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ADHD Disease Detection in Children Using Pose Estimation Technique

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ABSTRACT:

In this paper we presented a pioneering initiative merging healthcare and technology to address the challenges surrounding the diagnosis and monitoring of Attention Deficit Hyperactivity Disorder (ADHD) in children. With ADHD affecting approximately 0.8–1.5% of the global population, its impact on academic, social, and health domains underscores the urgency for improved diagnostic approaches. Present methods reliant on manual monitoring are susceptible to errors and inefficiencies, necessitating more robust solutions. This project proposes leveraging machine learning and computer vision to automate the identification of ADHD-related behaviours through body poses. By training Support Vector Machine (SVM) algorithms on datasets encompassing both typical and ADHD-associated poses, subtle distinctions can be analysed to detect abnormalities indicative of ADHD with enhanced accuracy. Such automation not only promises greater precision but also scalability and efficiency benefits over manual methods. By streamlining the diagnostic process, this approach enables earlier interventions, potentially improving outcomes for affected children. Furthermore, this interdisciplinary collaboration exemplifies the transformative potential of technology in healthcare, underscoring the importance of innovation and data-driven insights. Through this initiative, the project aims to establish a paradigm shift towards more efficient and effective diagnostic practices, ultimately enhancing the quality of life for children impacted by ADHD and their families on a global scale.

Keywords: *ADHD(Attention Deficit Hyperactivity Disorder), Pose estimation, Machine learning, Computer vision,Neurodevelopmental disorder, Behavioural analysis, Support Vector Machine (SVM), Image processing.*

1. INTRODUCTION

Attention Deficit Hyperactivity Disorder (ADHD) stands as a significant neurodevelopmental challenge affecting individuals worldwide. Characterized by enduring patterns of inattention, hyperactivity, and impulsivity, ADHD often manifests early in childhood and persists into adulthood, presenting multifaceted impacts across various domains of life. The complexities of ADHD necessitate a comprehensive understanding of its etiology, diagnostic approaches, treatment modalities, and the broader societal implications associated with its management. ADHD's prevalence varies globally, with estimates indicating substantial rates among children and adolescents. For instance, data from the Centers for Disease Control and Prevention (CDC) suggest that approximately 9.4% of children aged 2-17 in the United States have received an ADHD diagnosis[1]. This condition is more frequently diagnosed in boys than girls, although research suggests that gender disparities may reflect differences in symptom presentation and diagnostic biases rather than true prevalence variations. ADHD's pervasive nature extends beyond individual symptomatology, significantly affecting academic performance, social interactions, emotional well-being, and familial dynamics.

While the precise etiology[2] of ADHD remains elusive, research underscores the interplay of genetic, environmental, and neurobiological factors in its development. Genetic predispositions play a substantial role, with heritability estimates indicating a significant genetic component contributing to ADHD susceptibility. Additionally, environmental influences, such as prenatal exposure to toxins, maternal smoking, have been implicated in ADHD risk. Neurobiologically, abnormalities in neurotransmitter systems, particularly dopamine and norepinephrine, and alterations in brain structure and function, including deficits in prefrontal cortical regions, have been observed in individuals with ADHD. Diagnosing ADHD necessitates a thorough assessment by healthcare[3] professionals, involving the evaluation of symptoms across multiple settings and the exclusion of other medical or psychiatric conditions that may mimic ADHD. The Diagnostic and Statistical Manual of Mental Disorders (DSM-5) provides standardized criteria for diagnosing ADHD, encompassing two main symptom clusters: inattention and hyperactivity-impulsivity. These symptoms must persist for at least six months and significantly impair functioning in academic, social, or occupational domains to meet diagnostic thresholds. Clinicians employ a combination of structured interviews, rating scales, behavioural observations, and collateral information from caregivers and teachers to formulate an accurate diagnosis.

Effective management of ADHD typically involves a multimodal treatment approach tailored to individual needs and preferences. Behavioural therapy[4], including psychoeducation, cognitive-behavioural interventions, and parent training programs, plays a pivotal role in equipping individuals and families with skills to manage ADHD symptoms effectively. Medication, such as stimulants (e.g., methylphenidate, amphetamine) and non-stimulants (e.g., atomoxetine, guanfacine), may be prescribed to target core symptoms of inattention, hyperactivity, and impulsivity. These pharmacological interventions

[5] are often complemented by educational accommodations, organizational strategies, and supportive services to optimize academic and psychosocial outcomes. ADHD's[6] impact on academic performance is profound, with affected individuals frequently experiencing difficulties in various aspects of learning, including attention regulation, organization, time management, and task completion. Academic underachievement, grade retention, and school dropout rates are elevated among students with ADHD, highlighting the need for targeted interventions[8] and support services to address academic challenges effectively. Socially, children and adolescents with ADHD often struggle to establish and maintain peer relationships due to impulsivity, social skill deficits, and difficulties in regulating emotions and behaviour. These social difficulties can contribute to feelings of loneliness, rejection, and low self-esteem, underscoring the importance of interventions aimed at enhancing social competence and peer acceptance.

Effective management of ADHD requires a collaborative and holistic approach involving healthcare providers, educators, families, and community resources. Educational accommodations, such as extended time on tests, preferential seating, and individualized instruction, help mitigate the impact of ADHD on academic performance and promote school success. Parent education and support programs equip caregivers with strategies to manage ADHD-related challenges at home, enhance parent-child communication, and foster positive parent-child relationships. Additionally, collaboration between healthcare providers and mental health professionals facilitates the provision of comprehensive care, including medication management, psychotherapy, and behavioural interventions tailored to individual needs. Recent advancements in technology, particularly in the fields of computer vision and machine learning, offer promising avenues for enhancing ADHD diagnosis and intervention. Projects such as Child ADHD Disease Detection Using Pose Estimation Technique exemplify innovative approaches to leveraging technology in ADHD screening and diagnosis. By analysing a child's posture from 2D photos using pose estimation technology and machine learning algorithms, this project aims to develop a non-invasive and efficient method for detecting ADHD. This novel approach holds the potential to revolutionize ADHD diagnosis, providing healthcare professionals with a reliable and accessible tool for early identification and intervention.

Ethical considerations are paramount in ADHD management, encompassing principles of autonomy, beneficence, nonmaleficence, and justice. Respect for individuals' autonomy entails involving them in decision-making processes regarding their treatment options, ensuring informed consent, and respecting their preferences and values. Beneficence obligates healthcare providers to act in the best interests of individuals with ADHD, prioritizing interventions that promote their well-being, enhance functioning, and improve quality of life. Nonmaleficence requires minimizing harm and avoiding interventions that may exacerbate ADHD symptoms or have adverse effects on physical or psychological health. Justice entails ensuring equitable access to diagnosis, treatment, and support services for individuals with ADHD, regardless of socioeconomic status, race, ethnicity, or geographic location. Attention Deficit Hyperactivity Disorder (ADHD) represents a complex and multifaceted neurodevelopmental condition with significant implications for individuals, families, and society at large. By understanding the etiology, diagnostic approaches, treatment modalities, and societal impacts associated with ADHD, healthcare professionals, educators, policymakers, and community stakeholders can work collaboratively to optimize outcomes and enhance quality of life for individuals affected by this condition. Innovative approaches, such as leveraging technology in ADHD diagnosis and intervention, hold promise for advancing our understanding of ADHD and improving the accessibility, efficiency, and effectiveness of its management in diverse populations. Through a comprehensive and compassionate approach, we can empower individuals with ADHD to thrive academically, socially, and emotionally, fostering resilience and well-being across the lifespan.

2. BACKGROUND STUDY

The application of Computer Vision techniques for monitoring individuals with Attention Deficit Hyperactivity Disorder (ADHD) and Autism Spectrum Disorder (ASD) [9] represents a burgeoning field poised to revolutionize neurodevelopmental disorder diagnosis and management. While still in its nascent stages, the integration of Computer Vision holds immense promise for automating the detection of behavioral markers associated with ADHD and ASD. By harnessing the power of advanced imaging technology and machine learning algorithms, researchers aim to develop objective, reliable, and scalable methods for assessing complex behavioral patterns characteristic of these conditions. The potential impact of such advancements is profound, offering the prospect of earlier detection, personalized intervention, and improved outcomes for individuals affected by ADHD and ASD. Moreover, Computer Vision technology has the potential to streamline the diagnostic process, reducing the burden on healthcare professionals and improving access to care for underserved populations. By automating certain aspects of diagnosis and monitoring, Computer Vision can help alleviate resource constraints and improve the efficiency of healthcare delivery systems. Additionally, the integration of machine learning algorithms [10] with Computer Vision techniques allows for the development of predictive models that can analyze large volumes of data to identify patterns and trends associated with ADHD and ASD. This data-driven approach enables researchers to uncover new insights into the underlying mechanisms of these disorders and develop more targeted interventions tailored to individual needs.

In recent years, significant strides have been made in utilizing Computer Vision techniques for ADHD detection. Researchers have explored innovative approaches to leverage this technology, including the use of depth-capturing cameras, which allow for the monitoring of individuals' activities and the extraction of three-dimensional skeletal models from image sequences. These models enable precise tracking of specific body gestures associated with ADHD indicators, such as hyperactivity and impulsivity. By analyzing subtle movements and postures captured by these cameras, researchers aim to develop objective measures of ADHD-related behaviors that can aid in diagnosis and monitoring. Despite these advancements, several challenges persist in the field of ADHD detection using Computer Vision techniques. One major challenge is the standardization of data collection protocols, as variations in imaging equipment, lighting conditions, and environmental factors can impact the accuracy and reliability of results.

CNNs have been extensively utilized for EEG data interpretation in ADHD detection. Studies by Amado-Caballero et al [11], Chen et al [12], and Moghaddari et al [13]. Demonstrated high accuracy using CNNs, indicating their potential in analyzing EEG data. Ahmadi et al [14]. Developed a sophisticated deep CNN model, achieving nearly perfect classification accuracy for ADHD subtypes. Additionally, effective pre-processing techniques and SVM parameter selection led to high accuracies in studies by Chang et al [5], Chen et al [15], and Rezaeezadeh et al [6]. Wavelet transform techniques, coupled with diverse classifiers, have also shown promise in ADHD classification tasks, as demonstrated by Tor et al [17].

Unique Approaches: Some studies took unique approaches, such as Tenev et al [18], who applied multiple classifiers to EEG data under various conditions to categorize ADHD subtypes and controls. Poil et al. emphasized the importance of considering age and frequency effects on ADHD-related EEG signal alterations, indicating crucial factors for future research. Non-wearable and wearable techniques, particularly those leveraging machine learning algorithms like SVM, CNNs[16], and wavelet transforms, hold promise for ADHD diagnosis. The exploration of non-wearable techniques, particularly video analysis, has propelled significant advancements in the field of depression detection. Researchers have leveraged the power of Convolutional Neural Networks (CNNs) to extract intricate facial features from video data, enabling the estimation of depression severity scores with unprecedented accuracy.

In pioneering studies by Zhu et al[19]. and Meshram and Rambola[20], CNNs were deployed to analyze static and dynamic facial expressions, respectively, leading to remarkable improvements in the estimation of depression severity scores. These breakthroughs underscore the potential of deep learning techniques in discerning subtle emotional cues encoded in facial expressions, offering valuable insights into an individual's mental state. Moreover, He et al[21]. delved deeper into dynamic facial features, revealing that the nuances of facial expressions captured over time can serve as potent indicators of depressive symptoms. By meticulously analyzing changes in facial expressions, researchers achieved a deeper understanding of the underlying emotional states, paving the way for more accurate and nuanced depression detection algorithms. Notably, Li et al[22]. adopted a novel approach by focusing on eye movement patterns as a potential predictor of depression. This innovative strategy underscores the diverse array of biological signals that can be harnessed for depression detection, transcending conventional methods and expanding the scope of diagnostic modalities. Furthermore, studies by Hong et al[23] delved into the intricate nuances of bipolar and unipolar disorders, employing sophisticated machine learning techniques to differentiate between these conditions and healthy controls. By analyzing action unit descriptors and motion vectors, researchers achieved commendable classification accuracy, shedding light on the distinct behavioral patterns associated with different mood disorders.

In a parallel line of research, Zhou et al[24]. introduced MR-DepressNet, a groundbreaking deep regression network that harnesses visual features to estimate depression severity. This innovative model represents a significant leap forward in depression assessment, harnessing the rich information embedded in visual cues to provide accurate and reliable estimates of depression severity. The pursuit of innovation in depression detection is further exemplified by the work of Tadalagi and Joshi, Shang et al., and Uddin, Joolee, and Lee[25], who combined various methodologies and techniques to develop robust depression detection frameworks. These interdisciplinary efforts underscore the collaborative nature of research in mental health diagnostics, where diverse perspectives converge to tackle complex challenges. Additionally, Song et al[16]. pioneered the extraction of multi-scale video-level features, offering a novel perspective on depression analysis. By leveraging spectral representations processed through CNNs and Artificial Neural Networks (ANNs)[26] researchers achieved competitive performance on benchmark datasets, demonstrating the potential of multi-scale feature extraction techniques in enhancing depression detection algorithms.

3. METHODOLOGY

a. Dataset

Gather video or motion capture data of children performing specific tasks or behaviours that are indicative of ADHD symptoms. Ensure the tasks are diverse and relevant to ADHD detection. Have experts annotate the data with labels indicating the presence or absence of ADHD symptoms based on the child's behaviour and pose during the tasks. Ensure the data is accurate, complete, and representative of the diverse population (e.g., age, gender, ethnicity) to avoid bias.

b. Data Pre-Processing

Clean the data to handle missing values and any noisy data points. Apply pose estimation techniques (e.g., OpenPose, PoseNet) to extract key points from the video data. These key points should represent body parts and their movements. Calculate relevant features[28] from the pose data, such as joint angles, distances between key points, and patterns of movement over time. Normalize the features to a common scale if necessary.

c. Feature Engineering

Experiment with different feature combinations based on the pose estimation data. These might include movement patterns, speed, and amplitude of motion in specific body parts. Incorporate knowledge from experts on ADHD to guide feature selection. For instance, focusing on specific types of movements known to be associated with ADHD symptoms. Explore potential interactions between different pose features to capture complex relationships.

d. Model Selection

Select machine learning algorithms suitable for classification, such as Decision Trees, Random Forests, Support Vector Machines, or neural networks[29]. Consider using models that offer explainability in decision-making to provide insights into which features or movements contribute most to ADHD detection.

e. Model Training

Split the data into training and testing sets (e.g., 80% training, 20% testing). Train the chosen model on the training data using the extracted features and labels. Optimize model performance by tuning hyperparameters.

f. Evaluation And Validation

Use appropriate classification evaluation metrics such as accuracy, precision, recall, F1-score, and AUC-ROC[30] to assess model performance. Implement cross-validation (e.g., k-fold) to ensure model performance is consistent across different data subsets and not reliant on any specific data split. Analyze which features and movements were most indicative of ADHD based on model outputs.

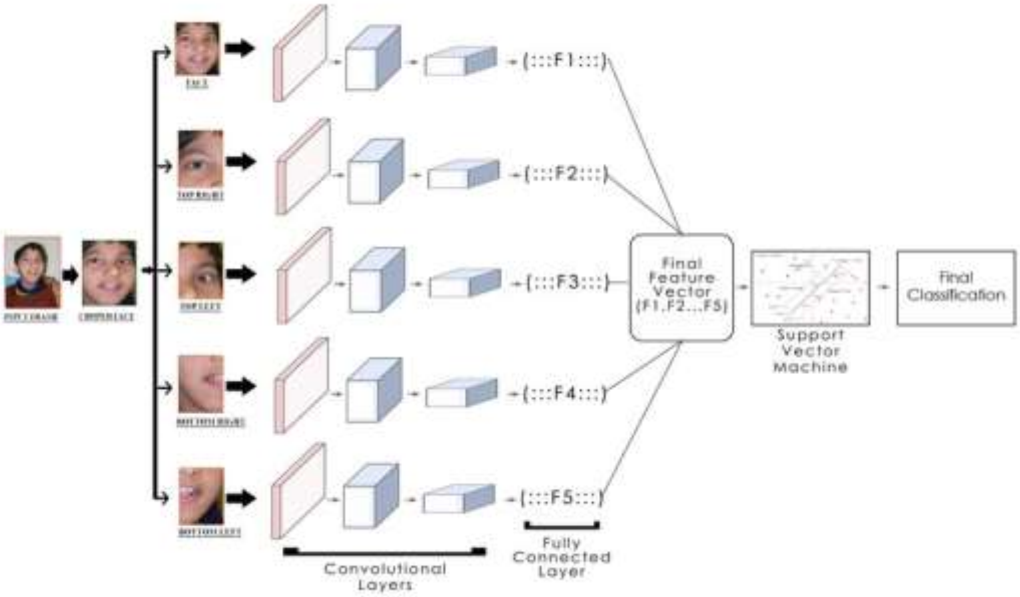


Fig 3.1: Architecture of Methodology

4. Result Analysis

The document's result analysis reveals pivotal insights into the dataset utilized for ADHD detection via pose estimation. With a substantial dataset consisting of 496 records, each encompassing 36 features, a comprehensive foundation is established for algorithm development.

Total records found in Dataset : 496
Total features found in each record : 36
Dataset Train & Test Split
70% dataset size used to train algorithms : 396
30% dataset size used to test algorithms : 100

Fig 4.1 Results of Training and Testing Datasets

Fig 4.2 shows the performance metrics of SVM algorithm

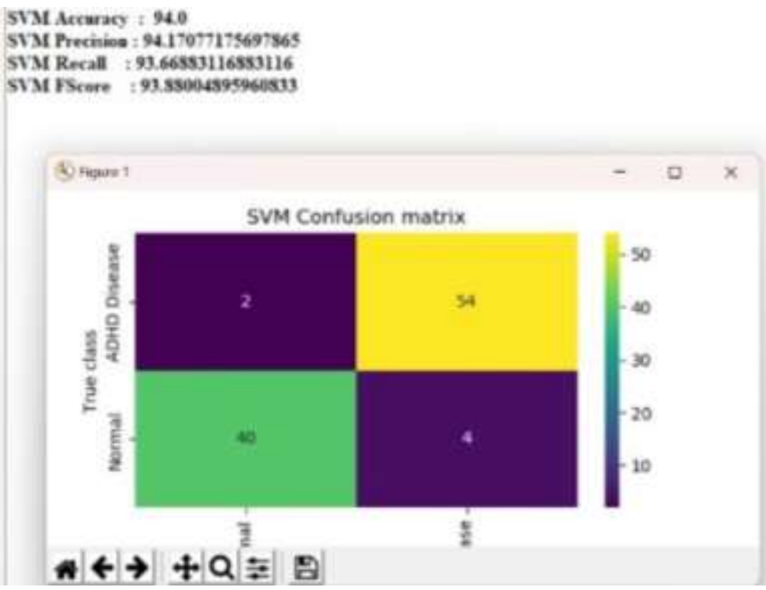
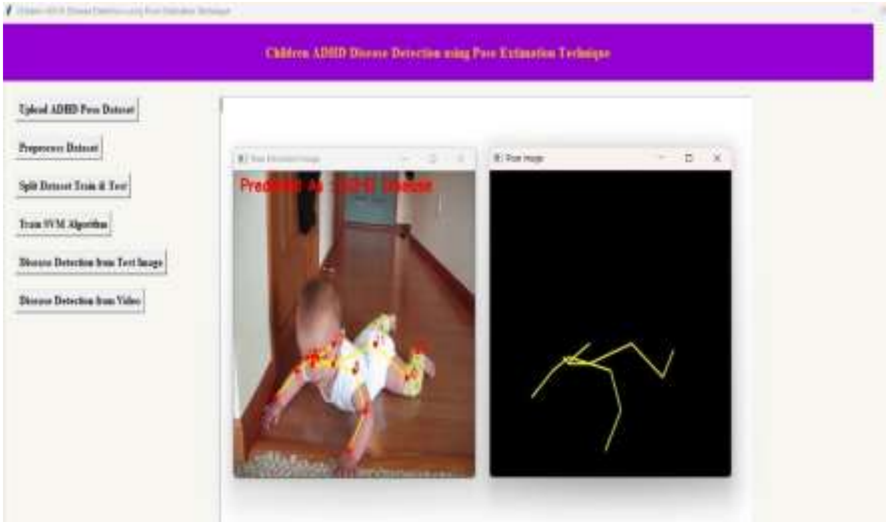


Fig 4.2: Performance Metrics of SVM algorithm



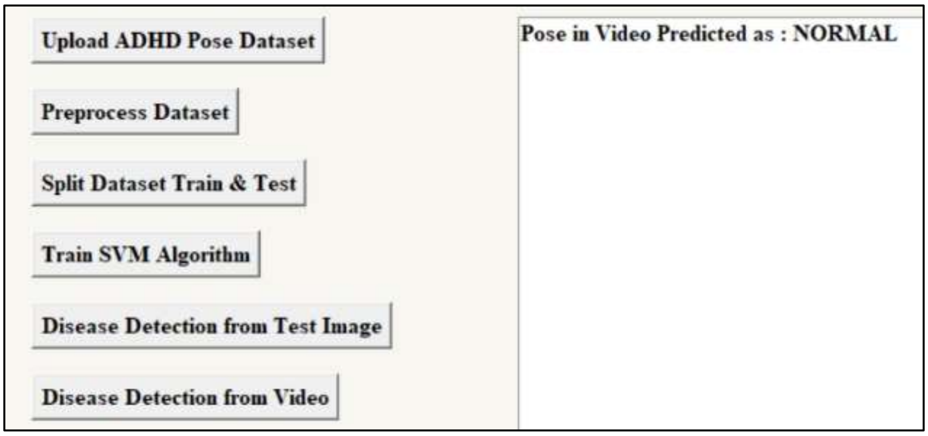


Fig 4.3.(a) ,(b) and (c) Predicted Outcomes

From fig 4.3 it is observed that, SVM model achieved an accuracy of 94.0%, precision at 94.17% highlights the accuracy of positive predictions.

5. Conclusion

The journey to understand and effectively address Attention Deficit Hyperactivity Disorder (ADHD) has been complex, marked by advancements in understanding its neurodevelopmental roots and its impact on various aspects of life. Technological innovations such as pose estimation and machine learning have opened new avenues for the diagnosis and intervention of ADHD, potentially improving traditional methods and providing personalized support. However, technological progress must be paired with a comprehensive approach involving healthcare providers, educators, families, and community resources to support individuals with ADHD in all areas of their lives. Ethical considerations such as respecting autonomy, promoting well-being, and ensuring equitable access to care are fundamental to ADHD management. Ongoing research and collaborative efforts are essential to advance our understanding of ADHD and advocate for inclusive and supportive policies. Through these efforts, we aim to reduce stigma, promote acceptance, and create a society where individuals with ADHD can thrive and reach their full potential.

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