.	$x' = R(x)$ $x' = R(x)$ $x' = R(x)$
	Flipping	Simulate reflections by flipping images horizontally or vertically.	$x' = F(x)$ $x' = F(x)$ $x' = F(x)$
	Scaling	Simulate different resolutions by resizing images.	$x' = S(x)$ $x' = S(x)$ $x' = S(x)$

Continued

Normalization	Intensity Normalization	Standardize pixel intensities to minimize lighting effects.	$x' = x - \mu\sigma$ $x' = \{x - \mu\}/\sigma$ $x' = \sigma x - \mu$
	Spatial Normalization	Ensure consistent image sizes and aspect ratios.	$x' = S(x)$ $x' = S(x)$ $x' = S(x)$

In computer vision, CNNs are often used to automatically learn hierarchical features from images. The activations of intermediate layers can serve as meaningful features for various tasks. The pivotal role CNN has shown in computer vision [48] with variants like MobileNet [49] and EfficientNet [50] and AlexNet [51] have led the adoption of CNN in image classification and objection detection tasks as well as in segmentation tasks.

CNNs are composed of multiple convolutional layers, pooling layers, and fully connected layers. The convolutional layers apply filters to the input data, scanning the data in both spatial and temporal dimensions.

Table 1 shows the references that discuss the various studies which have used various feature extraction techniques while **Table 2** shows a detailed summary of the various feature extraction methods.

4.4. Other Feature Extraction Techniques

The following techniques have been widely adopted for feature extraction and a great success has been realized.

4.4.1. Wavelet Transform

Wavelet transformation as applied in both signal and image processing, decomposes data into different frequency components, which frequency components will act as features for numerous analysis tasks.

Wavelet transformation has been applied in cancer detection [52], image compression [53], EEG Signal Analysis [54], audio signal processing [55] and fault detection in machinery [56] and a great success has been achieved.

4.4.2. Histogram of Oriented Gradients (HOG)

HOG is a feature extraction method for object detection and image recognition. It computes the distribution of gradient orientations in an image, which is used to capture the shape and texture of objects.

HOG has been deployed with a great performance attained in various aspects of object detection and recognition [57] pedestrian detection [58], face detection [59], traffic sign recognition [60], human action recognition [61], and hand gesture recognition [62].

4.4.3. Local Binary Patterns (LBP)

LBP is used in image analysis for texture classification. It encodes the relationship between the intensity values of a pixel and its neighbors, capturing texture

information.

LBP has found applications in Face recognition [63], texture classification [64], object detection [65], face analysis [66], texture segmentation [67] and image retrieval [68] achieving an immense performance in specific tasks.

5. Considerations for Preprocessing and Feature Extraction

Preprocessing and feature extraction are pivotal stages in reading text data for machine learning and natural language processing (NLP) tasks. In preprocessing, the aim is to cleanse the text, rendering it more amenable to analysis. This process usually encompasses text cleaning, where superfluous special characters, symbols, and formatting are expunged to distill the text to its essence. For instance, when working with web data, it's essential to manage HTML tags effectively [69]. Tokenization, the act of breaking text into discrete tokens like words or sub words, establishes a structured foundation for analysis. This choice between word-level and subword-level tokenization hinges on the task and data characteristics at hand.

Lowercasing is a common practice to ensure consistency in text representation. Nevertheless, instances where capitalization bears significance, such as named entities, merit careful consideration. The culling of stop words—common words like “and” or “the” that hold little semantic value—can also enhance data quality. Although, in some cases, retaining stop words might be pertinent to the task's objectives. Stemming and lemmatization are methods employed to whittle down words to their base or root forms. This not only reduces vocabulary size but also harmonizes variants of words.

Managing contractions is another facet to contemplate. While converting contractions to their expanded forms (“don't” to “do not”) may be advantageous, it hinges on the language and context of analysis. Noise reduction, involving the excision of extraneous elements like URLs or email addresses, contributes to cleaner data. Moreover, deciding how to handle numbers—replacing them, normalizing them, or retaining them—depends on their relevance to the analysis [69].

Turning to feature extraction, Bag-of-Words (BoW) constructs a representation by tabulating word frequencies. Augmenting Bow with n-grams—successive sequences of words—can amplify contextual understanding. Term Frequency-Inverse Document Frequency (TF-IDF) bestows words with weights based on their document frequency and corpus-wide importance, an asset for delineating word significance [70]. Word embeddings, such as those hewn from pre-trained models like Word2Vec and GloVe, map words to vectors in a continuous space, encapsulating semantic relationships.

Alternatively, contextual embeddings, stemming from models like BERT and GPT, furnish embeddings that are contingent on a word's context within a sentence or document, allowing for nuanced comprehension. Scaling numerical features ensures comparability among them, potentially heightening model perfor-

mance. Meanwhile, dimensionality reduction techniques like Principal Component Analysis (PCA) or t-SNE can be instrumental in managing high-dimensional feature spaces. The incorporation of domain-specific features, like linguistic attributes or external data, can also elevate model efficacy [71].

For longer documents, segmentation or summarization may be judicious, preserving salient information without inundating the model. These considerations underscore the intricate interplay between preprocessing and feature extraction, both of which must align seamlessly with the specific goals of the NLP task at hand. Rigorous experimentation is pivotal in ascertaining the optimal approaches that harmonize with the dataset's characteristics and desired outcomes.

6. Training and Evaluation

Training and evaluation are pivotal phases in model development. It covers aspects of a predictive model development and the mechanism of assessing its performance. [72] emphasis that these phases are central across various domains and tasks, ranging from image classification to natural language processing.

6.1. Training

Model training is a process by which a portion of data is used to make the model learn from. The model learns patterns and relationships from a labeled dataset to make decisions (predictions) when exposed to new unseen datasets. The dataset is usually divided into two portions of either 80% training and 20% validation datasets or 75%: 20% respectively depending on the volume of available data. During the model building phase, the model is made to learn from the training dataset for purposes of learning while the validation set is used in the process known as hyperparameter tuning.

[71] introduced AlexNet, a DNN model having a network of five convolutional layers and three fully connected layers. AlexNet demonstrated great depth as compared to past models with a combination of over 60 million parameters. It makes use of ImageNet dataset which consists of 1,000 categories of 1.2 million high-res images, marking a substantial dataset improvement compared to past studies. The key performance measure used is image classification accuracy which reduced the top-5 error rate to 15.3%. The AlexNet's model success gave rise to a wide scale adoption of deep learning in computer vision, with a great possibility of extracting hierarchical features from raw images. The paper's adoption of parallel processing, regularization techniques, and model visualization gave the researcher great strength, and its wide scale adoption came when AlexNet model was made Open source. During model training, the following steps are involved.

6.1.1. Data Preparation

Clean and preprocess the dataset by applying the necessary transformations, such as text preprocessing or image normalization, to ensure consistent and well-formatted data. With data preparation being a foundational step in data science for

purposes of ensuring quality and usability datasets, pandas' official documentation by [71] offers a detailed guide in data preparation using python. This discussion is extended further by the authors distinguished works in python for data analysis. [73] in their publication on the art of data cleaning gives a detailed look at strategies to uncover challenges related to data quality.

6.1.2. Feature Extraction

Represent the data in a suitable format for the chosen algorithm. For text data, this could involve vectorization using techniques like TF-IDF or word embeddings. In image data, feature extraction might involve resizing, cropping, and color normalization. As much as feature engineering is an independent process in machine learning, it borrows a lot of aspects in relation to data preprocessing. [74] in the publication, "feature engineering for machine learning" dives to how features engineering gives strength into areas of data preparation.

6.1.3. Model Selection

Choose an appropriate algorithm or architecture based on the nature of the problem. For instance, CNNs which are often used for image-related tasks, RNNs used for sequence data tasks like textual datasets amongst other models depending on the nature of the available data. For simpler tasks, linear regression models can be adopted as discussed by [74] and for complex tasks like that used in ImageNet classification, deep Convolutional Neural Networks as discussed by [75] can be adopted.

6.1.4. Model Training

Training dataset is fed into the chosen model and to minimize a chosen loss function, model parameters are iteratively being updated. The optimization process typically involves backpropagation and gradient descent with a notable stochastic Gradient Descent Algorithm [76] as used in the training of mostly Neural Network (NN) models amongst other models. During model training, it's essential to select an appropriate loss function to determine the variation between the actual and predicted values. [77] discussed a popular loss function known as log-loss function (logistic regression). For regression tests, the Mean Square Error (MSE) loss function has been used to quantify the variation between the actual numerical value and the predicted value.

6.1.5. Hyperparameter Tuning

Hyperparameters such as learning rate, batch size, and network architecture are adjusted to optimize the model's performance on the validation set.

Bayesian Optimization techniques have been widely adopted for hyperparameter tuning processes [78]. [79] introduces the grid search optimization technique where a range of values have been specified for each hyperparameter test and at each instance, the model is independently validated.

6.2. Evaluation

Model evaluation phase examines the model's performance on new dataset to

gauge how effective the model is in solving the desired goal and as well on its generalization ability. The evaluation process includes:

6.2.1. Splitting a Dataset

In model training, datasets are split into training and test datasets normally with either 75% to 25% or 80% to 20% proportions depending on the volume of the available data. A portion of the dataset (distinct from the training and validation datasets) is what is reserved as a test dataset. This data is used to simulate how the model will perform on real-world, unseen examples. [78] looks at data being split into the training dataset which seeks to make the model learn based on the features exposed to it, validation set examines model to make early assessments on model performance in one way fine tuning the hyperparameters.

6.2.2. Model Evaluation Metrics

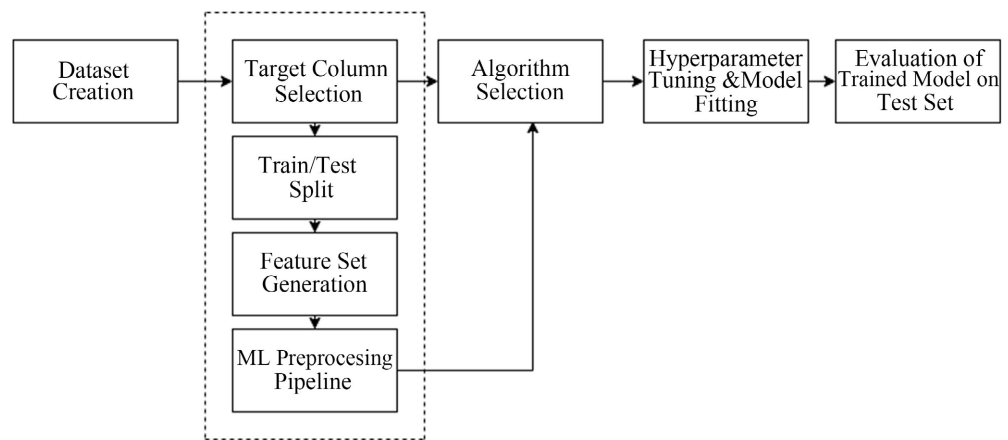


Figure 1. Model training and evaluation process.

Model Evaluation is a process of testing how well a trained model can accurately be able to perform its set task. Various metrics are used for model evaluation, and they depend on the nature of the problem being addressed. For classification tasks, metrics might include accuracy, precision, recall, F1-score, and ROC-AUC used specifically in cases where the dataset is imbalanced. [80] proposed using precision and recall while for regression tasks, metrics like Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) might be used with the intent of gauging the quality of the prediction. All these metrics are deployed with intent of identifying how well the model performs in real-world scenarios.

Model evaluation is used with a core aim of detecting overfitting where cross-validation techniques have been adopted as a means of reducing overfitting as discussed by [78]. It's important to choose the right evaluation techniques depending on the data being used. For cases of MRI Brain Imagery for studies aimed towards the detection of Alzheimer's Disease, recall can be used as opposed to accuracy given the false negatives and missed positives associated which are

always associated with medical diagnosis.

The entire process of model training from the dataset creation to the final stage of trained model evaluation is shown on **Figure 1**.

6.3. Visualizations

Visuals have been used to create a deeper understanding on the relationship between various features used in model training. Visualizations like confusion matrices, ROC curves, and precision-recall curves, provide a more comprehensive understanding of the model's behavior.

In both evaluation and interpretation, iterative processes might be necessary. Models can be fine-tuned, hyperparameters adjusted, and preprocessing techniques optimized to achieve the best possible performance. Regular validation of models on new and diverse datasets helps ensure robustness and reliability in various scenarios. [81] discusses key visualization techniques used for model selection. [80] discusses advanced visualization techniques which are used for visualizing high dimensional data in lower dimensional spaces with methods such as Principal Component Analysis (PCA) and t-Distributed Stochastic Neighbor Embedding (t-SNE).

7. Discussions

Deep learning models have shown tremendous promise in various clinical applications, including medical imaging analysis, disease diagnosis, personalized medicine, and clinical decision support systems. These models have achieved high accuracy in detecting breast cancer, diagnosing diabetic retinopathy, predicting cardiovascular disease risk, and personalizing cancer treatment plans. Additionally, they have been used to predict patient outcomes, such as mortality and readmission, and provide healthcare professionals with real-time, data-driven insights. However, despite their promise, deep learning models in clinical applications face several challenges. Clinical data is often noisy, heterogeneous, and limited, while regulatory concerns surround data privacy, security, and compliance. Deep learning models require thorough clinical validation, interpretability, and integration with existing workflows to ensure seamless adoption and utilization. Furthermore, addressing bias and variability, ensuring explainability and transparency, and mitigating cybersecurity concerns are crucial to the successful implementation of deep learning models in clinical applications.

8. Conclusions

In conclusion, the field of analyzing current deep learning models for brain disorder detection through neuroimaging data holds immense promise and potential. The methods and insights garnered from these models have the capacity to revolutionize the diagnosis and understanding of various neurological disorders to which Alzheimer's Disease falls. Very complex patterns are being extracted from neuroimaging datasets using deep learning architectures like CNN's, RNN's

and transformer-based models.

Amalgamating diverse neuroimaging modalities, including fMRI, PET, DTI, offers a comprehensive view of brain activity, connectivity, and structure. This multidimensional approach enables the models to capture nuanced relationships and anomalies associated with neurological disorders, ranging from Alzheimer's disease and schizophrenia to epilepsy and autism spectrum disorders.

Furthermore, the integration of transfer learning and pre-trained embeddings has expedited the training process and enhanced model generalization. These techniques enable the models to capitalize on knowledge acquired from large-scale datasets, facilitating the adaptation of learned features to specific brain disorder detection tasks. Moreover, the interpretability of deep learning models is gaining prominence, with efforts to elucidate the rationale behind the decisions made by these complex architectures. This not only engenders trust but also enriches the medical community's understanding of the disorders themselves.

Nonetheless, challenges persist, including the scarcity of labeled neuroimaging data, the need for robust validation strategies, and concerns about model transparency in clinical decision-making. As the field advances, collaboration between researchers, clinicians, and domain experts is paramount to ensure the ethical and responsible deployment of the image detection models for use in medical practice.

Constant exploration of deep learning models for brain disorder detection marks an exciting juncture in the realm of medical diagnostics. The convergence of technological innovation, sophisticated algorithms, and rich neuroimaging data has the potential to reshape how we comprehend, diagnose, and treat neurological disorders, thereby improving the lives of countless individuals. As this journey unfolds, continued research and vigilance will be essential to harness the full potential of these models while navigating the intricate ethical and practical considerations that come with their integration into the medical landscape.

In conclusion, the exploration of current deep learning models for brain disorder detection using neuroimaging data represents a frontier of immense promise and potential. The methodologies and insights derived from these models hold the power to revolutionize the diagnosis and comprehension of a spectrum of neurological disorders, including Alzheimer's Disease. These models extract highly complex patterns from neuroimaging datasets, employing architectures such as CNNs, RNNs, and transformer-based models.

The integration of various neuroimaging modalities, encompassing fMRI, PET, and DTI, provides a comprehensive perspective on brain activity, connectivity, and structure. This multidimensional approach empowers the models to capture subtle relationships and anomalies associated with a diverse array of neurological disorders, ranging from Alzheimer's disease and schizophrenia to epilepsy and autism spectrum disorders.

Additionally, the incorporation of transfer learning and pre-trained embeddings has expedited the training process and bolstered model generalization. These techniques enable the models to improve insights gleaned from expansive

datasets, facilitating the adaptation of learned features for specific brain disorder detection tasks. Furthermore, the pursuit of interpretability in deep learning models is gaining traction, with concerted efforts to illuminate the reasoning behind the decisions made by these intricate architectures. This not only fosters trust but also enriches the medical community's understanding of the disorders themselves.

Nevertheless, challenges persist, including the scarcity of labeled neuroimaging data, the imperative for robust validation strategies, and concerns regarding model transparency in clinical decision-making. As the field advances, collaborative efforts among researchers, clinicians, and domain experts are imperative to ensure the ethical and responsible deployment of image detection models in medical practice.

The ongoing exploration of deep learning models for brain disorder detection signifies an exciting juncture in the realm of medical diagnostics. The confluence of technological innovation, sophisticated algorithms, and rich neuroimaging data has the potential to reshape how we perceive, diagnose, and treat neurological disorders, ultimately enhancing the lives of countless individuals. As this journey continues, sustained research and vigilance will be paramount to harness the full potential of these models while navigating the intricate ethical and practical considerations inherent in their integration into the medical landscape.

Data Availability Statement

The data used to support the findings of this study are publicly available from open-source publications collected from google scholar and other publication databases. All papers used are cited and are added in the reference section.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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