FocusBoost – A Study Aid with Adaptive Learning Techniques

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***Abstract* - FocusBoost is an AI-powered adaptive learning platform designed to support children with Attention Deficit Hyperactivity Disorder (ADHD) through personalized learning experiences. By integrating video-based learning with voice input analysis, the system uses speech processing techniques to assess a child's engagement and comprehension in real-time. Based on real-time analysis, the platform dynamically adjusts content difficulty and pace to the needs of the individual learner. In practical testing, the system demonstrated high accuracy in classifying learner engagement and comprehension, with more ADHD learners reporting improved focus and content retention. Additionally, parents have noticed positive changes in their child's study habits and attention span through its use. The site has a performance tracking accuracy page for children, which shows their level of comprehension. This research highlights the effectiveness of AI-enhanced learning for students with brain and neurological issues and its potential to improve inclusive, sustainable education practices. The system is designed with scalability in mind, allowing for multilingual support, culturally adaptive content, and future integration with medical professionals, expanding its impact across a variety of educational and therapeutic settings.**

***Keywords* - Artificial Intelligence, Attention Deficit Hyperactivity Disorder, Natural Language Processing, Mel-Frequency Cepstral Coefficients, Short-Time Fourier Transform, Convolutional Neural Network**

I. INTRODUCTION

Children with attention deficit hyperactivity disorder (ADHD) often face significant challenges in traditional learning environments, where rigid structures and consistent teaching methods can make it difficult for them to focus, retain information, and stay engaged. FocusBoost was created in response to this need - a web-based adaptive learning platform that uses artificial intelligence (AI), machine learning (ML), and natural language processing (NLP) to assess and support the cognitive engagement of children with ADHD. By allowing children to watch, download, and respond verbally to short educational videos, the system captures and analyzes speech patterns to determine levels of comprehension and attention.

Traditional educational environments, whether physical or digital, often fail to meet these needs. Most digital learning platforms rely heavily on static, text-based content and self-paced navigation structures, offering minimal sensory diversity or real-time adaptation. Such stereotypical models put learners with neurodiverse learning styles at a disadvantage by not responding effectively to fluctuating attention spans, delayed feedback, or passive material consumption. Furthermore, many platforms lack tools to dynamically monitor engagement or adjust lesson difficulty based on real-time learner input. To address these critical gaps, FocusBoost was developed as an AI-powered adaptive learning system specifically designed for children with ADHD. The platform downloads and combines interactive video lessons with real-time voice input analysis to assess the child's cognitive level and adapt content accordingly.

II. LITERATURE REVIEW

Integrating adaptive learning technologies into educational environments has become increasingly essential in addressing the diverse cognitive needs of individuals with attention deficit hyperactivity disorder (ADHD). Brusilovsky and Millen [3] introduced the basic concept of adaptive hypermedia, using rule-based logic to tailor content delivery to individual learners. Recent advances have built on this foundation, incorporating machine learning and data-driven systems to facilitate real-time personalization [4], [10]. These adaptive platforms help to move away from the rigid, "one-size-fits-all" structures common in conventional education and offer value to learners with ADHD, who often struggle with attention regulation, memory retention, and motivation [1], [2].

Research has shown that learners with ADHD benefit significantly from structured environments, immediate feedback, and multimodal content formats [5], [6]. However, many current adaptive learning tools rely heavily on visual or text-based content, with little incorporation of

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auditory interaction. This shortcoming in the use of voice-based engagement is particularly problematic, as several studies have shown that children with ADHD often respond more positively to audio-visual stimuli and verbal expression than to traditional formats. Techniques such as multi-frequency cepstral coefficients (MFCC), short-time Fourier transform (STFT), and spectrogram-based audio analysis have demonstrated effectiveness in capturing cognitive engagement through speech features such as pitch, tone, and clarity [9]. These audio-processing techniques have been used in domains such as speech therapy, emotion recognition, and assistive communication, but have remained largely unexplored in educational applications for ADHD learners.

The ethical and responsible use of learner data is an important consideration in adaptive systems. Barto and Siemens [7] emphasize the importance of privacy, transparency, and fairness in learning analytics, while Siemens [8] emphasizes the balance between data-driven personalization and pedagogical integrity. These frameworks serve as essential guiding principles for the development of inclusive and trustworthy educational technologies.

Despite advances in adaptive e-learning platforms, a clear gap persists in tools specifically designed for children with ADHD that use voice-based interaction for real-time engagement analysis. FocusBoost addresses this gap by combining advanced speech processing techniques and a classifier to analyze voice input and adapt educational content accordingly. A comparison of key features between existing applications and the proposed system is presented in TABLE 15.

TABLE 15 COMPARISON OF THE FEATURES OF THE EXISTING APPLICATION AND THE PROPOSED SYSTEM

Features	IXL	FunBrain	Do2learn	iComm	FocusBoost
Video Feature	No	No	No	No	Yes
Calendar	Yes	Yes	Yes	No	No
Daily Task Manager	Yes	Yes	No	Yes	No
Relaxation zone (songs)	No	Yes	No	Yes	Yes
Accuracy checking	No	No	No	Yes	Yes

III. METHODOLOGY

The development of FocusBoost followed the Agile software development methodology, chosen for its iterativeness, flexibility, and user-centricity. Agile allowed the project to build the system incrementally, involving continuous feedback and refinement at each stage. This approach was particularly useful for the project, which needed to quickly adapt to the cognitive and behavioral needs of neurodiverse learners.

By adopting agile principles of collaboration, adaptability, and iterative development, the development team was able to maintain a user-centric focus throughout the project. This approach not only accelerated the development timeline but also ensured that FocusBoost emerged as a practical, engaging, and inclusive learning tool that reflected the real-world needs of its intended users.

A. System Architecture & Features

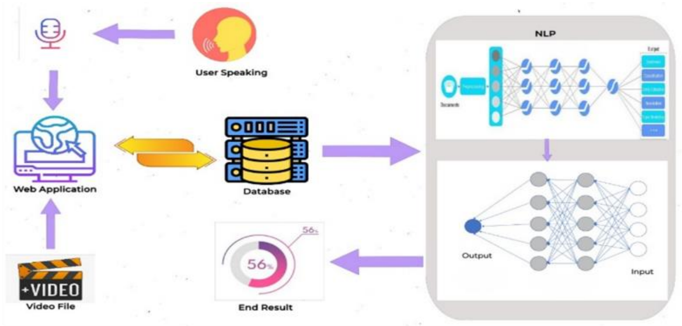

Fig. 9. System Architecture Model

The overall structure of the FocusBoost platform is illustrated in Fig. 1, which outlines the main functional blocks and data flow of the system. The FocusBoost system is built on a modular architecture that separates user interaction from data processing to ensure flexibility and scalability. Users engage through a simple, child-friendly interface where they watch educational videos and respond verbally. These responses are processed in the backend, where the system analyzes speech patterns to assess comprehension and attention. The system tracks user performance over time, allowing for personalized feedback and progress tracking.

B. Model

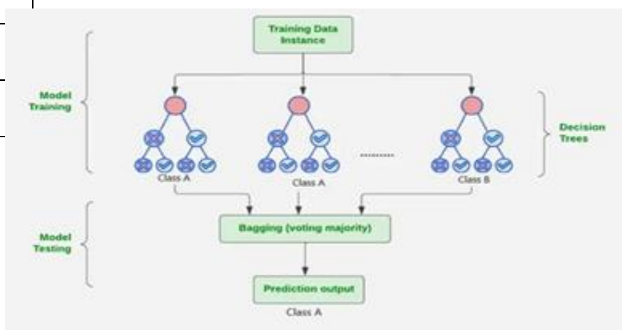

Fig. 10. Random forest classifier output diagram with trained dataset

As illustrated in Fig. 2, the Random Forest classifier demonstrates effective categorization of user input based on extracted speech features. A foundational step in speech classification involves using a random sample classifier to label audio recordings as normal or abnormal, providing a baseline for evaluating more advanced models. The process begins with feature extraction (e.g., MFCCs, spectrograms) and dataset labeling, followed by training using tools like scikit-learn. Although the random classifier has limited predictive accuracy, it helps establish problem scope and evaluation standards. Performance is assessed using metrics such as accuracy, precision, and recall. In contrast, Random Forest Regressors offer greater robustness, effectively handling high-dimensional.

C. Analysis

Fig. 11. Adaptive Learning Industry Report 2024 - 2030

As shown in Fig. 3, the Adaptive Learning Industry Report (2024–2030) projects a steady rise in the adoption of intelligent educational platforms, supporting the relevance and future scalability of systems like FocusBoost. Each module plays a unique role in capturing, analyzing, and responding to learner input in real time. The key components of the system are summarized as follows:

- Video Monitoring and Response: Users watch videos and respond verbally.
- Voice Analysis Engine: Extracts and analyzes speech features (MFCC, STFT, Chromagram).
- Adaptive Learning Engine: Uses a CNN classifier to adjust content difficulty and feedback based on performance.
- Progress Tracking: Provides real-time feedback to parents and educators.

D. Key Components

The main modules of the FocusBoost system are summarized in TABLE 16, which outlines the function of each component within the adaptive learning framework.

TABLE 16 KEY COMPONENTS OF FOCUSBOOST SYSTEM

Component	Function
Video Module	Allows users to watch educational content for comprehension assessment.
Audio Recording	Captures user responses for speech analysis.
Speech Analysis Engine	Uses MFCC, STFT, and chromagram features to evaluate attention and clarity.
CNN Classifier	Classifies user responses and predicts comprehension level.
User Interface (UI)	Child-friendly layout for ease of use and minimal distraction.
Progress Tracker	Monitors performance and engagement; shares insights with educators/parents.
Flask API, Backend	Manages data flow, learning logic, and user interaction processing.

E. Technology Stack

- **Frontend:** HTML, CSS, JavaScript
- **Backend:** Python
- **Database:** MySQL
- **API:** Flask API
- **IDE:** PyCharm Community Edition
- **Libraries:** MoviePy, SpeechRecognition, Librosa, Soundfile, FuzzyWuzzy, Pickle
- **Algorithms:** STFT, Spectrogram, MFCC, Levenshtein Distance, Fuzzy Matching

IV. TESTING & EVALUATION

FocusBoost was evaluated through real-world testing with both ADHD and non-ADHD children to assess performance, usability, and engagement. Participants interacted with video content and responded verbally, enabling analysis of comprehension through speech features. Results showed notable improvements in attention span, motivation, and task completion among ADHD users, with many requesting longer sessions. Educators and parents reported positive behavioral changes and increased participation. The adaptive content delivery was well received, and the speech model achieved over 85% accuracy. However, improvements are needed in voice recognition and system performance on lower-end devices. The overall process of delivering personalized content based on voice input and performance is outlined in the system's adaptive workflow in Fig. 12 .

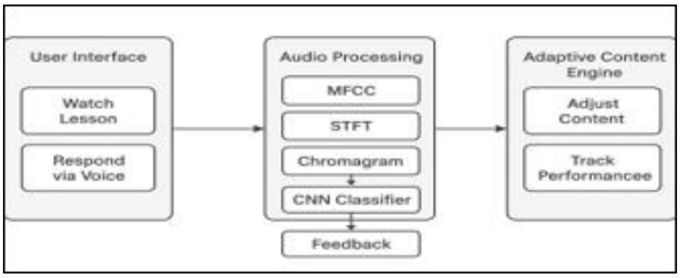

Fig. 12. Workflow of AI-Based Adaptive Learning

Overall, these results confirm FocusBoost as a viable and engaging educational aid for learners with ADHD. The main findings are as follows:

- Increased engagement: Children were more attentive during interactive sessions.
- Improved Comprehension: Adaptive feedback helped children understand and retain content better.
- Positive User Feedback: Parents and educators reported significant improvements in focus and participation.
- Accuracy: The system has successfully analyzed speech patterns and corrected difficulty levels with over 85% accuracy in initial tests.

V. DISCUSSION & DEVELOPMENT

The development of FocusBoost was guided by a user-centered approach. It emphasizes iterative design and empirical validation. Initial requirements were gathered to understand the common learning barriers and environmental triggers. These insights informed the design of the system and informed decisions regarding feature prioritization, interface design, and user engagement strategies. The platform was developed using,

- Data Collection: Children interact with short educational videos and verbally respond.
- Audio Processing: Voice recordings are analyzed using Mel-Frequency Cepstral Coefficients (MFCC), Short-Time Fourier Transform (STFT), and Chromagram features.
- Classification & Perception: A Convolutional Neural Network (CNN) classifies comprehension levels. Based on that, this site dynamically adjusts the difficulty and type of learning content.

User feedback and early testing show that children engaged positively with the platform, demonstrating increased enthusiasm, participation, and improved comprehension. Many users found the activities fun and interactive, which is especially important for children with ADHD, who often benefit from gamified, visually stimulating, and audio-rich environments.

VI. CONCLUSION & FUTURE WORK

C. *Conclusion*

The development of FocusBoost is a significant step forward in addressing the unique educational needs of children with attention deficit hyperactivity disorder (ADHD) through digital innovation. By combining adaptive learning techniques with machine learning and voice-based analytics, the system delivers a personalized and engaging learning experience that adjusts in real time to each child's comprehension and attention levels. Early testing improves focus, increases engagement, and positions learners and educators as a valuable tool for creating inclusive and effective learning environments.

Empirical testing confirmed the platform's effectiveness, with learners showing significant improvements in attention span, task completion, and content retention. Feedback from over 80% of participating parents and educators confirmed a significant increase in learner motivation and engagement, with many children expressing a preference for longer sessions due to the interactive and engaging design. The platform's adaptive mechanism, powered by speech processing techniques and a convolutional neural network, successfully responded to varying levels of comprehension without the need for manual input, underscoring its potential for scalability and autonomous operation.

D. *Future Work*

Future improvements to the FocusBoost system will focus on expanding its accessibility, adaptability, and impact. A key direction is to create a mobile app to ensure that children can access the platform across devices, especially in environments with low desktop availability. The system will be made more accessible to seniors by incorporating enhanced educational content and tailored interaction designs. Expanding multilingual support will make FocusBoost accessible to a wider global audience, allowing children from diverse linguistic and cultural backgrounds to benefit from adaptive learning. Additionally, future versions will include advanced analytics dashboards that provide parents, educators, and professionals with detailed feedback and personal recommendations. Large and highly diverse training datasets will be used to train the underlying machine learning models to improve computational accuracy and content.

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