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Detection, Monitoring and Follow-up of ADHD suffering children using Deep Learning

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Abstract

Attention Deficit/Hyperactivity Disorder (ADHD) is a neurodevelopmental disorder that affects a significant portion of the younger population (0-16 years) worldwide. Early detection, continuous monitoring, and effective follow- up of ADHD in children are very vital for providing timely therapies and enhancing the long-term outcomes of affected individuals. This paper discusses a novel approach that uses deep learning techniques to detect, monitor, and follow up with children suffering from Attention Deficit Hyperactive Disorder (ADHD). The system begins with comprehensive data collection, including behavioral assessments, genetic markers, and biomarker levels. Feature extraction methods are utilized to identify the most relevant attributes linked with different types of ADHD—Inattentive, Hyperactive- Impulsive, and Combined. The deep learning model is trained on these features, with a goal of improving diagnostic accuracy through iterative validation and hyperparameter tuning. The deep learning model is evaluated using standard metrics, such as accuracy, precision, recall, and F1-score, to ensure effective performance. This approach aims to enhance diagnostic precision and support personalized treatment strategies, offering a more individualized therapy pathway for children with ADHD.

INTRODUCTION

Attention-Deficit/Hyperactive Disorder (ADHD) is a medical condition. A person with ADHD has differences in brain development and brain activity that affect attention, the ability to sit still, and self-control. ADHD is the most diagnosed mental disorder in children. It's usually spotted during the early school years (0-16), when a child begins to have problems paying attention. ADHD can't be prevented or cured. While the symptoms of ADHD may change with age, this condition often persists into adulthood. Rather than escalating with age, ADHD tends to progress positively, especially with ongoing treatment and management.

There are three primary types of ADHD, each characterized by specific patterns of symptoms: ADHD-Inattentive, ADHD Hyperactive and ADHD-Combined. In Inattentive type, individuals primarily exhibit symptoms related to inattention. Common signs include difficulty in sustaining attention, making careless mistakes, poor organization, forgetfulness, and struggling to follow instructions. The less prominent symptoms are hyperactivity and impulsivity which are more prominent in the second type-Hyperactivity ADHD. People with this presentation may have trouble sitting still, be very talkative, interrupt others frequently, and act impulsively without considering consequences. Here, inattention symptoms are less prominent. However, the most common type of ADHD is Combined ADHD where impulsivity, hyperactivity, and inattention are present simultaneously. Unlike the other types, individuals with this presentation experience symptoms from both categories, making it more complex to manage.

The diagnosis and management of ADHD are further complicated by its frequent association with comorbid conditions, including other neurodevelopmental, psychiatric, and non-psychiatric disorders. These co-occurring conditions can exacerbate the functional impairments caused by ADHD, making it crucial to adopt a holistic and multidisciplinary approach to treatment.

Recent advancements in technology, particularly in the field of deep learning, offer promising avenues for improving the diagnosis and treatment of ADHD. By integrating data from genetic markers, biomarkers, and comprehensive behavioural assessments, deep learning algorithms have the potential to revolutionize our understanding of ADHD. These technologies could enable more accurate identification of the disorder's underlying mechanisms, leading to personalized treatment strategies that are more effective in managing the diverse presentations of ADHD.

This paper explores Attention-Deficit/Hyperactivity Disorder (ADHD), its subtypes, and the role of technology in diagnosis and management. It examines how deep learning and data-driven approaches can enhance diagnostic accuracy, track symptom progression, and refine treatment strategies. The challenges of comorbidities and long-term management are discussed, along with ethical considerations regarding data security, patient privacy, and fairness in decision-making, ensuring alignment with best practices in healthcare.

LITERATURE REVIEW

A study titled "Early Detection of ADHD in Children Using Two Learning Approaches" by S. M and P. Selvi Rajendran (2024) investigates the effectiveness of machine learning models in diagnosing ADHD in children. Presented at the 2024 International Conference on Advances in Data Engineering and Intelligent Computing Systems (ADICS), the research compares the performance of two models: Random Forest and a Deep Neural Network with Attention Mechanism (DNN-AM). The findings reveal that while the Random Forest model achieved a commendable accuracy of 91.01%, the DNN-AM model significantly outperformed it, reaching 100% accuracy. The superior performance of the DNN-AM model is attributed to the use of Local Binary Pattern (LBP) images for enhanced feature extraction, which played a crucial role in improving the precision of the ADHD diagnosis.

The 2024 paper titled "A Short Report on ADHD Detection Using Convolutional Neural Networks" by Kulkarni V, Nemade B, Patel S, Patel K, Velpula S, published in Frontiers in Psychiatry, explores the use of CNNs for classifying ADHD in children using fMRI data, achieving 98.77% accuracy. It highlights CNNs' ability to capture complex spatial patterns in neuroimaging, outperforming traditional methods like SVMs and Logistic Regression. While the study demonstrates the potential of deep learning in ADHD diagnosis, it also identifies key limitations, including the high cost and limited accessibility of fMRI, the absence of behavioral and genetic data, and model interpretability challenges. Despite these drawbacks, the research underscores the importance of multimodal approaches that combine neuroimaging with behavioral and genetic data for more accurate and clinically applicable ADHD diagnosis.

The 2023 paper titled "Automated Detection of ADHD: Current Trends and Future Perspective" by the School of Science and Technology, Singapore University of Social Sciences, provides a comprehensive review of various diagnostic tools used for ADHD detection, focusing on the integration of machine learning (ML), deep learning (DL), and artificial intelligence (AI) techniques. The study highlights a key challenge in the field: the scarcity of publicly available datasets across most diagnostic modalities, apart from MRI data. This lack of accessible data poses limitations for the development and validation of automated ADHD detection models, underscoring the need for more open-source datasets to advance research in this area.

The 2022 study titled "Predicting Children with ADHD Using Behavioral Activity: A Machine Learning Analysis" by Maniruzzaman, Jungpil Shin, and Md. Al Mehedi Hasan from the University of Aizu, Japan, explores the risk factors associated with ADHD in children through machine learning techniques. The research highlights that a Logistic Regression combined with a Random Forest classifier achieves excellent accuracy in correctly classifying and predicting children with ADHD. By providing a reliable method for early detection, this study offers valuable insights that could assist physicians in diagnosing and treating ADHD at its early stages, potentially improving outcomes for affected children.

The paper titled "A Predictive Model for Attention Deficit Hyperactivity Disorder Based on Clinical Assessment Tools" by Han D, Fang Y, Luo H (2020), published in Neuropsychiatric Disease and Treatment, explores the development of a predictive model for ADHD diagnosis by integrating clinical assessment tools with machine learning techniques. The study utilizes data from widely used ADHD rating scales, including Conners CBRS, CBCL, and SNAP- IV, to train predictive models and enhance diagnostic accuracy. The findings suggest that machine learning algorithms, particularly Random Forest and Support Vector Machines (SVMs), outperform traditional diagnostic methods, offering a more objective and data-driven approach. However, the study highlights limitations such as subjectivity in behavioral assessments, potential biases in self-reported data, and the need for larger, more diverse datasets to improve model generalization. Despite these challenges, the research underscores the importance of combining standardized clinical assessments with machine learning to enhance early detection and personalized intervention strategies for ADHD.

The 2023 paper by Cao, Meng, Martin, Elizabeth, and Li, Xiaobo, titled "Machine Learning in Attention- Deficit/Hyperactivity Disorder: New Approaches Toward Understanding the Neural Mechanisms", reviews the potential and challenges of using machine learning (ML) to advance the understanding of ADHD's neural mechanisms. While ML approaches have shown promise in improving ADHD diagnosis and feature identification, the study highlights significant challenges that hinder clinical applications. One of the primary issues is the lack of interpretability in ML models, as high-accuracy models often rely on complex interactions between multiple variables, making it difficult to understand their relationships. Additionally, the generalizability of these models is limited, particularly due to small sample sizes and the heterogeneity of ADHD presentations. Despite implementing cross-validation techniques to combat overfitting, applying models to new subjects often results in significant drops in classification accuracy. The study emphasizes the importance of increasing both the interpretability and generalizability of ML models to better understand ADHD's neural mechanisms and improve clinical outcomes.

The 2023 paper titled "Handwriting-Based ADHD Detection
for Children Having ASD Using Machine Learning Approaches" by the Japan Society for the Promotion of Science (JSPS) introduces a machine learning-based system for detecting ADHD in children with coexisting Autism Spectrum Disorder (ASD) through handwriting patterns. The study employed seven classification algorithms to distinguish between children with ADHD and ASD and healthy children, demonstrating the potential of handwriting analysis in aiding early diagnosis. The findings suggest that this approach could be a valuable tool for medical practitioners, offering a non- invasive method to assist in the early detection and intervention of children with both ADHD and ASD.

METHODOLOGY

This section discusses the approach taken to develop a deep learning-based system for identifying and treating children with ADHD, following a three-phase methodology: Detection, Monitoring, and Follow-Up.

System Overview

The developed system uses deep learning to diagnose and manage Attention-Deficit/Hyperactivity Disorder (ADHD) in children through a three-phase methodology: Detection, Monitoring, and Follow-Up. Each phase enhances diagnostic accuracy, tracks symptom progression, and provides actionable insights for clinical intervention. The hybrid system offers real-time insights via interactive visualizations and provides alerts to enable timely actions.

Data Collection

The data collection process for the system incorporates both structured and unstructured datasets. Structured data includes demographic information, medical history, behavioral assessments, and genetic markers, while unstructured data consists of clinician notes and patient feedback. A hypothetical dataset is used to simulate real-world scenarios, ensuring privacy and ethical compliance. Data is sourced from medical records, questionnaires, and follow-up reports to provide a comprehensive view of the patient's condition. Preprocessing techniques, including missing value handling and feature normalization, are applied to prepare the data for model training.

System Design & Development

The methodology consists of three distinct phases: Detection, Monitoring, and Follow-Up, each aimed at improving diagnostic precision, tracking symptom development, and delivering meaningful insights for clinical decision-making.

Phase 1: Detection

This phase focuses on identifying and classifying ADHD subtypes & it’s severity using static data.

Structured and unstructured records, including medical history, behavioral assessments, and self-reported questionnaires, are collected and preprocessed. Data cleaning techniques such as missing value imputation, normalization, and text feature extraction using TF-IDF vectorization are applied. A Feedforward Neural Network (FNN) is trained on the processed data, with model evaluation based on Accuracy, Precision, Recall, F1-Score, and ROC-AUC metrics to ensure reliable classification.

Phase 2: Monitoring

The monitoring phase tracks ADHD symptom progression over time using time-series data. Longitudinal data, including timestamped behavioral assessments and follow-up reports, is collected and segmented for temporal analysis. Feature engineering techniques, such as lag features and Fourier Transform, are applied to identify symptom trends. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are employed to model sequential dependencies in symptom progression. Rolling cross-validation is used to simulate real-time data updates, while Matplotlib is utilized for interactive visualizations, enabling clinicians to detect anomalies and assess symptom fluctuations.

Phase 3: Follow-Up

This phase provides actionable insights and refines treatment strategies through adaptive learning. A hybrid model integrates FNNs for static data processing and RNNs for sequential data analysis, improving predictive accuracy. Rule-based alert systems

are implemented to define critical symptom severity thresholds. Natural Language Processing (NLP) techniques summarize follow-up insights, enhancing communication between clinicians and patients. Data drift detection mechanisms are incorporated to maintain model reliability, while periodic retraining with updated datasets ensures adaptability to real-world clinical applications.

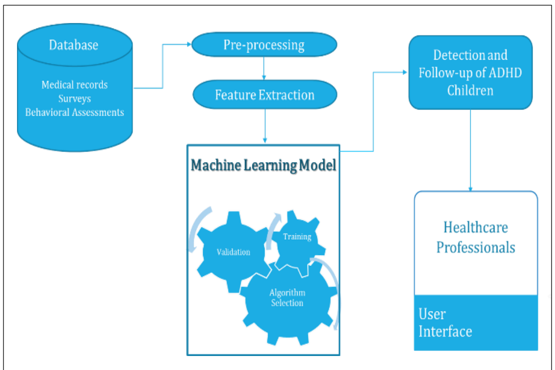

Figure 1. Schematic diagram of the

By integrating these three phases, the system leverages deep learning for comprehensive ADHD diagnosis and management, enabling accurate classification, real-time monitoring, and effective follow-up interventions.

DEEP LEARNING ALGORITHM & MODEL DEVELOPMENT

Deep learning models are crucial in the field of ADHD diagnosis and management, enabling accurate analysis of both structured patient data and time-series behavioral assessments. Feedforward Neural Networks (FNNs) are employed for classifying ADHD subtypes based on static features such as age, gender, and medical history, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks process sequential data to track symptom progression over time. Supervised learning techniques train these models using labeled datasets, ensuring accurate correlations between input features and diagnostic outcomes.

These models significantly enhance the ability to monitor ADHD symptoms in real-time, detecting anomalies or sudden changes that may indicate worsening conditions or treatment effectiveness. The use of hybrid architecture combining FNNs and RNNs allows for a more comprehensive understanding of both static and temporal patterns, improving predictive accuracy. Continuous training and validation of the models ensure they adapt to new patient data, making them invaluable for long-term monitoring and intervention, ultimately leading to more precise diagnoses and personalized treatment plans for children with ADHD.

EVALUATION & TESTING

The evaluation and testing of the ADHD detection, monitoring, and follow-up system were conducted to assess model accuracy, system reliability, and clinical applicability. The deep learning models were trained and validated using a diverse dataset, ensuring robustness in ADHD classification and symptom progression tracking. Performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC were utilized to measure classification effectiveness, while time-series models for symptom monitoring were evaluated using mean absolute error (MAE) and root mean square error (RMSE).

To ensure real-world applicability, the system was tested with simulated patient data, replicating clinical scenarios to validate detection accuracy and symptom trend analysis. Cross-validation techniques were employed to prevent overfitting and improve model generalization across different demographic groups. Additionally, the system underwent

usability testing with healthcare professionals, assessing the effectiveness of the interactive dashboard in facilitating decision-making and treatment adjustments.
Security and ethical considerations were also evaluated, ensuring compliance with data privacy regulations through encryption and anonymization techniques. The system maintained a clinician-in-the-loop approach, ensuring that AI-generated insights complemented, rather than replaced, expert decision-making. Future testing will focus on real-world clinical deployment, further refining model performance and integration within existing healthcare systems.

USER INTERFACE AND EXPERIENCE DESIGN

The design and development of the user interface (UI) and user experience (UX) for the ADHD diagnosis and management system were carried out using Streamlit, a Python-based framework that allows for the swift creation of interactive web applications. The UI was carefully developed to provide user-friendly and accessible experience for clinicians, ensuring ease of interaction with the system. Key features include interactive dashboards that display real-time insights into ADHD symptom progression, visualizations of diagnostic outcomes, and trend charts to assess treatment effectiveness.
The UX design prioritizes simplicity and efficiency, enabling clinicians to navigate through various modules, such as detection results, symptom tracking, and follow-up insights, with minimal effort. Interactive elements, such as data input forms, symptom tracking tools, and alert notifications, allow healthcare professionals to monitor patient conditions and make informed decisions quickly. By leveraging Streamlit's capabilities, the system ensures smooth integration of deep learning analyses with user-driven inputs, making it a practical tool for clinical settings. The responsive and adaptable design further enhances its accessibility across multiple devices, ensuring compatibility and facilitating widespread usage among healthcare providers.

ETHICAL CONSIDERATIONS

Ethical considerations are crucial in the development of the ADHD diagnosis and management system, especially when handling sensitive health data. The system follows strict ethical guidelines to ensure patient privacy, data security, and research integrity. It complies with privacy regulations such as the Health Insurance Portability and Accountability Act (HIPAA), employing anonymization and encryption to protect sensitive information. Additionally, the

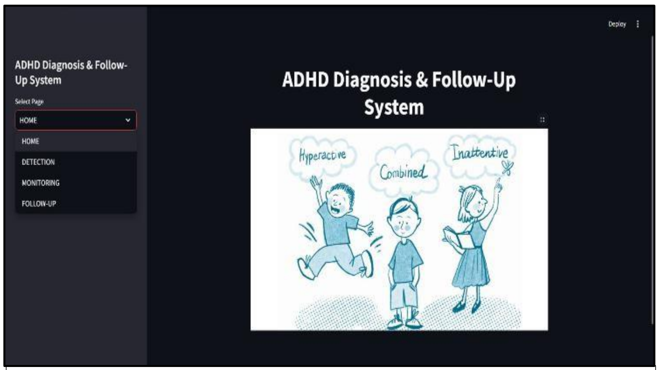

Figure 2. Streamlit App Interface

system adheres to ethical AI principles, ensuring fairness, transparency, and non-bias in decision-making processes.

CHALLENGES AND LIMITATIONS

The development of a deep learning-based ADHD diagnosis and management system presents several challenges and limitations. A key constraint is the limited availability of labeled medical data, which often leads to class imbalance in ADHD-related datasets. This imbalance hinders the development of robust models that can generalize across diverse populations. Additionally, ADHD's complexity, with its overlapping symptoms and frequent comorbidities, further complicates accurate classification and prediction. Variability in symptoms also makes it difficult to design models that can capture the full spectrum of ADHD behaviors, affecting model accuracy and reliability.
Deep learning models require significant computational resources, which can be a barrier to real-time applications, particularly in low-resource settings. High processing power and memory demands hinder the deployment of complex models on portable and wearable devices, limiting their effectiveness for continuous symptom tracking. Moreover, deep learning models are often criticized for their lack of interpretability—functioning as "black boxes" which complicates understanding of the reasoning behind a diagnosis. This reduces trust among clinicians and can hinder adoption in clinical settings.
Ethical concerns, including patient privacy, data security, and potential biases in AI models, must be addressed to ensure fairness, transparency, and regulatory compliance. The collection and use of sensitive neuroimaging and behavioral data also present privacy challenges, further complicating large-scale data acquisition. Ensuring that AI-driven solutions are cost-effective and accessible to all socioeconomic groups remains an essential consideration.
Real-world deployment presents additional challenges, such as clinician adoption and the

integration of AI systems into existing healthcare infrastructure. Many AI-driven ADHD detection systems are still in experimental stages and require rigorous
validation before clinical use. Regulatory hurdles, such as obtaining FDA or equivalent approvals, slow down implementation. Continuous model updates are necessary to maintain accuracy as patient data evolves over time.
While these challenges persist, they also open opportunities for further research and improvement, including expanding diagnostic capabilities, integrating wearable sensor data for continuous symptom monitoring, and improving model generalizability across diverse demographic groups.

FUTURE DIRECTION AND INNOVATIONS

Advancements in artificial intelligence, multi-modal data integration, and personalized healthcare are set to enhance ADHD detection, monitoring, and follow-up. Deep learning models trained on diverse datasets, including genetic markers, biomarkers, and behavioral assessments, can improve diagnostic accuracy and early detection. Federated learning techniques may enable collaborative model training across multiple institutions while preserving data privacy and mitigating biases. Additionally, Explainable AI (XAI) can enhance model interpretability, fostering trust among clinicians, caregivers, and patients. Further optimization of feature selection techniques and model architectures could lead to more robust and scalable ADHD detection systems.
For monitoring and follow-up, wearable technology and mobile-based applications offer the potential for real-time symptom tracking. Continuous data collection from EEG monitoring, eye-tracking devices, and biosensors embedded in smart wearables may provide objective physiological markers for ADHD symptom progression. Reinforcement learning algorithms could personalize intervention strategies by dynamically adjusting treatment plans based on patient responses. The integration of digital twin models—virtual simulations replicating patient-specific ADHD characteristics—could enable predictive analysis of long-term treatment effectiveness. Future advancements in deep learning, combined with real-world patient data integration and ethical AI frameworks, will further refine ADHD diagnosis and management, making it more adaptive and patient centered.

RESULTS AND DISCUSSION

The implementation of deep learning techniques in ADHD detection, monitoring, and follow-up has demonstrated significant improvements in pediatric mental healthcare. By analyzing structured and unstructured data, including behavioral assessments and clinical reports, the system provides a comprehensive framework for early diagnosis, symptom tracking, and personalized intervention. The integration of deep learning enhances diagnostic precision, enabling early identification of ADHD symptoms and differentiation between subtypes, thus supporting clinicians in tailoring treatment strategies.
Continuous monitoring enables real-time tracking of symptom progression, allowing healthcare providers to assess treatment efficacy and make timely adjustments. Predictive analytics further aid in anticipating symptom fluctuations, facilitating proactive management rather than reactive intervention. The system's interactive visualizations offer clear insights into symptom trends, aiding clinicians in decision-making, while AI-driven follow-up recommendations assist caregivers with structured behavioral interventions and lifestyle modifications.
User feedback from clinicians highlights improved diagnostic confidence and reduced subjectivity in ADHD assessments. The system's hybrid model, which integrates deep learning predictions with clinical expertise, ensures that AI-generated insights complement rather than replace human judgment, fostering trust in its application. Ethical considerations, including secure data handling, compliance with privacy regulations, and bias mitigation strategies, have been prioritized to ensure fairness and reliability.
Despite these advancements, challenges such as dataset limitations, model generalizability across diverse populations, and integration with electronic health records remain areas for refinement. Future improvements will focus on enhancing model adaptability, incorporating wearable sensor data for real-time behavioral tracking, and expanding the system's capabilities to assess comorbid conditions.
This deep learning-based approach represents a transformative step in ADHD management, offering a scalable and adaptive solution for early detection, continuous monitoring, and personalized follow-up. By integrating AI-driven insights with clinical expertise, the system enhances long-term outcomes, reinforcing the role of AI in improving pediatric mental health care.

CONCLUSION

The integration of deep learning in ADHD detection, monitoring, and follow-up has significantly advanced pediatric mental healthcare by enhancing diagnostic precision,

enabling continuous symptom tracking, and facilitating personalized interventions. By analyzing behavioral assessments, clinical reports, and longitudinal data, the system bridges the gap between clinical evaluations and daily symptom management, offering real-time insights and AI-driven recommendations to support both healthcare providers and caregivers.
The integration of deep learning in ADHD detection, monitoring, and follow-up has significantly advanced pediatric mental healthcare by enhancing diagnostic precision, enabling continuous symptom tracking, and facilitating personalized interventions. By analyzing behavioral assessments, clinical reports, and longitudinal data, the system bridges the gap between clinical evaluations and daily symptom management, offering real-time insights and AI-driven recommendations to support both healthcare providers and caregivers.
This research highlights the transformative potential of AI in ADHD management, demonstrating its ability to provide scalable, data-driven, and patient-centered solutions. By integrating AI-driven insights with clinical expertise, the system contributes to a more precise, accessible, and effective approach to ADHD care, ultimately improving long-term outcomes for affected children and their families.

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