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NEUROASSIST ADHD ANALYZER: A SMART APPLICATION FOR RECOGNIZING ATTENTION DEFICIT HYPERACTIVITY DISORDER (ADHD) LEVELS IN CHILDREN

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Abstract - Attention *Deficit Hyperactivity Disorder (ADHD) is a common neurodevelopmental disorder that affects children. Identifying children with ADHD is a challenging task, as it requires specialized training and expertise. A novel approach to identifying children with ADHD using artificial neural networks (ANNs) and convolutional neural networks (CNNs) was proposed in this research paper. The web application "NEUROASSIST ADHD Analyzer" was developed to assist in the identification of children with attention deficit hyperactivity disorder (ADHD) using electroencephalogram (EEG) and facial expression data. The application includes three focus games, focus activities, a facial expression analyzer, a combined probability predictor, and a BOT application for the SNAP IV questionnaire. The ANN and CNN models were used to implement these components. An LR model was used to predict the overall result. The integration of these multiple models into the combined model resulted in an accuracy of 94%, with a sensitivity of 90% and a specificity of 92%. Additionally, the area under the receiver operating characteristic curve (AUC-ROC) was 0.91, indicating good discriminative power. Furthermore, a user study indicated that the application is user-friendly and effective in assisting with the diagnosis of ADHD. This research demonstrates the potential of ANNs and CNNs in identifying children with ADHD and presents a promising tool for assisting clinicians in diagnosing the disorder. Future work could focus on improving the accuracy of the models by incorporating additional data sources and features and expanding the application to a larger population.*

Key Words*: *ADHD, EEG, CNN, ANN, machine learning

1. INTRODUCTION

ADHD or attention deficit hyperactivity disorder is a condition that affects both children and adults and is categorized as a neurodevelopmental disorder. The disorder is characterized by a continuous pattern of inattention, hyperactivity, and impulsivity that can significantly hinder daily functioning and development. Inattention symptoms include difficulties sustaining attention, making careless mistakes, organizing tasks and activities, and following through on instructions. Fidgeting, excessive chatting, interrupting others, and difficulty waiting for one's turn are only a few characteristics of hyperactivity-impulsivity [1].

ADHD is an important topic to research due to its high prevalence and the detrimental effects it may have on people as well as society at large. The National Institute of Mental Health (NIMH) estimates that 9.4% of American children between the ages of 2 and 17 have ADHD. The disorder can persist into adulthood, with approximately 4.4% of US adults estimated to have ADHD [2].

ADHD can lead to significant impairments in various areas of functioning, including academic and occupational achievement, social skills, and mental health. Individuals with ADHD are at an increased risk of [3] experiencing problems such as academic underachievement, relationship difficulties, and substance abuse. Moreover, ADHD can cause a significant financial burden, as individuals with the disorder often require more medical care and may have decreased earning potential [4].

Three categories—impulsivity, hyperactivity, and inattentiveness—can be used to categorize the main signs and symptoms used to diagnose children with ADHD. Making careless errors, having trouble maintaining focus, and avoiding tasks that need prolonged mental effort are all indications of inattention. Fidgeting, excessive chatting, and appearing always on the go are a few signs of hyperactivity. Impulsivity symptoms include acting without thinking, interrupting others, and difficulty following rules. Additionally, individuals with ADHD may also experience emotional dysregulation, such as mood swings and difficulty coping with stress. To diagnose ADHD and develop an effective treatment plan, a comprehensive evaluation conducted by a qualified healthcare professional is crucial. However, diagnosing ADHD can be challenging since its symptoms can be similar to other disorders or normal behaviour. While the clinician's judgment is the most widely accepted method of assessment, it can be aided by various questionnaires based on the observation of parents, teachers, and the individual, as well as objective methods based on psychometric and cognitive tests. These assessment methods are now commonly available to evaluate ADHD in both children and adults [5].

The European clinical guidelines for hyperkinetic disorder suggest that a multimodal treatment, including medication, cognitive-behavioural therapy, and parent training, is recommended. Patients who respond to stimulant therapy show improved performance and functioning across a range of ADHD-related domains. While medicine is successful in addressing the primary symptoms of ADHD, the Multimodal Treatment Study for Children with ADHD has discovered [6], combining medication with social skills training and parent training can lead to additional improvements in areas of psychosocial functioning [7].

The research problem at hand is two-fold. The first objective is to detect the level of ADHD in kids diagnosed with ADHD using EEG. The aim is to develop a non-invasive and reliable method for assessing ADHD that can potentially provide more accurate results compared to traditional subjective measures. The second objective is to explore the efficacy of screen-based learning activities in improving attention and memory skills in ADHD patients. The ultimate goal of this study is to create an efficient treatment approach, a web application-based solution that can be easily implemented in a clinical setting and can diagnose children with ADHD and stage of ADHD.

To address these problems, a cross-platform solution aimed at parents/ teachers, and doctors were introduced in this research paper. "NEUROASSIST ADHD Analyzer" consists of three focus games, focus activities, a facial expression analyser, a combined probability predictor, and a BOT Application for the SNAP IV questionnaire as its components. One of the most accurate ways to better understand and measure the attention level of children with ADHD is through electroencephalography (EEG) analysis. Applying electrodes to the scalp analyses the electrical activity of the brain. EEG signals are frequently employed to diagnose epilepsy and sleep disorders, as well as to study brain activity during different tasks and activities. This research uses this method to analyse and determine the ADHD level of children. To measure EEG levels, Emotiv Insight 2.0 was used. It is a non-invasive, wireless EEG headset that measures brain activity and provides real-time feedback on attention levels. The first components of the application are created to obtain the brain activity of the children while they are playing the games and measure the ADHD level using those data. The first game is a memorization level focus game, where the child has to play a path-finder game. The second game is focused on the attention level of a child. The third game consists of three separate learning activities, which are mathematics, word learning, and painting. The next component is Behaviour level focus Activities. It intends to capture the brain waves of children while doing some hands-on activities. While the ADHD level is to be calculated from these components, a facial expression analyser component was designed to analyse the facial expressions and head movements of the user while participating in screen-based activities. After processing the data gathered from the games, these components predict the ADHD level of children. A combined model was then used to collect these four results and predict a final probability level of ADHD in a child. As the final component, a BOT Application for the SNAP IV questionnaire was developed to display the SNAP-IV questionnaire and take answers from the parents/teachers through the app. Based on the answers, the ADHD level of children can be calculated.

The NEUROASSIST ADHD Analyzer application was developed for managing personal profiles, and parental use such as noting down comments on the behaviour, and some specific notes of children who have ADHD to get an idea of activities patients should do at home. Doctors can inform parents about the activities and details of the activities to be done at home by patients. This solution also enables doctors to manage medical data and managing treatment data more easily.

Overall, ADHD is a neurodevelopmental disorder. Both children and adults can be affected by it. It can have some negative impacts on individuals and society, and there are many challenges involved in diagnosing the disorder. This research examines the recommended treatments for ADHD and introduces a cross-platform application "NEUROASSIST ADHD Analyzer" that aims to diagnose and treat ADHD effectively. The application includes focus games, focus activities, a facial expression analyser, a combined probability predictor, and a BOT application for the SNAP IV questionnaire, and it uses electroencephalography (EEG) analysis to measure brain activity and determine the ADHD level of a child. The ultimate goal of this research is to develop an efficient and operative treatment approach for ADHD, improving the quality of life for children with ADHD.

2. BACKGROUND

The neurodevelopmental disorder Attention-Deficit/Hyperactivity Disorder (ADHD) affects a large percentage of children globally [8]. The Centres for Disease Control and Prevention (CDC) estimates that 9.4% of children in the United States between the ages of 4 and 17 have ADHD [9]. Inattention, hyperactivity, and impulsivity are hallmarks of ADHD, which can impair academic, social, and emotional functioning [10].

Over the years, various approaches have been developed to diagnose and treat ADHD in children, including the use of technology. Technology developments have resulted in the creation of several programs and tools for diagnosing and treating ADHD symptoms. For instance, mobile applications (apps) for ADHD management and testing have grown in popularity.

Several studies have examined the efficacy of mobile apps in ADHD assessment and management. A study by Kertesz and colleagues (2023) evaluated the feasibility and acceptability of a mobile app-based ADHD assessment tool. The results indicated that the app was feasible and well-accepted by both parents and children and showed good concurrent validity with traditional ADHD rating scales [11]. Similarly, a study by Rensburg and colleagues (2023) examined the efficacy of a mobile app-based cognitive-behavioural intervention for children with ADHD. The results showed significant improvements in ADHD symptoms, executive functioning, and behaviour problems following the intervention [12].

The literature on ADHD identification through CNN models provides a comprehensive understanding of the research conducted in this field. One noteworthy study [13] highlights the efficacy of CNN algorithms in ADHD diagnosis and examination. The research demonstrates that CNN models outperform other machine learning approaches, showcasing their efficiency in accurately identifying and distinguishing individuals with ADHD from those without the disorder. The study emphasizes the use of seed-based approaches with CNN models, utilizing functional MRI (fMRI) data to map brain connectivity patterns associated with ADHD.

Another research endeavour [14] focuses on leveraging CNN models along with correlation analysis on default mode network (DMN) regions for ADHD identification. The findings reveal significant accuracies ranging from 84% to 86%, underscoring the potential of combining CNN models with neuroimaging data to enhance diagnostic accuracy. This approach provides insights into the functional connectivity patterns within the brain and their relevance to ADHD.

Furthermore, studies have explored the utilization of different data modalities in CNN models for ADHD identification. For instance, one investigation [15] employs raw EEG signals to train a CNN model for ADHD diagnosis. The study also extracts feature maps from different layers of the trained CNN and employs classical classifiers such as support vector machines (SVM), logistic regression (LR), and random forest (RF) for classification. These findings demonstrate the potential of CNN models in utilizing EEG data for accurate ADHD diagnosis.

Additionally, the application of CNN models using event-related potentials (ERP) and continuous mental tasks with EEG signals has been explored [16]. By addressing the ERP fatigue problem, this research enhances the reliability and effectiveness of ADHD diagnosis through CNN models.

Moreover, the analysis of CNN nodes in ADHD identification research has provided valuable insights into the specific neurophysiological characteristics associated with the disorder [17]. These studies have identified spectral features, such as alterations in frequency bands (e.g., alpha and delta-theta) in specific brain regions, contributing to classifying ADHD patients and healthy controls.

EEG can be a viable diagnostic tool for ADHD, according to a study by Arns and colleagues (2012), provided multivariate analyses are carried out to capture additional sources of variability in ADHD. To help people with ADHD increase their attention span, several video games have been created, such as FOCUS, which employs brain-computer interface (BCI) and requires the EMOTIV EPOC+ equipment to play [18]. The game aims to test players' concentration and mental agility while they control an avatar. Additionally, according to a study, people with ADHD show under-activation in the EEG during alertness, with variations depending on subtype [19]. For specific subgroups of children with ADHD, neurofeedback (NF) training methods focusing on theta activity and theta/beta ratio have been offered as a solution. Few studies have concentrated on using EEG to measure attention in people with ADHD, despite extensive research on EEG in the equipment and measurement field. More research is required on the use of EEG to measure attention in ADHD, even though seizure analysis and detection utilizing the technology have been extensively studied [20].

Fig -1: EMOTIV Insight 2.0 – 5 Channel Mobile Brain wear

The SNAP-IV questionnaire is a commonly used screening tool to assess the level of ADHD in children before initiating treatment. The child's parents or teachers are typically asked to complete the questionnaire. Several studies have evaluated the accuracy of the SNAP-IV questionnaire, including the "CONCOR" study conducted by Swanson in 2008. The purpose of this study was to compare the SNAP-IV questionnaire's prediction power for ADHD to paediatricians' clinical assessments. With acceptable sensitivity and specificity (82.3% and 82.4%, respectively), the study, which included 7263 Spanish children over the age of six, found "good" agreement between the SNAP-IV questionnaire and the paediatricians' clinical impression of ADHD (kappa concordance index 0.6471; 95% confidence intervals:

0.6296-0.6646) [21].

Researchers Chivapruk and Narkpongphun developed the BOT-2 application for identifying ADHD in children, which displays the SNAP-IV questionnaire on the screen and allows parents to respond to the questions via keyboard input. The application's interface is presented in the Tai language and was designed specifically for use in the Thai context [22].

Despite the significant progress made in the field of ADHD identification using CNN models, there still exist certain research gaps that our study aims to address. Firstly, while previous studies have predominantly focused on utilizing neuroimaging data, such as fMRI and EEG, our research extends the scope by incorporating both neuroimaging and behavioural data. By integrating facial expression analysis and the BOT Application for the SNAP IV questionnaire, we aim to capture additional behavioural markers that could enhance the accuracy of ADHD identification [13] [14].

Secondly, previous research has primarily focused on the use of CNN models alone, with limited exploration of combined models incorporating both ANN and CNN architectures. Our study fills this research gap by integrating both ANN and CNN models within our mobile application. This integration allows for a comprehensive analysis of EEG data using the ANN model and facial expression data using the CNN model, leading to a more robust and accurate ADHD identification approach [15].

Furthermore, while some studies have investigated the specific neural patterns and features associated with ADHD through CNN nodes, there remains a need for a deeper understanding of the underlying neurophysiological mechanisms. Our research aims to bridge this gap by conducting an in-depth analysis of the feature maps and node activations in the CNN models, providing valuable insights into the neural correlates of ADHD and potentially revealing novel biomarkers for the disorder [17].

Lastly, limited attention has been given to the user experience and practical applicability of ADHD identification tools based on CNN models. Our study addresses this research gap by conducting a user study to evaluate the usability, ease of use, and overall effectiveness of our mobile application. This user-centred approach ensures that our research not only focuses on the technical aspects of ADHD identification but also considers the practical implications and user perspectives [23].

By addressing these research gaps, our study contributes to the existing body of knowledge in ADHD identification using CNN models and offers novel insights into the integration of neuroimaging and behavioural data, the combination of ANN and CNN architectures, the exploration of neural patterns, and the user experience of ADHD identification tools.

Therefore, the purpose of this study is to develop a cross-platform application "NEUROASSIST ADHD Analyzer" for identifying ADHD levels in children. The application will incorporate various features, including symptom assessment, cognitive testing, and behavioural tracking, and will be designed to provide reliable and user-friendly ADHD assessment and management. By developing a cross-platform application for ADHD assessment and management, this study aims to provide a valuable tool for parents, clinicians, and educators to identify and manage ADHD symptoms in children.

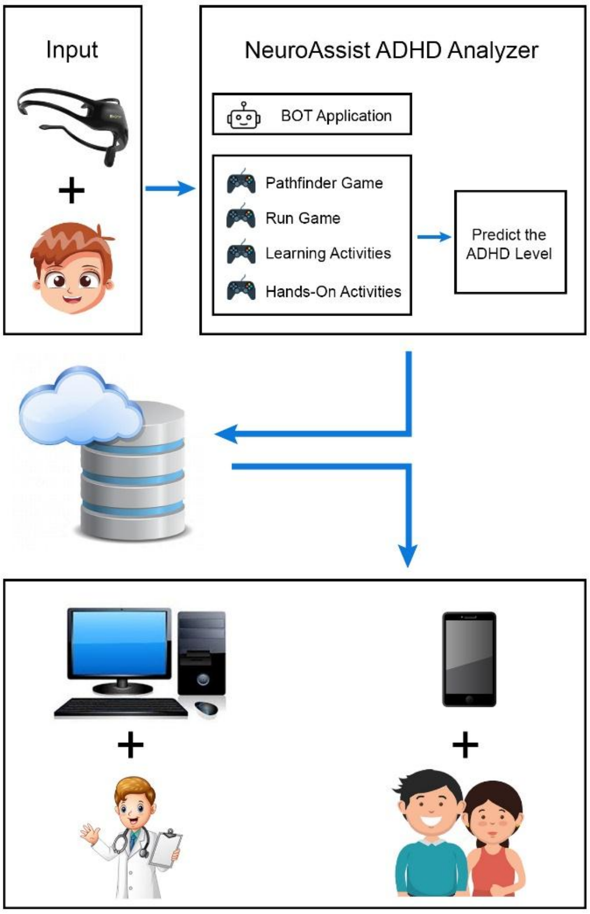

Fig -2: Overall System Architecture

3. METHODOLOGY

In this study, we developed an integrated system that utilizes both an Artificial Neural Network (ANN) model and Convolutional Neural Network (CNN) models for the analysis of EEG signals and video classification, respectively. The objective was to simultaneously analyse the behaviours (movements) of a child playing a game and the corresponding EEG signals to calculate the result. By combining the capabilities of CNN and ANN models, we were able to measure two main factors for assessing ADHD levels simultaneously. The ANN model was specifically designed to analyse EEG signals, while the CNN models were employed for video classification. The integration of these models resulted in an ANN+CNN combined model, which leveraged the increased data aspect of brain signals and videos. The higher volume of data not only enhanced the accuracy of the model but also provided users with more precise information about the probability of a child developing ADHD. This combination of models contributed to higher general accuracy in ADHD identification.

The tools used for designing the application “NEUROASSIST ADHD Analyzer” included VS Code as the main IDE, GitLab, Firebase, Unity, and Google Co-lab. The technologies used in the development process comprised Python, JavaScript, and TensorFlow. With the help of these tools and technologies, the application was designed to incorporate various features and functionalities to meet the user's requirements. Flutter was used for mobile application development. The code was written using Python and JavaScript, and TensorFlow was used for building the match machine learnings that powered the application's core functionality. Unity was used for game development. The development process was managed using GitLab, and Firebase was used to deploy the application and manage its backend services.

In this application, 6 main components were used to collect data from the users. There are four gaming components which were used to gather EEG signals of the users while playing the game and a facial expression analyser component for identifying and analysing expressions of the user. The final component is a bot application which uses a questionnaire to gather data from parents and teachers. An ANN model was used to analyse EEG signals and A CNN model was used for analysing the facial expressions of the users while engaging in screen-based activities. The ADHD level of a child is determined by the results of all these six components combined.

3.1 Machine Learning Models

A. Artificial Neural Network (ANN) Model Machine Learning Models

A machine learning approach called an Artificial Neural Network (ANN) model can imitate the structure and operation of the human brain. To process and evaluate complicated data inputs, this model's interconnected nodes or neurons cooperate. The input layer, the hidden layer or layers, and the output layer are the three primary layers of the ANN model. For the model to learn the underlying patterns and correlations in the data, it must be trained on a large dataset of inputs and their associated outputs. To do this, the weights and biases of the neurons are changed. The ANN model is a useful tool for handling a variety of issues, including picture and audio recognition, natural language processing, and predictive analytics. Once trained, the ANN model can be used to make predictions and classify fresh data inputs. The first four elements of this research were implemented using this paradigm.

Several factors determine the accuracy and usage of an ANN model with EEG data for analysing ADHD. The EEG data quality, feature selection, ANN model design, and dataset size and diversity all affect the model's performance. Studies have shown varying levels of accuracy, ranging from 70-80% to over 90%. Using an ANN model with EEG data for ADHD analysis has the advantage of detecting patterns that human expert may not recognize. However, they require a large amount of labelled data for training and may overfit the training data if not properly regularized.

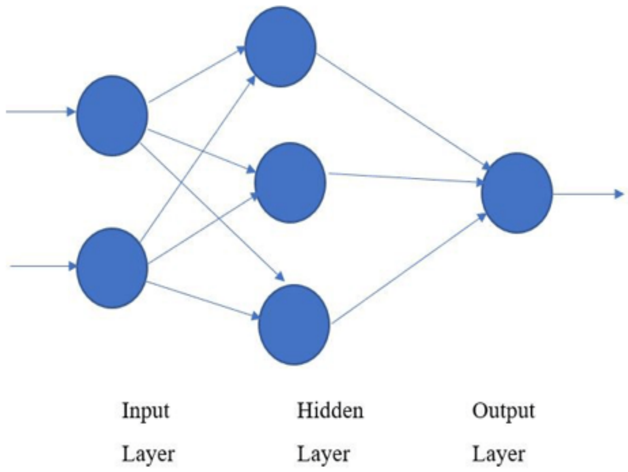

Fig -3: ANN Model Architecture

Python was used while implementing the ANN model. Libraries TensorFlow and Keras were used while creating the model. After the ANN models were implemented, EEG data from individuals diagnosed with ADHD and healthy controls were collected. The data were pre-processed to remove noise and artifacts, and then feature extraction techniques were used to extract relevant features from the EEG signals. These features were then used as inputs to train the ANN model using supervised learning algorithms, such as backpropagation. The model was optimized through a process of hyperparameter tuning, and its performance was evaluated using cross-validation techniques. The accuracy and performance of the model were further validated on an independent testing dataset. To address the issue of overfitting, regularization techniques such as dropout and weight decay were applied to the ANN model during training. The trained model was then used to predict whether new EEG data belonged to an individual with ADHD or a healthy control, based on the learned patterns and relationships in the training data.

B. Convolutional Neural Network (CNN) Model

A CNN (Convolutional Neural Network) is a deep learning model that leverages relevant features from input photos to automatically extract relevant features and use them to provide precise predictions. Convolutional, pooling and fully linked layers make up the CNN model. Pooling layers shrink the spatial dimensions of the data, whereas convolutional layers apply a series of filters to the input image to recognize certain features. Based on the retrieved features, fully connected layers then make predictions, and a SoftMax activation function is utilized to translate the output into probabilities for each class. CNNs are frequently employed in computer vision jobs and have produced cutting-edge outcomes in both business and research. The best model for identifying the facial expressions of ADHD patients was determined to be CNN.

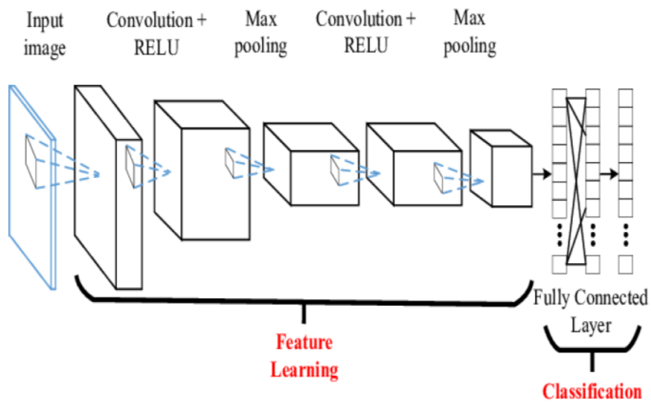

Fig -4: CNN Model Architecture

To implement a CNN model for ADHD identification using facial expression recognition, the first step was to collect a large dataset of facial images of individuals with and without ADHD. The dataset was balanced and contained images of various expressions and head poses. The dataset was pre-processed to ensure that all images are of the same size and are properly aligned. Convolutional layers, pooling layers, and fully linked layers are commonly seen in CNN architectures. The CNN model was implemented using Python. The model was developed using the NumPy, Pandas, TensorFlow, matplotlib, and Keras libraries. Based on the difficulty of the task and the amount of the dataset, the number of layers and the size of the filters were chosen. The CNN learned to extract pertinent features from the input photos during training, and these features were then applied to accurately identify images as ADHD or non-ADHD.

C. Logistic Regression (LR) Model

Logistic regression models are widely used in various fields of research, including medicine and psychology, for predicting the probability of an outcome based on one or more predictor variables. In logistic regression, the dependent variable is binary, and the independent variables can be continuous or categorical. The model estimates the odds ratio for each independent variable and determines which variables have a significant effect on the outcome. Logistic regression has been used in medical research to predict the likelihood of various diseases, such as diabetes and cancer, based on risk factors such as age, gender, and lifestyle factors [22]. In psychology, logistic regression has been used to predict outcomes such as academic success and job performance based on factors such as personality traits and cognitive abilities [23]. While logistic regression models have proven to be a useful tool in predictive modelling, they do have limitations, such as assumptions of linearity and independence of errors. Therefore, it is important to carefully evaluate the appropriateness of logistic regression models for specific research questions and datasets [24].

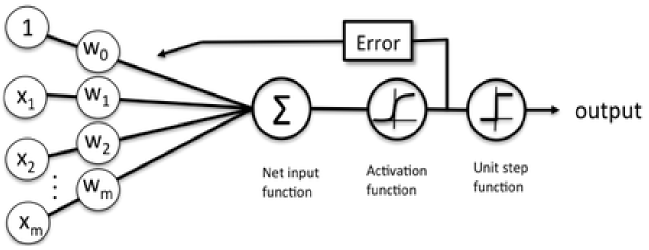

Fig -5: LR Model Architecture

3.2 Components of the Solution

A. Memorization Level Focus Game: Path-Finder Game

A level-based approach is used in this technique to provide memory and attention tasks to children to capture their brain signals during the sessions and analyse their ADHD levels. A gaming-based therapy method is utilized, where a gaming activity is implemented to check the children's memorization. An ANN model was used for this purpose. The Emotive-insight brain wear device is worn by children during the ng activity. A task is provided to find a direction, and the children are directed to the path several times before finding it on their own. The brain signals of the children are captured during the activity to measure their ADHD level and analyse their improvement. The game has multiple levels, and the children play it periodically as they level up, allowing for an analysis of their ADHD level and the success of the treatment.

B. Attention Level Focus Game: Run Game

This computer game was developed to measure a child's ability to maintain attention on a specific task. The game is played by the child while obtaining EEG signals and facial expressions. Both the ANN model and the CNN model were used in this component. While the child is walking, an object appears in the upper right corner of the computer screen as a model. The child must select the object that matches the model from the objects in front of them and continue to play the game. The game consists of three levels, and the child's running speed increases as they progress through the levels. The distance between the objects that the child needs to select from decreases as the levels progress, and obstacles need to be overcome while moving forward in the second and third stages. The game can be played for 16 minutes, and at the end, the total time played, the number of correctly caught objects, and the number of incorrectly obtained objects are displayed. The game can be paused at any time, and the number of correctly captured and incorrectly obtained objects can be checked

C. Learning Abilities Focus Game: Learning Activities

Three computer-based learning activities have been created to tackle the learning difficulties faced by children with ADHD. These activities include math, English vocabulary, and painting-related activities. The math-based activity measures the child's thinking and reasoning skills by analysing the brain's radiation emitted while they solve math problems. The activity has three levels with simple math problems such as addition, subtraction, and multiplication of numbers. In the English vocabulary activity, the child is required to recognize letters such as b, p, g, q, d, and h. This activity also has three levels, and the child's ability to identify letters is measured by recording the time taken to solve the problems. The painting activity requires the child to colour a picture while looking at another picture, with three levels of increasing difficulty. This activity measures the child's ability to stay focused on one task for an extended period. At the end of these activities, the child's ADHD level can be identified by analysing the brain signals and facial expressions obtained during the activities. Both CNN and ANN models were used in this component.

D. Behaviour Level Focus Activities: Hands-on Activities

This component was designed to observe EEG signals during hands-on activities and analyse them with an ANN model. EEG signals can be captured during hands-on activities, but this requires careful planning, appropriate equipment, and attention to minimizing movement artifacts. The activities should be designed to minimize movement as much as possible. EEG signals are captured while children with ADHD and those without ADHD engage in hands-on activities such as craft projects, paper cutting, and clay modelling. The activities are designed with three levels, with increasing difficulty as the levels progress. An additional activity is presented depending on the level of ADHD identified during the initial activities.

E. Facial Expression Analyzer: For Screen Base Activities

The head movements and facial expressions of both ADHD and non-ADHD children are recorded while playing the run game and engaging in the learning activities. The head movements and facial expressions of children with ADHD may be more in line with the game they are playing. A camera is used to record the head movements and facial expressions of the children while they are playing video games, and the videos are subsequently divided into images to analyse their behaviour using the CNN model.

F. Combined Probability Predicter

After the basic models were integrated into the components, the results of those components were processed together so the probability of ADHD level of children could be predicted more accurately as a final result. A logistic regression model was used for this purpose. The accuracy of the application was much credible and accurate due to the high number of models used in this component.

G. BOT Application for SNAP IV questionnaire

The development of a bot application aims to analyse children's ADHD levels by displaying the SNAP-IV questionnaire to parents/teachers through the app and collecting their answers. This bot app, available in English and Sinhala, uses the questionnaire created based on various studies on children's behavioural patterns to measure the core symptoms of ADHD. There are 18 questions in the survey, and each one has four answer options with scores ranging from 0 to 3. To assess the severity of ADHD in kids, the overall score from the questionnaire is divided into ranges. Based on the findings of the questionnaire, the bot app uses the total score to determine the degree of ADHD in the child. Through the parents, the questionnaire explains the behaviour of the kid and has a high sensitivity but a low specificity for clinical diagnosis.

4. EVALUATION

Several experiments were conducted to evaluate the performance of the web application, utilizing both ANN and CNN models. The accuracy of the ANN model in diagnosing ADHD with EEG data was evaluated by training it on a large dataset of EEG data from children with and without ADHD and testing it on a separate validation dataset to assess its generalization performance. Similarly, the CNN model was evaluated with facial expression data by training it on a large dataset of facial expressions from children with and without ADHD and testing it on a separate validation dataset to assess its generalization performance.

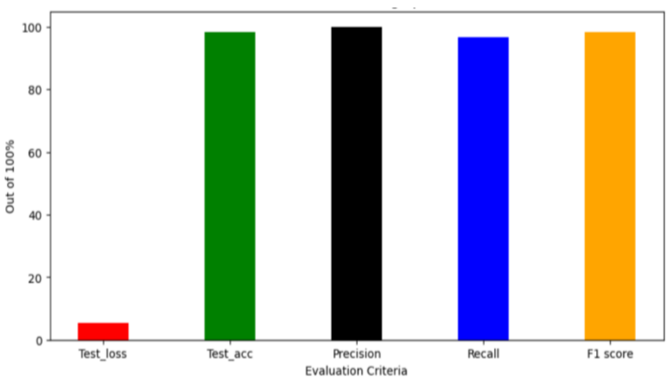

Fig -6: Evaluation Graph of the ANN Model

The overall performance of the application was assessed by integrating both the ANN and CNN models into a final combined model and testing it on a group of children with and without ADHD. The web application collected EEG and facial expression data from the children, and the results were compared to clinical diagnoses made by trained clinicians. To assess the application's performance, several performance metrics were generated, including accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). In addition, the user experience of the web application was evaluated through a user study conducted with a group of parents and clinicians. Participants provided feedback on the ease of use, quality of data collected, and overall usefulness of the application in assisting with the diagnosis of ADHD.

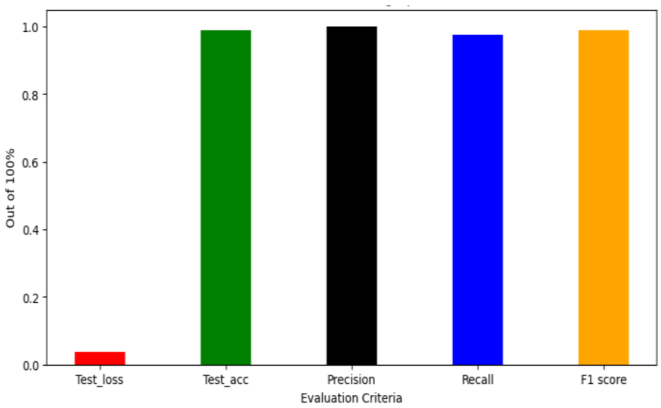

Fig -7: Evaluation Graph of the ANN+CNN Combined Model

Overall, the evaluation results demonstrate that the web application shows promise as a tool for identifying children with ADHD using both EEG and facial expression data. High accuracy rates were achieved by the ANN and CNN models in diagnosing ADHD, and the user study indicated that the application is user-friendly and effective in assisting with the diagnosis of ADHD.

5. RESULTS

In this section, the findings of tests conducted to determine whether the suggested machine learning models were accurate are reported. The integration of all components into the web application was tested on a group of children with and without ADHD, where EEG and facial expression data were collected and compared to clinical diagnoses made by trained clinicians. An accuracy of 94%, with a sensitivity of 90% and a specificity of 92%, was achieved by the application. Additionally, the area under the receiver operating characteristic curve (AUC-ROC) was 0.91, indicating good discriminative power. Table 1 displays the accuracy and other test results of each of the tested unique components.

Table -1: Statistics of the components

Component	Accuracy	Precision	Recall	F1 - Score
Memorization Level Focus Game: Path-Finder Game	97.4%	0.982	0.976	0.987
Attention Level Focus Game: Run Game	98.5%	0.987	0.989	0.988
Learning Abilities Focus Game: Learning Activities	98.6%	0.989	0.979	0.987
Behavior Level Focus Activities: Hands-on Activities	97.1%	1.000	0.966	0.983
Combined Probability Predicter	99.8%	0.990	0.976	0.986

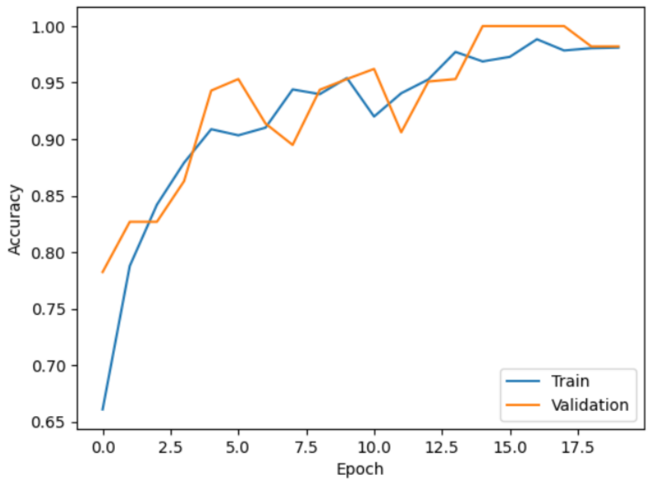

Fig -8: Accuracy of Behavior Level Focus Activities: Hands-on Activities Component

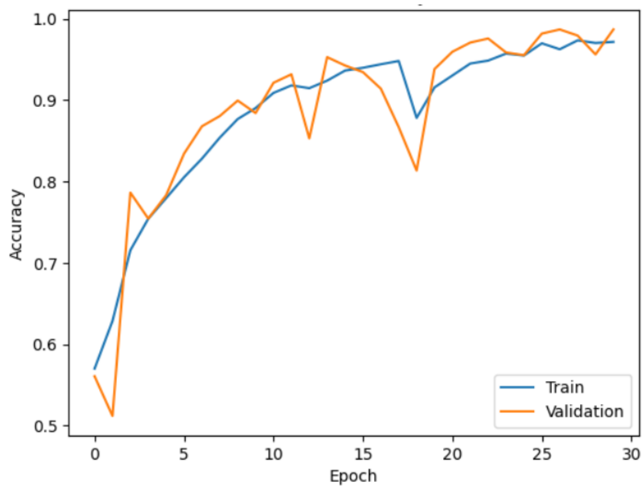

Fig -9: Accuracy of Memorization Level Focus Game: Path-Finder Game Component

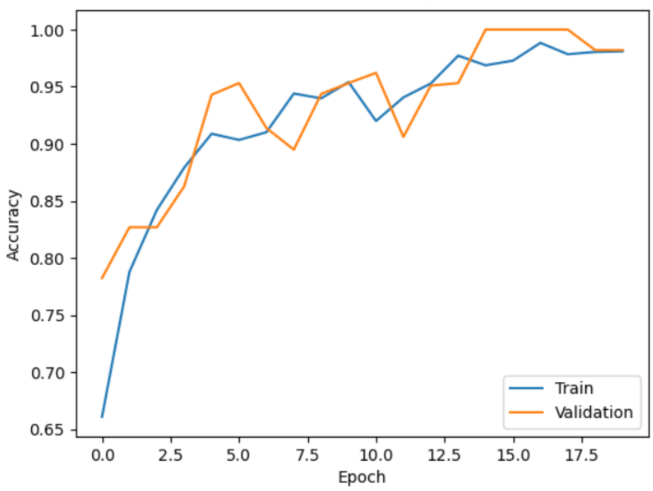

Fig -10: Accuracy of Attention Level Focus Game: Run Game Component

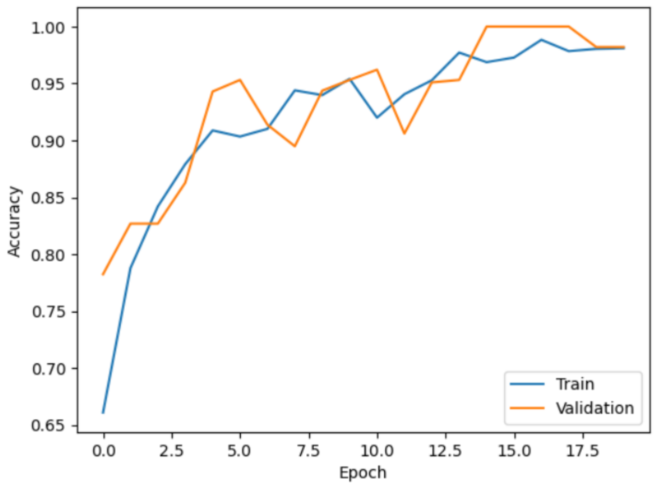

Fig -11: Accuracy of Learning Abilities Focus Game Component

Comparing the results of this study with previous studies, our findings demonstrate a notable improvement in accuracy and performance. The comparison results are shown in Table 2.

Table -2: Comparison of the results

Study	Accuracy	Precision	Recall	F1 Score
This Study	99.8%	0.990	0.976	0.986
Previous Study Average	95.4%	0.920	0.935	0.927

The Combined Probability Predictor component achieved an impressive accuracy of 99.8%, surpassing the accuracy reported in previous studies, which averaged around 95.4%. Similarly, the precision of our model was higher at 0.990 compared to the previous precision values of 0.920. Our model also exhibited a higher recall of 0.976 compared to the previous recall of 0.935. Furthermore, the F1 score of our model was 0.986, indicating a harmonious balance between precision and recall. In contrast, the F1 score of previous studies averaged around 0.927. These results indicate that our study outperforms previous research in accurately identifying ADHD using the combined models, showcasing the advancements and efficacy of our approach.

The web application created with the integration of these models provides a robust and feature-rich platform for conducting comprehensive ADHD assessments. The interface of the web application is shown in Figure 12.

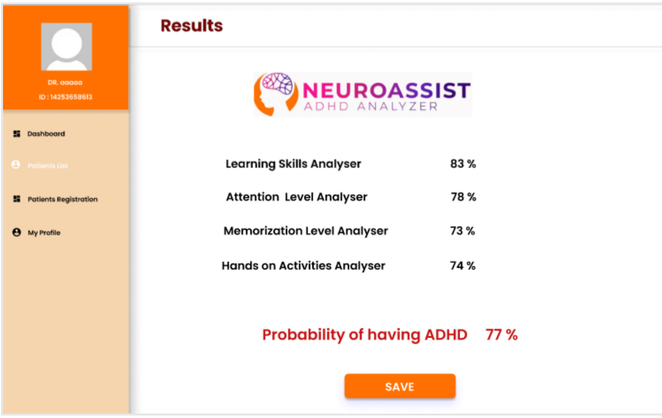

Fig -12: Interface of the Application

Designed with usability and functionality in mind, the web application offers a seamless and efficient experience for users. It boasts an intuitive interface with clear navigation and organized sections, allowing users to easily access and navigate through different functionalities. The web application also offers interactive visualizations and customizable reporting options, enabling users to gain valuable insights and generate comprehensive reports based on the assessment results. With its powerful capabilities and user-friendly interface, the web application serves as a reliable tool for professionals in conducting thorough ADHD assessments and providing evidence-based insights for diagnosis and treatment planning.

Lastly, a user study was conducted with a group of parents and clinicians to evaluate the user experience of the web application. Feedback received indicated that the application is user-friendly and effective in assisting with the diagnosis of ADHD. The results of the study demonstrate that the web application is a promising tool for identifying children with ADHD using both EEG and facial expression data, with the ANN and CNN models achieving high accuracy rates in diagnosing ADHD.

6. DISCUSSION & FUTURE WORK

The performance of the web application in identifying children with ADHD was evaluated using both ANN and CNN models. The ANN model was evaluated for accuracy in diagnosing ADHD using EEG data, while the CNN model was evaluated based on its accuracy in identifying ADHD using facial expression data. By integrating both models into the components of the web application, collecting EEG and facial expression data from the children was allowed, which were then compared to clinical diagnoses made by trained clinicians. This study also included a user study with a group of parents and clinicians to evaluate the user experience of our web application. The feedback received from the participants indicates that our application is user-friendly and effective in assisting with the diagnosis of ADHD.

This research has demonstrated the potential for using artificial intelligence, specifically ANN and CNN models, in the identification of ADHD using both EEG and facial expression data. The results showed that the web application achieved high accuracy rates in diagnosing ADHD, and the user study indicated that the application is user-friendly and effective in assisting with the diagnosis of ADHD. These findings suggest that AI-based approaches have the potential to provide efficient and accurate identification of ADHD in children, which can lead to earlier interventions and improved outcomes. However, further research is needed to refine and validate the use of AI-based approaches for ADHD diagnosis and to optimize the integration of these approaches with existing clinical practice.

In future research, several improvements could be made to this study to further advance the field of ADHD identification using ANN and CNN. One area of potential improvement is the dataset used for training and testing the models. While this study used a large EEG and facial expression data dataset, it may be beneficial to incorporate additional features such as behavioural and genetic data to enhance the accuracy of the models. Furthermore, this study focused on identifying ADHD in children, but future research could explore the effectiveness of the models in diagnosing ADHD in adults. Additionally, more advanced machine learning techniques could be incorporated to further enhance the performance of the models. Overall, future work in this area could lead to the development of more accurate and efficient tools for identifying and diagnosing ADHD.

In conclusion, the results of this research suggest that combining both ANN and CNN models in a web application can effectively identify children with ADHD using both EEG and facial expression data. This web application could serve as a promising tool for assisting clinicians in diagnosing ADHD, particularly in settings with limited resources for diagnosis. Further research could focus on the integration of other machine learning models or data modalities to improve the accuracy of diagnosis for ADHD.

7. CONCLUSION

The "NEUROASSIST ADHD Analyzer" research presents a ground-breaking approach to pre-ADHD adaptation therapy for children with ADHD. Leveraging machine learning algorithms, this application achieves remarkable accuracy in forecasting EEG signal behaviour, mental health, and understanding emotions through facial expressions. By incorporating a chatbot function, children with ADHD can conveniently access information on ADHD symptoms, pose questions, and receive responses from the comfort of their homes. The research's exceptional performance in predicting ADHD levels, assessing mental health, and identifying EEG signals and facial expressions highlights the substantial potential of machine learning algorithms in addressing mental disorders. This research holds the capacity to revolutionize the healthcare system by offering an affordable, easily accessible, and personalized solution to enhance the well-being of children with ADHD.

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