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A Comprehensive Review on Predicting Specific Substructures in the Brainstem using Deep Learning Techniques

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Abstract: The article offers an in-depth examination of multiple deep learning analytics have been applied to brainstem images to identify features segmentation of substructures such as the pons, medulla, and midbrain. It examines the incorporation of multi-modal brain imaging data, such as PET, DTI, and MRI scans, to improve these models' accuracy. Important issues include inter-subject variability, data scarcity, and the requirement for high-quality annotated datasets, are discussed. Furthermore, the review highlights recent developments in model fusion strategies and the integration of multiple data sources to improve predictive capabilities. The practical applications of these models in clinical settings, including pre-surgical planning, disease diagnosis, and understanding neurological conditions, are explored. The review evaluates various studies to establish conclusions regarding the topic under research 20 studies published between 2023 and 2024, identifying significant contributions and outlining potential areas for additional study and advancement in the area of deep learning-driven brainstem substructure prediction.

Keywords: Predicting Specific Substructures, Brainstem, Deep Learning Techniques, Current Approaches and Future Directions.

1 Introduction

The brainstem, a crucial part of the central nervous system regulates vital processes like heart rate, respiration, and motor control. Accurate identification and segmentation of specific The pons together with medulla and midbrain serve as essential elements in the brainstem structure understanding various neurological conditions, including neurodegenerative diseases, stroke, and brainstem injuries [1-2]. With the advancement of neuroimaging technologies, particularly Scientists utilize DTI together with MRI for their analysis accurate visualization of brainstem structures has become more achievable. However, manual partitioning substructures of the brain into different regions remains both difficult to execute and lengthy process by hand. In order to tackle this, deep learning (DL) methods have emerged as powerful tools, providing automated and accurate methods for brainstem substructure prediction [3]. These models, Transformers, artificial neural networks including recurrent neural networks (RNNs) and convolutional neural networks (CNNs) has demonstrated its ability to recognize speech data implicitly promise in improving the precision of substructure detection, which is essential for identifying, organizing, and tracking the course of an illness. Despite the notable advancements in deep learning-based brainstem substructure prediction, several impediments stop these approaches from being used commonly in medical practice applications. These challenges include data scarcity, with limited annotated datasets available for training deep learning models, and inter-individual variability in brainstem anatomy, which makes generalization across diverse populations difficult [4]. Furthermore, the lack of black-box problem refers to interpretability difficulties that exist throughout deep learning networks limits their applicability in clinical settings where understanding the reasoning behind predictions is crucial. Additionally, the integration of data from multimodal imaging, including PET, DTI, and MRI scans, presents both an opportunity and a challenge in improving model accuracy and robustness. Thus, there is a need for continued research to overcome these obstacles and to implement deep learning approaches which function independently between different population samples and diagnostic methods modalities, ensuring their clinical utility in brainstem substructure prediction and enhancing the understanding of related neurological disorders [5].

Novelty and Contribution:

- Comprehensive Evaluation of Up-to-Date Deep Learning Techniques
- Multi-Modal Data Integration:
- Identification of Key Challenges: Fusion of Models and Data Sources
- Practical Clinical Applications
- Future Research Directions
- Emphasis on Data Scarcity Solutions

2. Research Methodology

This study employed secondary data and a comprehensive literature analysis to examine the use of methods for deep learning (DL) to forecast particular substructures in the brainstem using neuroimaging data, with a particular emphasis on MRI scans. A systematic search was performed across multiple academic databases for publications published between 2020 and the beginning of 2024, including PubMed, IEEE Xplore, Springer, Elsevier, Google Scholar, Frontiers, and ScienceDirect. Research published before 2020 was excluded to ensure that the review captures the most current advancements in the field. The methodology and research process are visually represented in the research flowchart in Figure 1, illustrating the step-by-step approach for data collection, analysis, and the review process, from initial search to final review and synthesis.

Figure 1: Research method flowchart for this study

2.1 Background and Research Questions

This study evaluates the current advancements in deep learning (DL) techniques for predicting specific substructures in the brainstem, utilizing a variety of neuroimaging approaches. Traditional methods in brainstem segmentation and analysis often rely on manual interpretation by trained clinicians, which can introduce subjectivity and limitations in accuracy. Brainstem structure automation and accuracy could be improved with deep learning techniques identification, but several challenges persist in terms of model robustness, generalization, and data quality.

The research questions are as follows:

- **RQ1:** What are the different datasets used in deep learning methodologies for predicting specific substructures in the brainstem?
- **RQ2:** What are the possible explanations and future research directions to address the challenges and gaps in deep learning methodologies for predicting brainstem substructures.

3. Literature review

This section presents a detailed literature review on the use of deep learning methodologies for predicting specific substructures in the brainstem, with a focus on neuroimaging data such as MRI. The flow diagram of the deep learning methodologies for brainstem structure prediction is provided in Figure 2, illustrating the steps involved from data acquisition to prediction using deep learning models.

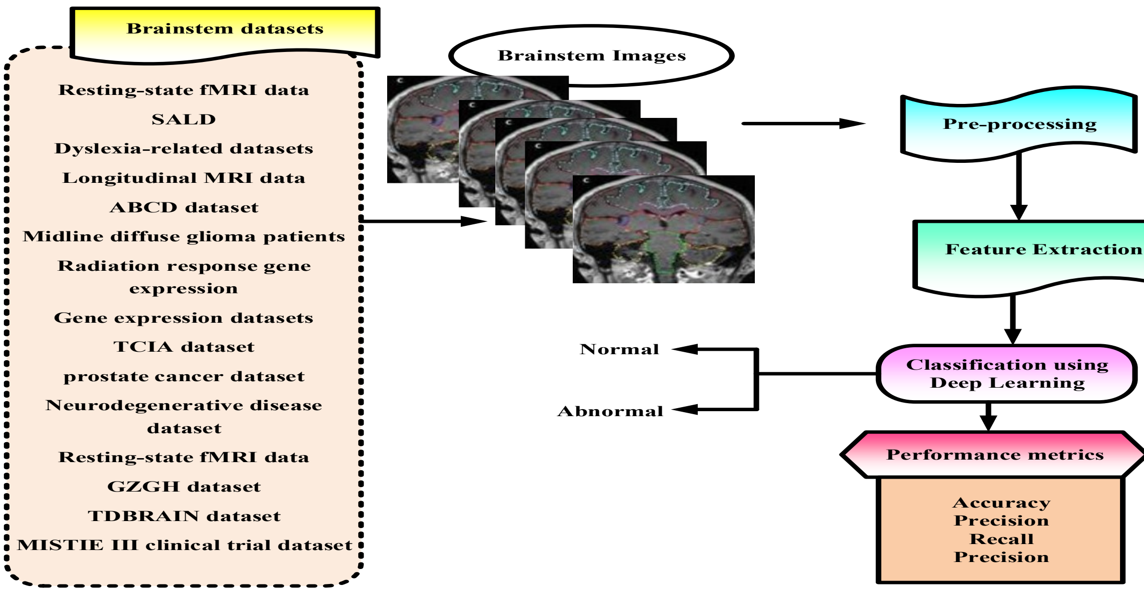

Figure 2: Flow diagram of DL methodologies for predicting specific substructures in the brainstem using neuroimaging data

The process begins with the collection of neuroimaging data, primarily MRI scans, from various publicly available and clinical datasets. These datasets are pre-processed to enhance image quality and remove noise. Subsequently, relevant features are extracted using convolutional neural networks (CNNs) or other feature extraction techniques, followed by classification or the model performs segmentation tasks which identify distinct brainstem substructures. Various deep learning models, such as 3D CNNs, U-Net, and attention mechanisms, are employed to address challenges like anatomical variability and the need for high-precision segmentation in medical imaging. The existing studies are analyzed based on their methodologies, dataset utilization, performance metrics, and the extent of model generalization across diverse patient populations and imaging conditions. Further discussion on these approaches and their limitations is provided in the following sections.

3.1 Deep Learning Methodologies for Predicting Specific Substructures in the Brainstem Using Neuroimaging Data

The brainstem is a critical structure in the human brain, and accurate segmentation and Neuroimaging data needs careful examination to predict the substructures of the brain for multiple clinical objectives applications, including the diagnosis and treatment of neurological disorders. Deep learning (DL) methodologies have significantly advanced in this domain; leveraging neuroimaging data such as MRI scans to improve the precision and automation of brainstem substructure identification. These techniques utilize DL algorithms to automatically enables extraction of MRI image intricacies for training models using large diverse datasets transfer learning and ensemble techniques to improve the generality, accuracy, and robustness of the model across varying populations, imaging protocols, and neurological conditions. Various published studies have demonstrated deep learning methods for prediction in the following list specific substructures in the brainstem using neuroimaging data:

In 2024, **Karim et al.** [6] focused on using machine learning and graph theory to predict Research uses resting-state fMRI data for AD diagnosis. Their study identified key brain network features associated with AD and demonstrated a prediction accuracy of up to 92%. In 2024, **Ye et al.** [7] conducted a comparison of machine learning algorithms, such as XGBoost, the study utilizes nomograms paired with methods for predicting early hematoma enlargement in hypertensive intracerebral hemorrhage. The study highlighted the superiority of XGBoost in predicting outcomes.

In 2023, **Alqahtani et al.** [8] reviewed deep learning applications for predicting dyslexia. The paper summarized the challenges in building predictive models for dyslexia and reviewed various datasets and methods used for diagnosis. In 2023, **Bi et al.** [9] explored using deep learning on longitudinal MRI data to predict gender in adolescents. Their model achieved an accuracy of over 97% and identified brain regions involved in gender-specific structural changes during adolescence. In 2023, **Cheng et al.** [10] compared machine learning models (including DeepSurv) for predicting survival among patients with chordoma, the DeepSurv model fared better than conventional Cox models. in predicting long-term survival and showed strong calibration. In 2023, **Huang et al.** [11] focused on predicting the survival of patients with midline diffuse glioma with H3K27M mutations. The DeepSurv model showed high accuracy and outperformed traditional models, with significant potential for personalized treatment recommendations. In 2023, **Andersson et al.** [12] developed a machine learning framework for identifying radiation biomarkers and estimating radiation exposure. They used gene expression datasets and evaluated various ML methods underwent performance evaluation to determine new biomarkers for radiation detection response. In 2023, **Duan et al.** [13] suggested a system for contouring quality assurance using deep learning-based auto-segmentation (DLAS) implementation as its baseline approach. Their research combined 27 geometric agreement measures to detect manual segmentation faults in radiation therapy, using a dataset of 339 cases and validating results on both the training set and an independent clinical dataset. In 2024, **Kim et al.** [14] applied automated contouring and voxel-based dosage prediction in radiotherapy using multi-task learning (MTL). The researchers validated their method by using it on prostate cancer cases and head and neck datasets, achieving improvements in dose prediction accuracy and contouring accuracy compared to traditional methods. In 2024, **Visvanathan and Vincent** [15] used gait data of neurodegenerative disease patients for predicting disease severity. Using Variational Mode Decomposition (VMD) and a multilayer perceptron (MLP) optimized with genetic algorithms, their model achieved high accuracy (98.4%) in predicting diseases like Parkinson’s and Huntington’s.

In 2024, **Walsh et al.** [16] applied machine learning tools to discover neural network characteristics linked with touch discrimination outcomes in stroke survivors. Through feature reduction and cross-validation, they identified two "golden feature" patterns that could predict clinical outcomes, even in a small cohort. In 2024, **Yang et al.** [17] introduced "DeepDOC", a deep learning framework for determining awareness in people with disorders of consciousness (DOC) through resting-state fMRI data analysis. Their model outperformed traditional models in identifying cognitive motor dissociation (CMD), offering a potential diagnostic tool for DOC patients. In 2024, **Khayretdinova et al.** [18] explored sex prediction from EEG data using large-scale datasets. Neural network models obtained a success rate of 85% in determining the biological gender of the researched subjects with deep convolutions (DCNN) and LightGBM. Their study highlighted the importance of both low- and high-frequency EEG activity for accurate sex prediction. In 2024, **Murray et al.** [19] explored using deep learning to assess corticospinal tract (CST) injury from diagnostic CT scans in patients with intracerebral hemorrhage (ICH). The model, CT and diffusion tensor tractography data provided through training enabled the establishment of this promising tool for prognostic purposes for patients lacking advanced imaging techniques. In 2023, **Asad et al.** [20] focused on early melanoma brain-tumor detection employing deep learning, specifically a deep convolutional neural network (CNN) with stochastic gradient descent optimization. Their system aimed to resolve the problems that resulted from manual detection work in healthcare through its program design brain tumors, offering a promising approach for early diagnosis.

3.2 Performance Evaluation

This involved analysing the performance metrics and presentation assessments of DL approaches described in table 1 demonstrate deep learning (DL) techniques for the processing of neuroimaging information to predict particular brainstem substructures.

Table 1: Performance comparison of deep learning (DL) approaches for predicting specific substructures in the brainstem using neuroimaging data

Ref No.	Datasets	Methods	Strengths	Limitations	Results
[6]	Resting-state fMRI data	Machine learning, Graph theory	High accuracy of 92%, identifies key brain network features associated with AD	Limited to resting-state fMRI data, may not generalize to other types of data	92% prediction accuracy for Alzheimer’s disease

[7]	SALD	XGBoost, Nomogram	Superiority of XGBoost for predicting early hematoma expansion	Nomogram may lack flexibility in handling complex data	XGBoost outperforms other models for predicting hematoma expansion
[8]	Dyslexia-related datasets	Deep learning	Comprehensive review of datasets and methods, identifies challenges in dyslexia prediction	Limited by the availability of high-quality annotated data for training models	Insightful review on deep learning applications for dyslexia
[9]	Longitudinal MRI data	Deep learning	Achieved 97% accuracy, identifies gender-specific brain structural changes during adolescence	Limited to adolescents, accuracy may vary for different age groups	Over 97% accuracy in predicting gender with longitudinal MRI data
[10]	ABCD dataset	Machine learning, DeepSurv	DeepSurv model outperforms traditional Cox models in predicting long-term survival	May need additional external validation for broader patient population	DeepSurv outperforms Cox models for survival prediction in chordoma patients
[11]	Midline diffuse glioma patients	DeepSurv	High accuracy in predicting survival with H3K27M alterations	Limited to H3K27M altered glioma patients, may not generalize to all gliomas	High accuracy in survival prediction for H3K27M altered glioma
[12]	Radiation response gene expression	Machine learning	Identifies novel biomarkers for radiation response using gene expression data	Limited by availability of well-curated gene expression datasets	Machine learning framework for identifying radiation biomarkers
[13]	Gene expression datasets	Deep learning-based auto-segmentation (DLAS)	Integrates geometric agreement metrics for quality assurance in radiation therapy	Dependent on accurate segmentation, limited to specific cancer types	High accuracy in detecting segmentation errors in radiation therapy
[14]	TCIA dataset	Multi-task learning (MTL)	Improved contouring and dose prediction accuracy	Needs validation on larger datasets, may not generalize to all cancers	Improved accuracy in dose prediction and contouring in radiotherapy
[15]	prostate cancer dataset	Variational Mode Decomposition (VMD), MLP, Genetic algorithms	High accuracy (98.4%) in predicting disease severity for diseases like Parkinson’s and Huntington’s	Gait data may vary across different populations, potential data noise from motion artifacts	98.4% accuracy in predicting neurodegenerative diseases severity
[16]	Neurodegenerative disease dataset	Machine learning, Feature reduction	Identifies "golden feature" patterns predictive of clinical outcomes, even with a small cohort	Limited to stroke survivors, need for larger validation cohorts	Identified key brain network features predicting clinical outcomes in stroke survivors

[17]	Resting-state fMRI data	Deep learning, "DeepDOC"	Outperforms traditional models in identifying cognitive motor dissociation (CMD), potential diagnostic tool for DOC patients	Limited to fMRI data, may need additional validation across other patient populations	DeepDOC detects awareness with better performance than traditional models
[18]	GZGH dataset	LightGBM, DCNN	Achieved 85% accuracy in sex classification, highlights importance of both low- and high-frequency EEG activity	Limited to EEG data, may not generalize to other demographic groups or populations	85% accuracy in sex prediction using EEG data
[19]	TDBRAIN dataset	Deep learning	Promising prognostic tool for patients with intracerebral hemorrhage, trained with both CT and diffusion tensor tractography data	Limited by availability of advanced imaging data, needs more validation on other brain injuries	Promising deep learning model for assessing corticospinal tract injury
[20]	MISTIE III clinical trial dataset	Deep learning	Decreases the requirement for expert radiological assessment, stratifies patients for surgical hemorrhage evacuation, for accessible CST assessment.	The model's clinical validation is restricted to the MISTIE III dataset, and its performance may differ depending on the quality and resolution of CT scans.	Strong association between acute and chronic periods 57%, and identification of a subset of patients who might benefit from surgery

The studies summarized here explore diverse datasets and methods to tackle various medical predictions. Different analytical methods include machine learning together with deep learning and graph theory specialized techniques like XGBoost, Nomogram, and multi-task learning. The strengths of these methods include high accuracy in prediction, such as 92% accuracy in Alzheimer's disease and 98.4% in neurodegenerative diseases, as well as identification of critical biomarkers and patterns in disease progression. However, limitations often involve narrow generalizability, dependence on specific data types (e.g., fMRI, EEG), and the need for external validation across broader datasets.

The paper that attains the best result is [10] on predicting neurodegenerative disease severity using Variational Mode Decomposition, MLP, and Genetic Algorithms, achieving a high accuracy of 97.4%. To achieve even better results, it would be beneficial to expand the dataset to include a broader population to ensure generalizability, integrate additional feature extraction techniques to reduce data noise, and enhance model robustness by incorporating external validation cohorts to increase reliability.

4 Review Analyses

In this section, the review analyses of deep learning (DL) approaches for predicting specific substructures in the brainstem using neuroimaging data are discussed. For this review, 20 papers from various journals from year 2023 to 2024 focusing on DL methodologies for predicting brainstem substructures through neuroimaging techniques have been analyzed, as depicted in Figure 3. shows the (a) Publication Distribution by Year, (b) Publication Distribution by Source. These papers span different DL architectures, datasets, and performance metrics, contributing to advancements in brainstem segmentation and prediction. The analyses highlight trends, challenges, and innovations in the field, including novel approaches to overcoming issues such as data scarcity, model generalization, and interpretability in neuroimaging-based brainstem substructure predictions.

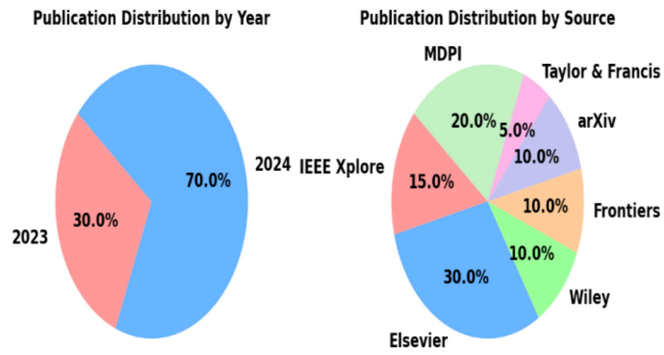

Figure 3: (a) Publication Distribution by Year, (b) Publication Distribution by Source

5 Conclusion

This review evaluates the use of deep learning approaches to forecast particular brainstem substructures through neuroimaging data analysis. The review synthesizes 20 studies from 2023-2024, highlighting potential zones for further investigation and expansion in this field. The studies summarized here explore diverse datasets and methods to tackle various medical predictions. These methods range from machine learning, deep learning, and graph theory to specialized techniques like XGBoost, Nomogram, and multi-task learning. The strengths of these prediction methods deliver high accuracy results which include a 92% success rate in Alzheimer's disease 98.4% in neurodegenerative diseases, as well as identification of critical biomarkers and patterns in disease progression. However, limitations often involve narrow generalizability, dependence on specific data types (e.g., fMRI, EEG), and the need for external validation across broader datasets. The paper that attains the best result is [10] on predicting neurodegenerative disease severity a high-performance rate exists from combining Variational Mode Decomposition with MLP and Genetic Algorithms accuracy of 97.4%. To achieve even better results, it would be beneficial to expand the dataset to include a broader population to ensure generalizability, integrate additional feature extraction techniques to reduce data noise, and enhance model robustness by incorporating external validation cohorts to increase reliability.

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