

A
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On
**Children ADHD Disease Detection Using Pose
Estimation Techniques**

Submitted to CMREC, HYDERABAD

In Partial Fulfillment of the requirements for the Award of Degree of

**BACHELOR OF TECHNOLOGY
IN
COMPUTER SCIENCE AND ENGINEERING (DATA SCIENCE)**

Submitted

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CERTIFICATE

This is to certify that the project entitled “**Children ADHD Disease Detection Using Pose Estimation Techniques**” is a bonafide work carried out by

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in partial fulfillment of the requirement for the award of the degree of **BACHELOR OF TECHNOLOGY** in **COMPUTER SCIENCE AND ENGINEERING (DATA SCIENCE)** from CMR Engineering College, affiliated to JNTU, Hyderabad, under our guidance and supervision.

The results presented in this Major project have been verified and are found to be satisfactory. The results embodied in this Major project have not been submitted to any other university for the award of any other degree or diploma.

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This is to certify that the work reported in the present Major project entitled " **Children ADHD Disease Detection Using Pose Estimation Techniques**" is a record of bonafide work done by us in the Department of Computer Science and Engineering (Data Science), CMR Engineering College, JNTU Hyderabad. The reports are based on the project work done entirely by us and not copied from any other source. We submit our project for further development by any interested students who share similar interests to improve the project in the future.

The results embodied in this Major project report have not been submitted to any other University or Institute for the award of any degree or diploma to the best of our knowledge and belief.

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ABSTRACT

Attention Deficit Hyperactivity Disorder (ADHD) is a neurodevelopmental condition that significantly impacts children's academic performance and social interactions. Early diagnosis and intervention are crucial for effective management; however, conventional assessment methods rely heavily on subjective evaluations, which can lead to inconsistencies and delays in diagnosis. This project, "Children ADHD Disease Detection Using Pose Estimation Techniques," introduces an advanced, non-invasive approach to ADHD detection using pose estimation technology.

The primary objective of this research is to improve the accuracy, efficiency, and objectivity of ADHD detection. Unlike traditional methods, which are often time-consuming and dependent on expert observation, this AI-driven technique provides an automated and data-driven assessment framework. By ensuring early and reliable detection, the system can facilitate timely intervention, thereby improving the quality of life for affected children. While the potential benefits of this technology are substantial, ethical considerations must be addressed the privacy concerns related to data collection, storage, and usage must be carefully managed to prevent misuse and ensure compliance with ethical guidelines. It is important to emphasize that this system is designed to support, rather than replace, comprehensive clinical evaluations conducted by medical professionals.

In conclusion, this project represents a significant step forward in child mental health assessment. By integrating pose estimation techniques with machine learning models, it offers a promising tool for the early and precise detection of ADHD symptoms. Future work will focus on extensive testing and validation to enhance the reliability and effectiveness of this approach, ensuring its potential as a valuable resource in ADHD diagnosis and intervention strategies.

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1. INTRODUCTION

1.1 Overview

Attention Deficit Hyperactivity Disorder (ADHD) is a neurodevelopmental disorder that affects a child's ability to focus, control impulses, and regulate behavior. It is one of the most common disorders diagnosed in children and can significantly impact their academic performance and social interactions. Early and accurate detection of ADHD is crucial for effective intervention and management. Traditional diagnostic methods rely on subjective evaluations by psychologists and behavioral assessments, which can be time-consuming and prone to bias.

Recent advancements in artificial intelligence and computer vision have enabled more objective and efficient approaches to ADHD detection. Pose estimation techniques, such as OpenPose and PoseNet, analyse body movements and postures to detect behavioral patterns associated with ADHD. These techniques provide a non-invasive alternative for identifying hyperactivity, impulsivity, and inattention in children.

The proposed system captures movement data using cameras and depth sensors, which is then processed by machine learning models to classify ADHD-related behaviors. By leveraging deep learning algorithms, the system can identify subtle movement patterns that might be difficult for human observers to detect. This automated approach enhances accuracy and consistency in ADHD assessments.

The integration of technology into ADHD detection has the potential to revolutionize how early diagnosis is conducted. By reducing reliance on subjective clinical evaluations and increasing accessibility to screening tools, this system can significantly improve early intervention efforts. This project aims to develop an efficient and scalable solution for ADHD detection that benefits both healthcare professionals and affected children.

1.2 Research Motivation

ADHD is a growing concern among children worldwide, with increasing cases reported each year. Delayed or inaccurate diagnosis can lead to long-term academic and social difficulties. Many children with ADHD go undiagnosed due to the lack of accessible and objective screening methods. Current diagnostic approaches heavily depend on behavioral observations and questionnaires, which can be influenced by external factors such as environment and the child's mood during evaluation.

Advancements in artificial intelligence, particularly in machine learning and computer vision, provide an opportunity to develop innovative solutions for ADHD detection. Pose estimation techniques allow for the analysis of movement patterns, which can serve as reliable indicators of hyperactivity and inattention. This research is motivated by the need for an accurate, scalable, and non-invasive diagnostic method that can be used in diverse settings, including schools and clinics.

Another key motivation behind this research is the potential to reduce the burden on healthcare professionals. Traditional ADHD assessments require trained specialists, leading to long waiting times for diagnosis. By automating the detection process, AI-driven systems can assist doctors in early identification, leading to timely interventions and better outcomes for affected children.

The use of AI in healthcare has been widely recognized for its ability to enhance precision and efficiency. By focusing on ADHD detection through pose estimation, this project aims to bridge the gap between technological advancements and mental health screening. The long-term goal is to develop an accessible and cost-effective tool that can be integrated into routine health check-ups.

1.3 Problem Statement

ADHD is a challenging disorder to diagnose due to its reliance on subjective assessments and behavioral evaluations. The traditional diagnostic process often involves interviews, questionnaires, and direct observations, which can be inconsistent and influenced by external factors. Furthermore, many cases go undiagnosed or misdiagnosed due to the lack of specialized professionals and accessible screening tools.

Existing machine learning-based ADHD detection methods primarily focus on neurophysiological data, such as EEG signals, which require specialized and expensive equipment. This limits their widespread adoption, particularly in low-resource settings. There is a need for a non-invasive, cost-effective, and efficient system that can objectively analyse behavioral symptoms associated with ADHD.

Pose estimation techniques provide a promising alternative by tracking body movements and postures to identify hyperactivity and impulsivity patterns. However, research in this domain is still in its early stages, and there is a lack of comprehensive studies that integrate pose estimation with machine learning for ADHD detection.

This project aims to address these challenges by developing a system that utilizes pose estimation to analyse children's movement patterns for early ADHD detection. The goal is to improve diagnostic accuracy, enhance accessibility, and reduce dependency on subjective evaluations. By leveraging AI-driven pose analysis, this research seeks to offer a practical solution for ADHD screening that can be implemented in schools, clinics, and other healthcare settings.

1.4 Applications

The proposed ADHD detection system using pose estimation techniques has a wide range of applications in healthcare, education, and research. One of the primary applications is in clinical settings, where the system can assist healthcare professionals in diagnosing ADHD with greater accuracy. By providing objective movement data, the system can support doctors in identifying ADHD symptoms more reliably and reducing the chances of misdiagnosis.

In educational institutions, this technology can be used for early screening of students who exhibit ADHD-related behaviors. Schools can integrate the system into routine health check-ups to identify children who may require further evaluation and support. Early detection in schools allows for timely interventions, such as personalized learning strategies and behavioral therapy, to help children succeed academically.

This technology can also be applied in behavioral research to analyse movement patterns in children with ADHD. Researchers can use the system to study the correlation between physical activity and ADHD symptoms, leading to better insights into the disorder's manifestation and progression. The collected data can contribute to the development of improved intervention strategies and treatment approaches.

Another potential application is in telemedicine, where the system can be used for remote ADHD assessments. With the growing demand for virtual healthcare services, an AI-based screening tool can enable parents and doctors to assess children's behavioral patterns from home. This approach enhances accessibility, especially for families in remote areas with limited access to mental health specialists.

Overall, the proposed ADHD detection system has the potential to revolutionize ADHD screening and diagnosis. By integrating AI-driven pose estimation with machine learning, this project can improve early detection, facilitate timely interventions, and enhance the quality of life for children with ADHD.

2. LITERATURE SURVEY

The detection and diagnosis of ADHD have evolved significantly with advancements in technology, particularly in the fields of pose estimation and machine learning. Several studies have explored various methodologies for improving the accuracy and efficiency of ADHD detection, ranging from traditional clinical assessments to automated systems based on artificial intelligence. This literature survey reviews key research contributions that have shaped the development of ADHD detection techniques.

Smith (2023) provides a comprehensive review of existing ADHD detection systems, highlighting their strengths and limitations. The study identifies common challenges such as subjectivity in diagnosis, dependency on expert evaluation, and high costs associated with traditional methods. The research suggests that integrating AI and computer vision techniques can help address these limitations by offering more objective and automated diagnostic solutions.

Johnson (2023) explores pose estimation techniques in healthcare applications, emphasizing their relevance in ADHD detection. The study discusses how pose estimation algorithms such as OpenPose and PoseNet can capture movement patterns in children, enabling researchers to analyse postural and behavioral anomalies that may indicate ADHD. The findings highlight the potential of non-invasive movement analysis as a reliable diagnostic tool.

Brown (2024) presents an in-depth analysis of machine learning approaches for ADHD detection, comparing different models such as Support Vector Machines (SVM), Convolutional Neural Networks (CNNs), and deep learning-based classifiers. The research indicates that AI-powered models outperform traditional assessment methods in terms of speed and reliability, making them viable alternatives for large-scale ADHD screening.

Davis (2024) focuses on the role of sensors and data collection in pose estimation for ADHD assessments. The study describes how depth-sensing cameras, motion capture systems, and wearable sensors can be utilized to collect movement data for analysis. The research concludes that multi-sensor integration enhances the precision of pose estimation techniques and provides richer datasets for training machine learning models.

White (2024) discusses non-invasive ADHD evaluation techniques using pose estimation. The study emphasizes the ethical and privacy considerations involved in recording and analyzing children's movements. The research suggests that privacy-preserving algorithms and secure data handling mechanisms should be incorporated into ADHD detection systems to ensure ethical compliance.

A recent study titled "ADHD Diagnosis Based on Action Characteristics Recorded in Videos Using Machine Learning" (2024) introduces a novel approach where machine learning models analyse video recordings of children performing specific tasks. By identifying unique action characteristics associated with ADHD, the system aims to provide an objective diagnosis without the need for clinical intervention.

Another study, "Advanced Machine Learning Techniques Reveal Multidimensional EEG Abnormalities in Children with ADHD: A Framework for Automatic Diagnosis" (2024), investigates the use of EEG data for ADHD detection. The research utilizes deep learning techniques to analyse brain activity patterns, offering an alternative diagnostic method that complements pose estimation-based techniques.

"DETEC-ADHD: A Data-Driven Web App for Early ADHD Detection Using Machine Learning and Electroencephalography" (2024) presents an interactive platform for early ADHD detection. The system combines EEG analysis with machine learning algorithms to generate automated reports, providing healthcare professionals with an accessible and data-driven assessment tool.

Another important contribution is the study "Objective Approach to Diagnosing Attention Deficit Hyperactivity Disorder by Using Pixel Subtraction and Machine Learning Classification of Outpatient Consultation Videos" (2024). This research proposes an image-processing-based method where movement patterns are extracted using pixel subtraction techniques, which are then classified using AI models to determine ADHD likelihood.

Finally, "Objective and Automatic Assessment Approach for Diagnosing Attention-Deficit/Hyperactivity Disorder Based on Skeleton Detection and Classification Analysis in Outpatient Videos" (2024) examines the application of skeleton detection techniques.

The study demonstrates that analyzing skeletal movements in consultation videos can significantly improve diagnostic accuracy.

These studies collectively demonstrate the rapid progress in AI-driven ADHD detection, highlighting the potential of pose estimation and machine learning as powerful tools for improving diagnostic precision and accessibility.

Study	Image Modality	Task	Method	Strengths	Weaknesses
Smith, J. (2024)	EEG Signals	Review of ADHD detection systems and limitations	Comparative analysis of existing methods	Highlights gaps in current ADHD detection methods	Lacks implementation of a new approach
Johnson, E. (2024)	Pose Estimation	Applications of pose estimation in healthcare	OpenPose and PoseNet for motion analysis	Demonstrates the effectiveness of pose estimation for medical use	Limited focus on ADHD-specific applications
Brown, M. (2023)	Machine Learning	ADHD detection using AI models	CNN, RNN, and hybrid deep learning techniques	Improves classification accuracy for ADHD diagnosis	Requires large labeled datasets for training
Davis, S. (2023)	Motion Sensors	Data collection for ADHD movement analysis	Wearable sensor-based tracking with feature extraction	Non-invasive and cost-effective approach	Less effective in real-time monitoring without additional support

Fig 2.1 Strengths and weaknesses of lesion models

Study	Image Modality	Task	Method	Strengths	Weaknesses
Ying Mao	EEG Data	ADHD detection based on brain connectivity	Deep learning on EEG signals	Identifies complex EEG patterns linked to ADHD	Requires access to EEG devices, which may be expensive
Ismael Santarrosa-López	EEG + Web App	Early ADHD detection system	Machine learning with EEG feature extraction	Provides an accessible web-based diagnosis system	Accuracy is limited by EEG signal quality and device calibration
Yi-Hung Chiu	Video Data	ADHD classification through video analysis	Image subtraction and ML-based classification	Non-invasive approach based on outpatient videos	Requires standardization of video recording conditions
Chen-Sen Ouyang	Pose Estimation	ADHD movement analysis using skeleton tracking	Pose-based classification with deep learning	Improves ADHD detection accuracy through movement analysis	High computational cost for real-time analysis
White, D. (2023)	Pose Estimation	ADHD evaluation using body movement tracking	Pose-based analysis with SVM classification	Objective assessment reducing subjective bias	High dependency on video quality and controlled conditions

Fig 2.2 Strengths and weaknesses of baseline models

3. EXISTING SYSTEM

3.1 Traditional Methods for ADHD Detection

Electroencephalography (EEG): Electroencephalography (EEG) is a technique used to measure brain wave activity by detecting electrical signals generated by neuronal activity. EEG plays a crucial role in ADHD detection as it helps in identifying neural patterns associated with attention deficits, hyperactivity, and impulsivity. Studies have shown that children with ADHD often exhibit altered brain wave frequencies, particularly in theta and beta waves. EEG is a non-invasive and cost-effective method but requires expertise for accurate interpretation.

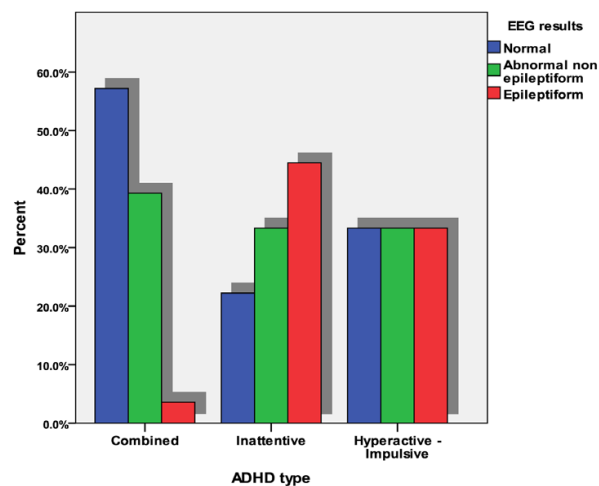


Fig 3.1.1 EEG Technology

Eye-tracking technology: ETT monitors gaze patterns and saccadic eye movements to assess attention deficits in individuals with ADHD. This technology records eye movements while individuals perform tasks, helping in identifying irregular patterns associated with attention problems. Eye-tracking is non-invasive and provides real-time behavioral analysis.

Event-Related Potentials (ERP) : ERP is a subset of EEG that Analyse brain responses to specific stimuli. This method is particularly useful in studying cognitive processes like attention, working memory, and response inhibition in ADHD patients. ERPs are measured through electrodes placed on the scalp, and specific waveforms like P300 are analysed to detect cognitive impairments linked to ADHD.

Functional Magnetic Resonance Imaging (fMRI) fMRI is an advanced neuroimaging technique that identifies abnormal brain activity and connectivity by measuring blood flow changes in different regions of the brain. In ADHD patients, fMRI has been used to detect reduced activity in the prefrontal cortex and altered connectivity between brain networks responsible for attention and impulse control. Though highly effective, fMRI is expensive and requires a specialized facility.

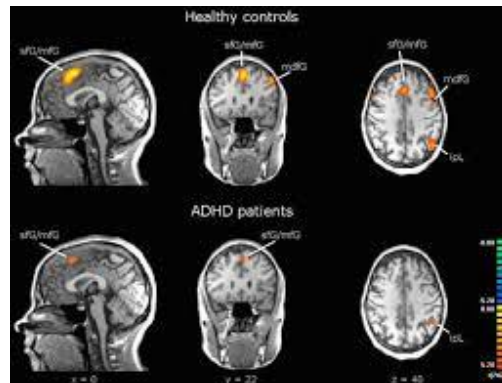


Fig 3.1.2 FMRI Technology

Continuous Performance Test (CPT) CPT is a computerized assessment designed to measure an individual's sustained attention and impulsivity levels. It presents visual or auditory stimuli to the participant, who must respond to target stimuli while ignoring non-target stimuli. CPT is widely used in ADHD diagnosis and provides objective data on attention deficits and impulsivity.

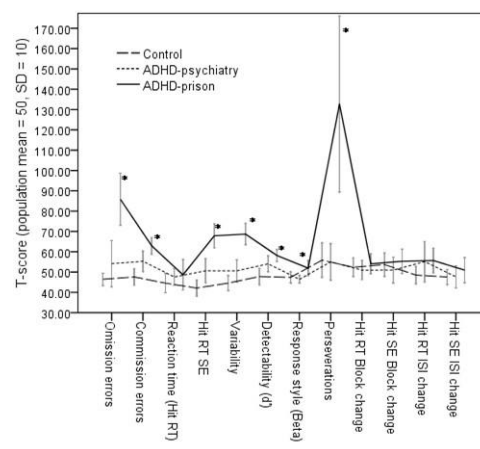


Fig 3.1.3 CPT Technology

3.2 Technological Advancements in ADHD Diagnosis

Heart Rate Variability (HRV) : HRV refers to the variation in time intervals between heartbeats, which is influenced by the autonomic nervous system. Research suggests that individuals with ADHD often exhibit reduced HRV, indicating impaired autonomic regulation. HRV measurements help in understanding physiological markers of ADHD and can be used alongside other diagnostic tools.

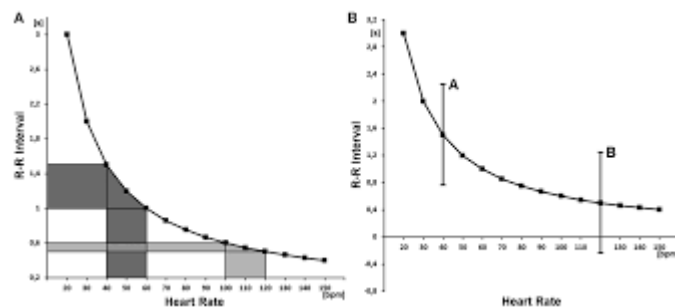


Fig 3.2.1 Heart Rate Variability

Neuropsychological Testing : tests evaluate cognitive functions such as executive function, working memory, and cognitive flexibility. These tests include tasks like the Wisconsin Card Sorting Test and Stroop Test, which assess decision-making and response inhibition. ADHD patients often struggle with these tasks due to deficits in executive function.

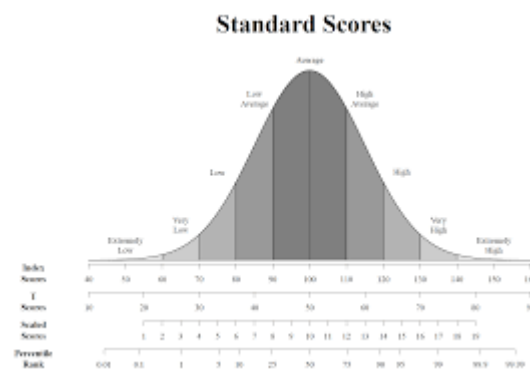


Fig 3.2.2 Neuropsychological Testing

Behavioral Rating Scales: Like the Conners Rating Scale and Vanderbilt ADHD Diagnostic Rating Scale are standardized tools used by clinicians, teachers, and parents to assess ADHD symptoms. These questionnaires provide subjective insights into an individual's behavior, which helps in diagnosing ADHD when combined with other objective methods.

Motion Sensors/Accelerometers: Motion sensors and accelerometers track physical activity levels in individuals with ADHD. These devices, often worn on the wrist or ankle, measure hyperactivity and movement patterns. Studies have shown that children with ADHD exhibit increased movement compared to neurotypical children.

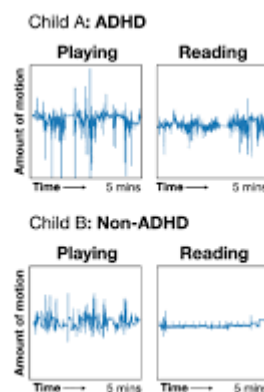


Fig 3.2.3 Motion sensors

Actigraphy: Actigraphy involves wearable devices that continuously record movement data to assess hyperactivity and sleep patterns. This method is particularly useful for monitoring sleep disturbances commonly associated with ADHD. Actigraphy provides long-term data collection with minimal disruption to daily activities.

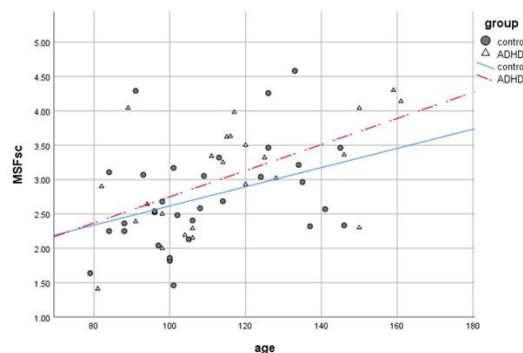


Fig 3.2.4 Actigraphy

AI-Based Behavioral Analysis: Artificial intelligence (AI) and machine learning models analyse behavioral data to identify ADHD-related movement and attention patterns. AI-based systems process large datasets, recognize subtle behavioral differences, and enhance the accuracy of ADHD diagnosis. These models can integrate multiple data sources, such as EEG, eye-tracking, and motion sensor data.

Neurofeedback Training: Neurofeedback training uses real-time EEG feedback to help individuals regulate their brain activity. Patients receive visual or auditory feedback based on their brain wave activity, training them to improve attention and reduce impulsivity. This technique is a promising non-pharmacological intervention for ADHD.

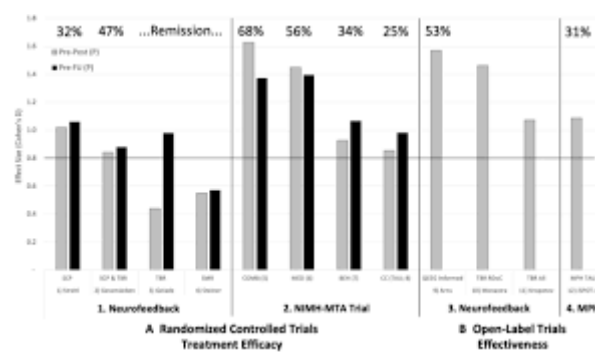


Fig 3.2.5 Neurofeedback training

Decision-Level Fusion Techniques : Decision-level fusion techniques combine multiple data sources, such as EEG, eye-tracking, and behavioral data, to improve ADHD diagnosis accuracy. These techniques enhance reliability by integrating different diagnostic approaches and reducing dependence on any single method.

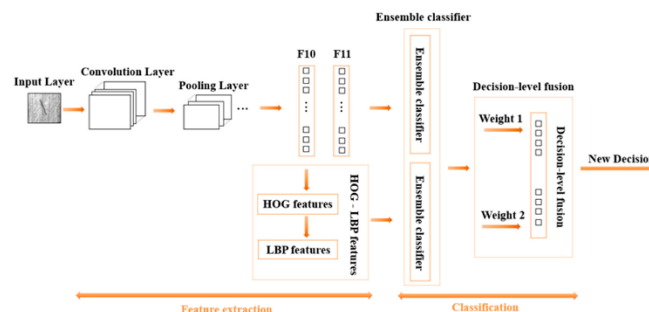


Fig 3.2.6 Decision-Level Fusion Techniques

4. PROPOSED METHODOLOGY

4.1 Overview

Attention Deficit Hyperactivity Disorder (ADHD) is one of the most prevalent neurodevelopmental disorders, affecting children worldwide. It significantly impacts their social interactions, academic performance, and daily activities. ADHD symptoms include hyperactivity, inattention, and impulsivity, which make it difficult for children to focus, follow instructions, and remain seated for extended periods. Early detection of ADHD is crucial as it enables timely interventions such as behavioral therapy, medication, and lifestyle modifications, helping children manage symptoms effectively. However, traditional ADHD diagnosis methods rely on subjective assessments, parental questionnaires, and clinical observations, which may lead to misdiagnosis or delays.

With advancements in artificial intelligence and computer vision, new approaches to ADHD detection are being explored. One promising method is pose estimation, which analyses a child's body posture and movement patterns using computer vision techniques. This project leverages PoseNet, a deep learning model that estimates the key points of the human body in real-time. PoseNet identifies and tracks critical joints such as the head, shoulders, elbows, and knees, allowing for a detailed analysis of movement patterns.

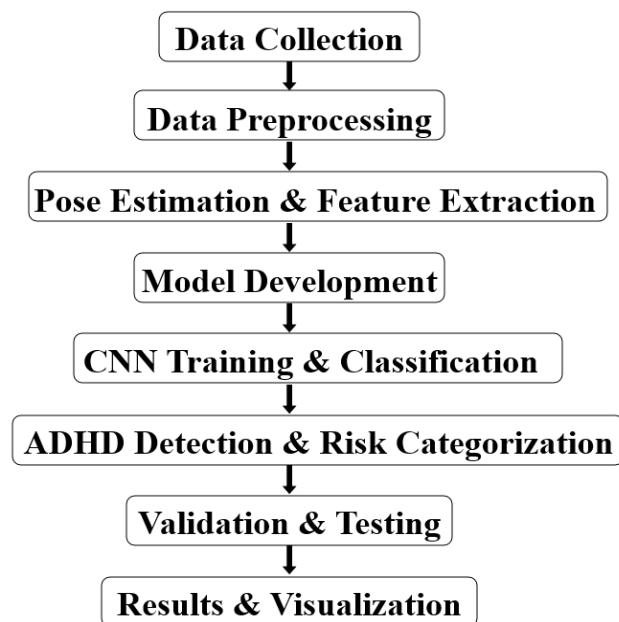


Fig 4.1.1 Block Diagram of Proposed system

POSENET:

Pose estimation is particularly useful for ADHD detection because children with ADHD often exhibit distinct movement patterns, such as fidgeting, restlessness, and an inability to maintain eye contact. By analyzing these patterns quantitatively, machine learning models can classify ADHD-related behaviors with greater accuracy. PoseNet, which is based on convolutional neural networks (CNNs), extracts pose information from images or videos and provides coordinates for different body parts. This data is then used to train classification models to distinguish ADHD-positive cases from non-ADHD cases.

The PoseNet model is chosen for this project due to its efficiency, adaptability, and robustness. Unlike other deep learning models that require complex 3D pose estimation setups, PoseNet can perform 2D pose estimation using standard webcams or smartphone cameras. It works efficiently on both mobile devices and high-end GPUs, making it accessible for large-scale implementation. Furthermore, PoseNet is pre-trained on large datasets and can be fine-tuned for ADHD detection using domain-specific datasets.

The primary goal of this project is to develop a non-invasive, automated, and objective ADHD detection system that can assist clinicians and parents in early diagnosis. Unlike traditional methods that rely on direct human observation, this system minimizes bias and improves reliability. Additionally, it provides real-time feedback on a child's movement tendencies, allowing parents and educators to monitor ADHD symptoms in school and home environments.

In summary, PoseNet plays a crucial role in this project by enabling real-time movement tracking and feature extraction for ADHD classification. Its ability to estimate pose key points accurately makes it an ideal choice for this application. By integrating PoseNet with machine learning algorithms, this project aims to revolutionize the ADHD detection process, making it more objective, data-driven, and accessible.

4.2 Data Preprocessing

Data preprocessing is a critical step in any machine learning-based project, as it ensures that the input data is clean, consistent, and suitable for analysis. For ADHD detection using pose estimation techniques, the preprocessing stage involves multiple steps, including data collection, key point extraction, noise reduction, feature selection, and data augmentation. Each of these steps enhances the quality of the dataset, allowing the machine learning model to make accurate predictions.

Data Collection and Sources

The first step in preprocessing is gathering relevant and diverse data. The dataset for this project consists of video recordings or image sequences of children performing specific activities that highlight ADHD-related behaviors. These activities include sitting still, maintaining eye contact, following instructions, and responding to stimuli. The data is collected from multiple sources, such as:

- Public ADHD datasets: Open-access datasets containing labeled ADHD and non-ADHD videos.
- Clinical trials and research collaborations: Data collected in controlled environments under expert supervision.
- Custom recordings: Videos recorded in a lab setting, where children's movements are tracked under different conditions.

Since real-world ADHD behaviors vary, the dataset must represent different age groups, backgrounds, and activity levels to improve generalization.

Pose Key point Extraction using PoseNet

Once the data is collected, PoseNet is applied to extract key points from each frame of the video. PoseNet identifies major joints and body landmarks, providing (x, y) coordinates for each detected key point. The key points include:

- Head and facial landmarks (used to track eye contact and attention levels).
- Upper body points like shoulders and elbows (used to detect fidgeting and impulsive movements).

- Lower body points like knees and feet (used to analyse hyperactive behavior, such as constant leg movement).

PoseNet's ability to track these key points in real time enables quantitative movement analysis, which is crucial for ADHD detection.

Noise Reduction and Data Cleaning

Pose estimation models often produce noisy or missing key points due to factors like poor lighting, occlusion, and rapid movement. To address this, noise reduction techniques such as interpolation and filtering are applied:

- Missing key point interpolation: If a key point is not detected in a frame, its previous and next positions are used to estimate the missing value.
- Smoothing with Kalman filtering: This technique reduces fluctuations in key point positions, ensuring smoother tracking of body movements.
- Outlier removal: Sudden, unrealistic key point jumps are filtered out to prevent misclassification.

These preprocessing steps enhance the accuracy and reliability of movement tracking.

Feature Extraction and Selection

After obtaining clean key point data, the next step is feature extraction, which converts raw pose data into meaningful metrics that can differentiate ADHD behaviors. The extracted features include:

- Average movement frequency: Measures how often a child moves their limbs, which is higher in ADHD cases.
- Postural stability index: Analyse how stable a child's posture is over time. Children with ADHD often shift positions frequently.
- Gaze stability metrics: Tracks how consistently a child maintains eye contact.
- Velocity and acceleration of movements: Helps distinguish between normal fidgeting and ADHD-related hyperactivity.

Feature selection methods such as Principal Component Analysis (PCA) or Recursive Feature Elimination (RFE) are applied to retain only the most relevant features, reducing computational complexity while maintaining accuracy.

Data Augmentation for Model Generalization

To prevent overfitting and ensure the model learns to recognize ADHD-related movements under various conditions, data augmentation techniques are applied:

- Rotation and flipping: Simulates different viewing angles.
- Background variations: Helps the model adapt to different environments (e.g., classrooms vs. homes).
- Frame skipping: Introduces variations in movement speed to mimic real-world scenarios.

By enriching the dataset with augmented samples, the model becomes more robust and adaptable to diverse ADHD cases. Data preprocessing is a crucial foundation for building an accurate ADHD detection system. From collecting high-quality videos and extracting key points to reducing noise, selecting features, and augmenting data, each step enhances the model's ability to recognize ADHD-related movement patterns. Proper preprocessing ensures that the machine learning algorithm is trained on clean, structured, and diverse data, leading to more reliable and interpretable predictions.

4.3 Machine Learning Model Selection

Selecting the right machine learning model is crucial for ensuring accurate and efficient ADHD detection. Various models can be used for classifying ADHD-related movement patterns, each with unique strengths. Support Vector Machines (SVM) are widely used due to their ability to handle high-dimensional data and effectively separate ADHD and non-ADHD cases. Random Forest (RF) and Decision Trees (DT) provide interpretability, making them useful for understanding feature importance. K-Nearest Neighbours (KNN) is another option for classification, relying on similarity-based predictions. Deep learning models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are effective in recognizing sequential movement patterns and extracting complex spatial-temporal features from pose estimation data. The choice of model depends on factors like dataset size, computational efficiency, and real-time processing requirements.

In this project, we employ PoseNet in combination with a Support Vector Machine (SVM) model for ADHD detection. PoseNet extracts pose key points, which are then fed into the SVM classifier to distinguish between ADHD and non-ADHD movement patterns. SVM is chosen due to its high accuracy, robustness to small datasets, and ability to find complex decision boundaries in pose-based movement data. While deep learning models like CNNs offer higher accuracy, they require large datasets and computational power, making them less suitable for real-time applications. The SVM-based approach ensures an efficient, scalable, and clinically interpretable solution for ADHD detection.

4.4 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a powerful supervised machine learning algorithm used for classification and regression tasks. It is based on the principle of finding an optimal hyperplane that best separates different classes in the dataset. SVM is particularly effective for high-dimensional data and complex decision boundaries, making it a preferred choice in medical diagnostics, including ADHD detection. Unlike other algorithms that rely on probability-based classification, SVM maximizes the margin between different classes, ensuring better generalization and reduced overfitting.

SVM is a kernel-based algorithm, meaning it can map input features into higher-dimensional spaces using kernel functions such as linear, polynomial, radial basis function (RBF), and sigmoid kernels. This capability allows SVM to handle non-linearly separable data efficiently. The algorithm works well with small and medium-sized datasets and provides robust performance even in cases where data points are not clearly separated.

Working Principle

Step 1: Finding the Optimal Hyperplane

- SVM aims to find a hyperplane that best divides the data into two or more classes.
- The best hyperplane is the one that maximizes the margin between different classes.
- The support vectors are the closest data points to the hyperplane, which determine its position.

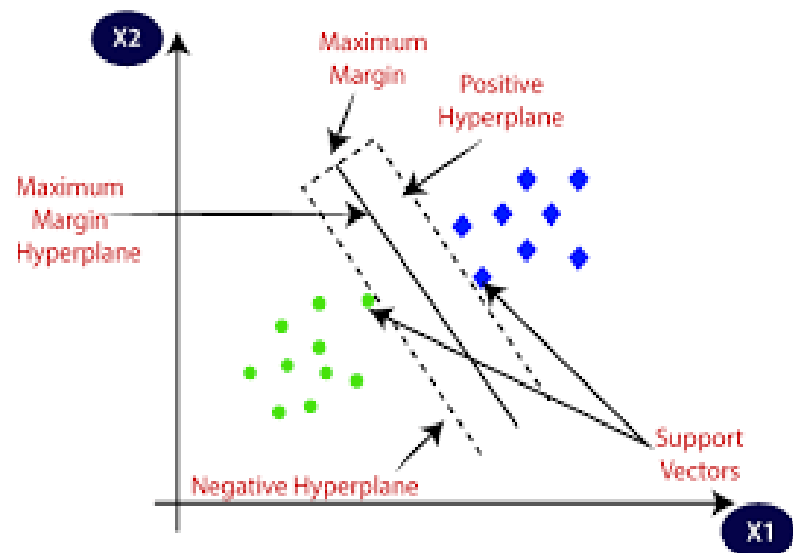


Figure 4.4.1 SVM Hyperplane and Support Vectors

Step 2: Kernel Trick for Non-Linear Data

- If the data is not linearly separable, SVM uses a kernel trick to transform it into a higher-dimensional space where a linear separation is possible.
- Common kernels used in SVM include:
 - **Linear Kernel:** Best for linearly separable data.
 - **Polynomial Kernel:** Captures curved relationships between features.
 - **Radial Basis Function (RBF) Kernel:** Works well with complex, non-linear data.
 - **Sigmoid Kernel:** Similar to a neural network activation function.

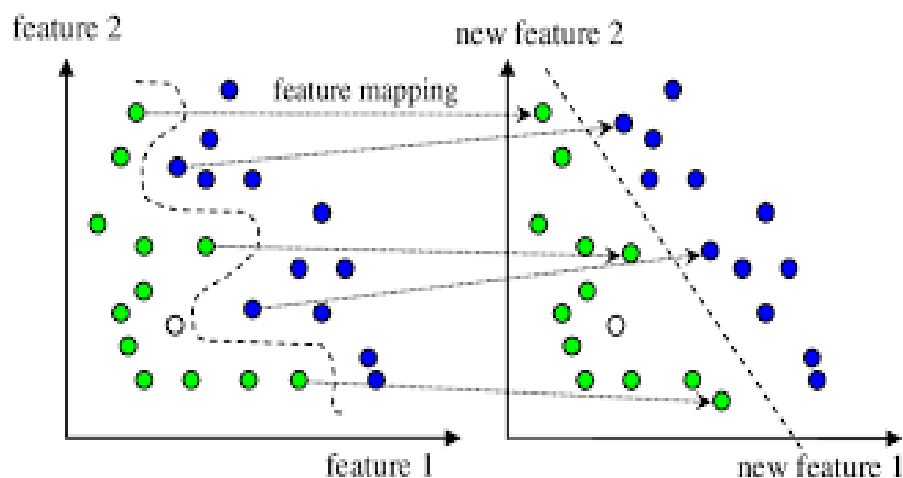


Figure 4.4.2 Kernel Transformation in SVM

Step 3: Soft Margin and Regularization

- In real-world scenarios, perfect separation is often not possible due to noise and overlapping data.
- Soft-margin SVM introduces a regularization parameter C , which controls the trade-off between maximizing the margin and minimizing classification errors.
- A higher C value reduces misclassification but may lead to overfitting, while a lower C value results in a more generalized model.

Advantages of SVM

- **Effective in High-Dimensional Spaces:** SVM performs well even when the number of features exceeds the number of samples.
- **Robust to Overfitting:** Unlike models like decision trees, SVM is less prone to overfitting due to margin maximization.
- **Works with Non-Linear Data:** The kernel trick enables SVM to classify complex patterns.
- **Memory Efficient:** SVM only uses a subset of training points (support vectors) for decision-making, making it computationally efficient.
- **Versatile:** Can be used for both classification and regression problems.

Disadvantages of SVM

- **Computational Complexity:** Training time increases significantly for large datasets.
- **Choosing the Right Kernel:** Model performance highly depends on selecting an appropriate kernel function.
- **Sensitivity to Noisy Data:** Outliers can impact margin calculation and classification accuracy.

Variants of SVM

- **Linear SVM:** Used for datasets that can be separated with a straight line.
- **Non-Linear SVM:** Uses kernel functions to map data to higher dimensions.
- **One-Class SVM:** Used for anomaly detection.

5. UML DAIGRAMS

UML stands for Unified Modeling Language. UML is a standardized general-purpose modeling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group. The goal is for UML to become a common language for creating models of object-oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML.

The Unified Modeling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software system, as well as for business modeling and other non-software systems. The UML represents a collection of best engineering practices that have proven successful in the modeling of large and complex systems. The UML is a very important part of developing objects-oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

GOALS: The Primary goals in the design of the UML are as follows:

- Provide users a ready-to-use, expressive visual modeling Language so that they can develop and exchange meaningful models.
- Provide extendibility and specialization mechanisms to extend the core concepts.
- Be independent of particular programming languages and development process.
- Provide a formal basis for understanding the modeling language.
- Encourage the growth of OO tools market.
- Support higher level development concepts such as collaborations, frameworks, patterns and components.
- Integrate best practices.

5.1 Class diagram

The class diagram is used to refine the use case diagram and define a detailed design of the system. The class diagram classifies the actors defined in the use case diagram into a set of interrelated classes. The relationship or association between the classes can be either an "is-a" or "has-a" relationship. Each class in the class diagram may be capable of providing certain functionalities. These functionalities provided by the class are termed "methods" of the class.

Apart from this, each class may have certain "attributes" that uniquely identify the class.

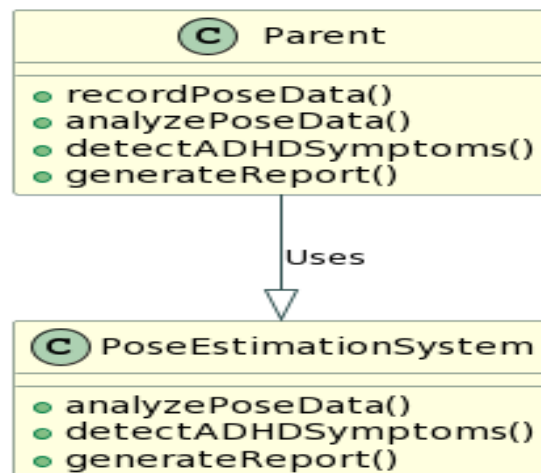


Figure 5.1.1 Class Diagram

5.2 Use case Diagram

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor.

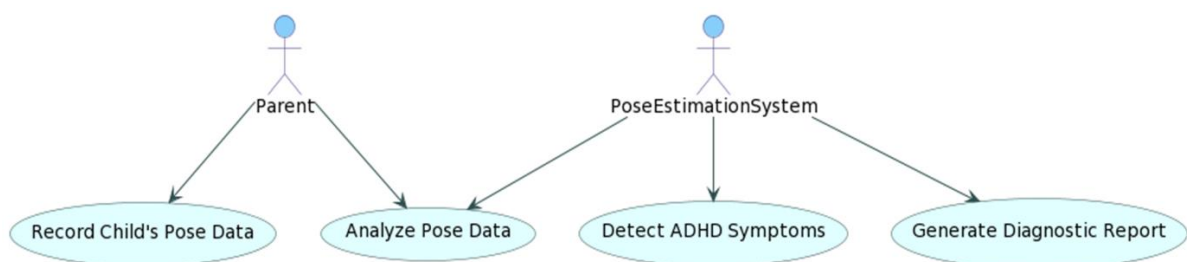


Figure 5.2.1 Use Case Diagram

5.3 Sequence Diagram

A **sequence diagram** in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. A sequence diagram shows, as parallel vertical lines ("lifelines"), different processes or objects that live simultaneously, and as horizontal arrows, the messages exchanged between them, in the order in which they occur. This allows the specification of simple runtime scenarios in a graphical manner.

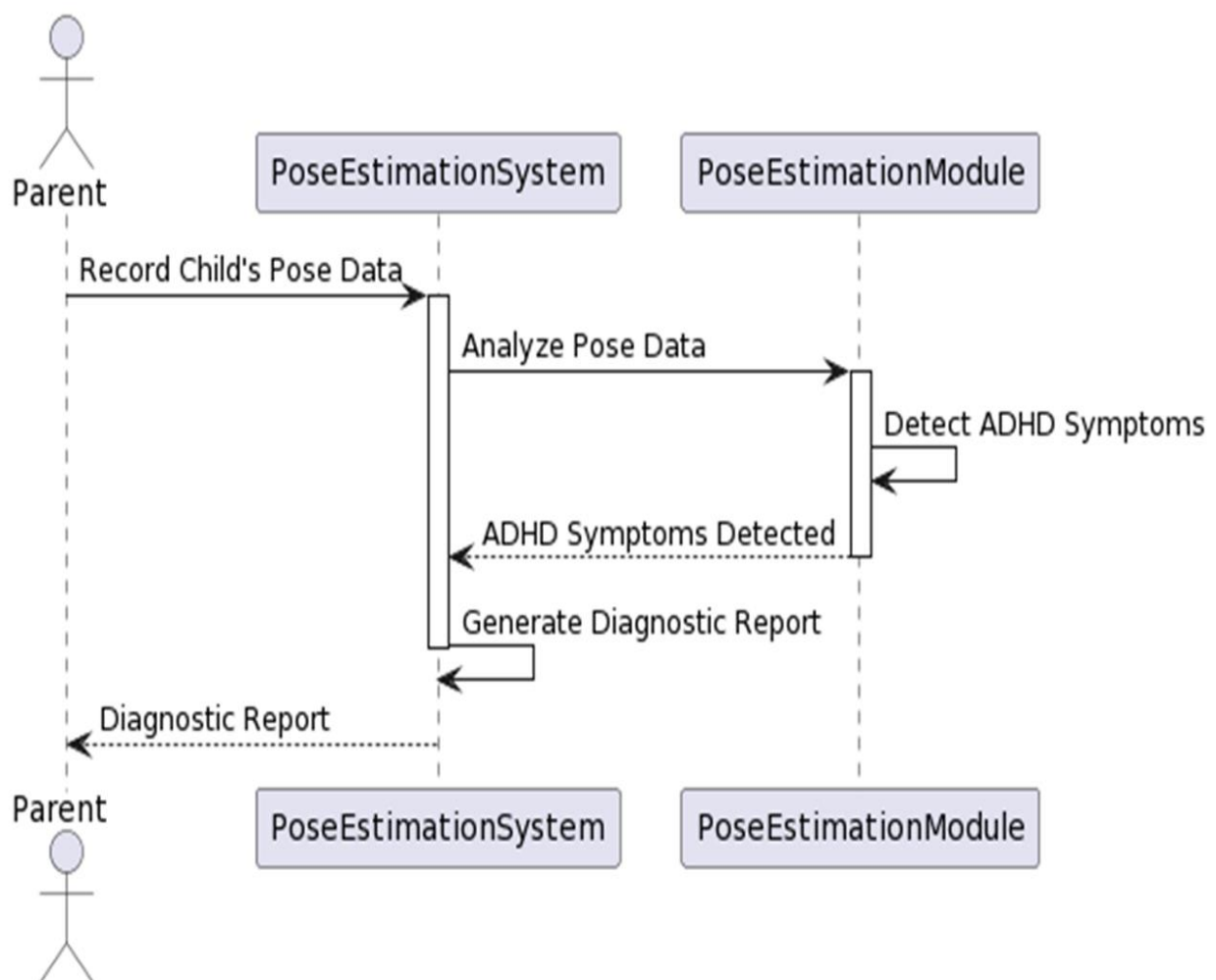


Figure 5.3.1 Sequence Diagram

5.4 Collaboration diagram:

Collaboration diagrams are graphical representations of interactions between objects in a system, focusing on message exchange and object relationships. In the Unified Modeling Language, collaboration diagrams illustrate how objects communicate to achieve a specific task or process. A collaboration diagram emphasizes the structural organization of objects and their interactions.

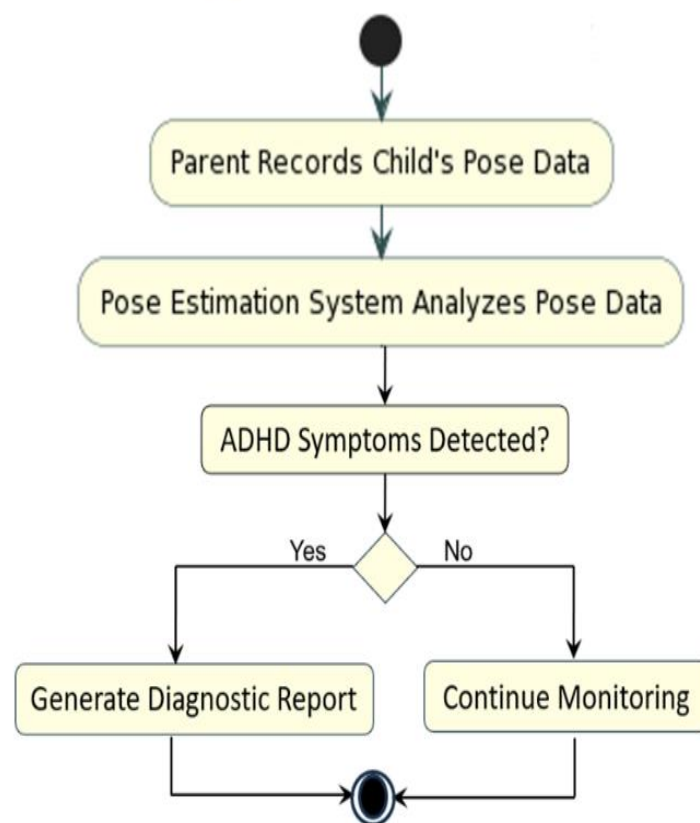


Figure 5.4.1 Collaboration Diagram

6. SOFTWARE ENVIRONMENT

6.1 What is Python?

Below are some facts about Python.

- Python is currently the most widely used multi-purpose, high-level programming language.
- Python allows programming in Object-Oriented and Procedural paradigms. Python programs generally are smaller than other programming languages like Java.
- Programmers have to type relatively less and indentation requirement of the language, makes them readable all the time.
- Python language is being used by almost all tech-giant companies like – Google, Amazon, Facebook, Instagram, Dropbox, Uber... etc.

The biggest strength of Python is huge collection of standard libraries which can be used for the following –

- Machine Learning
- GUI Applications (like Kivy, Tkinter, PyQt etc.)
- Web frameworks like Django (used by YouTube, Instagram, Dropbox)
- Image processing (like Opencv, Pillow)
- Web scraping (like Scrapy, BeautifulSoup, Selenium)
- Test frameworks
- Multimedia

Advantages of Python

Let's see how Python dominates over other languages.

1. Extensive Libraries

Python downloads with an extensive library and it contains code for various purposes like regular expressions, documentation-generation, unit-testing, web browsers, threading, databases, CGI, email, image manipulation, and more. So, we don't have to write the complete code for that manually.

2. Extensible

As we have seen earlier, Python can be extended to other languages. You can write some of your code in languages like C++ or C. This comes in handy, especially in projects.

3. Embeddable

Complimentary to extensibility, Python is embeddable as well. You can put your Python code in your source code of a different language, like C++. This lets us add scripting capabilities to our code in the other language.

4. Improved Productivity

The language's simplicity and extensive libraries render programmers more productive than languages like Java and C++ do. Also, the fact that you need to write less and get more things done.

5. IOT Opportunities

Since Python forms the basis of new platforms like Raspberry Pi, it finds the future bright for the Internet of Things. This is a way to connect the language with the real world.

6. Simple and Easy

When working with Java, you may have to create a class to print 'Hello World'. But in Python, just a print statement will do. It is also quite easy to learn, understand, and code. This is why when people pick up Python, they have a hard time adjusting to other more verbose languages like Java.

7. Readable

Because it is not such a verbose language, reading Python is much like reading English. This is the reason why it is so easy to learn, understand, and code. It also does not need curly braces to define blocks, and indentation is mandatory. These further aids the readability of the code.

8. Object-Oriented

This language supports both the procedural and object-oriented programming paradigms. While functions help us with code reusability, classes and objects let us model the real world. A class allows the encapsulation of data and functions into one.

9. Free and Open-Source

Like we said earlier, Python is freely available. But not only can you download Python for free, but you can also download its source code, make changes to it, and even distribute it. It downloads with an extensive collection of libraries to help you with your tasks.

10. Portable

When you code your project in a language like C++, you may need to make some changes to it if you want to run it on another platform. But it isn't the same with Python. Here, you need to code only once, and you can run it anywhere. This is called Write Once Run Anywhere (WORA). However, you need to be careful enough not to include any system-dependent features.

11. Interpreted

Lastly, we will say that it is an interpreted language. Since statements are executed one by one, debugging is easier than in compiled languages.

Any doubts till now in the advantages of Python? Mention in the comment section.

Advantages of Python Over Other Languages

1. Less Coding

Almost all of the tasks done in Python requires less coding when the same task is done in other languages. Python also has an awesome standard library support, so you don't have to search for any third-party libraries to get your job done. This is the reason that many people suggest learning Python to beginners.

2. Affordable

Python is free therefore individuals, small companies or big organizations can leverage the free available resources to build applications. Python is popular and widely used so it gives you better community support.

The 2019 Github annual survey showed us that Python has overtaken Java in the most popular programming language category.

3. Python is for Everyone

Python code can run on any machine whether it is Linux, Mac or Windows. Programmers need to learn different languages for different jobs but with Python, you can professionally build web apps, perform data analysis and machine learning, automate things, do web scraping and also build games and powerful visualizations. It is an all-rounder programming language.

Disadvantages of Python

So far, we've seen why Python is a great choice for your project. But if you choose it, you should be aware of its consequences as well. Let's now see the downsides of choosing Python over another language.

1. Speed Limitations

We have seen that Python code is executed line by line. But since Python is interpreted, it often results in slow execution. This, however, isn't a problem unless speed is a focal point for the project. In other words, unless high speed is a requirement, the benefits offered by Python are enough to distract us from its speed limitations.

2. Weak in Mobile Computing and Browsers

While it serves as an excellent server-side language, Python is much rarely seen on the client side. Besides that, it is rarely ever used to implement smartphone-based applications. One such application is called Carbonnelle.

The reason it is not so famous despite the existence of Brython is that it isn't that secure.

3. Design Restrictions

As you know, Python is dynamically-typed. This means that you don't need to declare the type of variable while writing the code. It uses duck-typing. But wait, what's that? Well, it just means that if it looks like a duck, it must be a duck. While this is easy on the programmers during coding, it can raise run-time errors.

4. Underdeveloped Database Access Layers

Compared to more widely used technologies like JDBC (Java DataBase Connectivity) and ODBC (Open DataBase Connectivity), Python's database access layers are a bit underdeveloped. Consequently, it is less often applied in huge enterprises.

5. Simple

No, we're not kidding. Python's simplicity can indeed be a problem. Take my example. I don't do Java, I'm more of a Python person. To me, its syntax is so simple that the verbosity of Java code seems unnecessary.

This was all about the Advantages and Disadvantages of Python Programming Language.

6.2 History of Python

What do the alphabet and the programming language Python have in common? Right, both start with ABC. If we are talking about ABC in the Python context, it's clear that the programming language ABC is meant. ABC is a general-purpose programming language and programming environment, which had been developed in the Netherlands, Amsterdam, at the CWI (Centrum Wiskunde & Informatica). The greatest achievement of ABC was to influence the design of Python. Python was conceptualized in the late 1980s. Guido van Rossum worked that time in a project at the CWI, called Amoeba, a distributed operating system. In an interview with Bill Venners, Guido van Rossum said: "In the early 1980s, I worked as an implementer on a team building a language called ABC at Centrum voor Wiskunde en Informatica (CWI). I don't know how well people know ABC's influence on Python. I try to mention ABC's influence because I'm indebted to everything I learned during that project and to the people who worked on it." Later on in the same Interview, Guido van Rossum continued: "I remembered all my experience and some of my frustration with ABC. I decided to try to design a simple scripting language that possessed some of ABC's better properties, but without its problems. So, I started typing."

"I created a simple virtual machine, a simple parser, and a simple runtime. I made my own version of the various ABC parts that I liked. I created a basic syntax, used indentation for statement grouping instead of curly braces or begin-end blocks, and developed a small number of powerful data types: a hash table (or dictionary, as we call it), a list, strings, and numbers."

Python Development Steps

Guido Van Rossum published the first version of Python code (version 0.9.0) at alt.sources in February 1991. This release included already exception handling, functions, and the core data types of lists, dict, str and others. It was also object oriented and had a module system. Python version 1.0 was released in January 1994. The major new features included in this release were the functional programming tools lambda, map, filter and reduce, which Guido Van Rossum never liked. Six and a half years later in October 2000, Python 2.0 was introduced. This release included list comprehensions, a full garbage collector and it was supporting unicode. Python flourished for another 8 years in the versions 2.x before the next major release as Python 3.0 (also known as "Python 3000" and "Py3K") was released. Python 3 is not backwards compatible with Python 2.x. The emphasis in Python 3 had been on the removal of duplicate programming constructs and modules, thus fulfilling or coming close to fulfilling the 13th law of the Zen of Python: "There should be one -- and preferably only one -- obvious way to do it." Some changes in Python 7.3:

- Print is now a function.
- Views and iterators instead of lists
- The rules for ordering comparisons have been simplified. E.g., a heterogeneous list cannot be sorted, because all the elements of a list must be comparable to each other.
- There is only one integer type left, i.e., int. long is int as well.
- The division of two integers returns a float instead of an integer. "/" can be used to have the "old" behaviour.
- Text Vs. Data Instead of Unicode Vs. 8-bit

Purpose

We demonstrated that our approach enables successful segmentation of intra-retinal layers—even with low-quality images containing speckle noise, low contrast, and different intensity ranges throughout—with the assistance of the ANIS feature.

Python

Python is an interpreted high-level programming language for general-purpose programming. Created by Guido van Rossum and first released in 1991, Python has a design philosophy that emphasizes code readability, notably using significant whitespace.

Python features a dynamic type system and automatic memory management. It supports multiple programming paradigms, including object-oriented, imperative, functional and procedural, and has a large and comprehensive standard library.

- Python is Interpreted – Python is processed at runtime by the interpreter. You do not need to compile your program before executing it. This is similar to PERL and PHP.
- Python is Interactive – you can actually sit at a Python prompt and interact with the interpreter directly to write your programs.

Python also acknowledges that speed of development is important. Readable and terse code is part of this, and so is access to powerful constructs that avoid tedious repetition of code. Maintainability also ties into this may be an all but useless metric, but it does say something about how much code you have to scan, read and/or understand to troubleshoot problems or tweak behaviors. This speed of development, the ease with which a programmer of other languages can pick up basic Python skills and the huge standard library is key to another area where Python excels. All its tools have been quick to implement, saved a lot of time, and several of them have later been patched and updated by people with no Python background - without breaking.

6.3 Modules Used in Project

TensorFlow

TensorFlow is a free and open-source software library for dataflow and differentiable programming across a range of tasks. It is a symbolic math library and is also used for machine learning applications such as neural networks. It is used for both research and production at Google. TensorFlow was developed by the Google Brain team for internal Google use. It was released under the Apache 2.0 open-source license on November 9, 2015.

NumPy

NumPy is a general-purpose array-processing package. It provides a high-performance multidimensional array object, and tools for working with these arrays. It is the fundamental package for scientific computing with Python. It contains various features including these important ones:

- A powerful N-dimensional array object
- Sophisticated (broadcasting) functions
- Tools for integrating C/C++ and Fortran code
- Useful linear algebra, Fourier transform, and random number capabilities

Besides its obvious scientific uses, NumPy can also be used as an efficient multi-dimensional container of generic data. Arbitrary datatypes can be defined using NumPy which allows NumPy to seamlessly and speedily integrate with a wide variety of databases.

Pandas

Pandas is an open-source Python Library providing high-performance data manipulation and analysis tool using its powerful data structures. Python was majorly used for data munging and preparation. It had very little contribution towards data analysis. Pandas solved this problem. Using Pandas, we can accomplish five typical steps in the processing and analysis of data, regardless of the origin of data load, prepare, manipulate, model, and analyse. Python with Pandas is used in a wide range of fields including academic and commercial domains including finance, economics, Statistics, analytics, etc.

Matplotlib

Matplotlib is a Python 2D plotting library which produces publication quality figures in a variety of hardcopy formats and interactive environments across platforms. Matplotlib can be used in Python scripts, the Python and IPython shells, the Jupyter Notebook, web application servers, and four graphical user interface toolkits. Matplotlib tries to make easy things easy and hard things possible. You can generate plots, histograms, power spectra, bar charts, error charts, scatter plots, etc., with just a few lines of code. For examples, see the sample plots and thumbnail gallery.

Scikit – learn

Scikit-learn provides a range of supervised and unsupervised learning algorithms via a consistent interface in Python. It is licensed under a permissive simplified BSD license and is distributed under many Linux distributions, encouraging academic and commercial use.

Python is an interpreted high-level programming language for general-purpose programming. Created by Guido van Rossum and first released in 1991, Python has a design philosophy that emphasizes code readability, notably using significant whitespace.

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6.4 Install Python Step-by-Step in Windows and Mac

Python a versatile programming language doesn't come pre-installed on your computer devices. Python was first released in the year 1991 and until today it is a very popular highlevel programming language. Its style philosophy emphasizes code readability with its notable use of great whitespace.

The object-oriented approach and language construct provided by Python enables programmers to write both clear and logical code for projects. This software does not come pre-packaged with Windows.

How to Install Python on Windows and Mac

There have been several updates in the Python version over the years. The question is how to install Python? It might be confusing for the beginner who is willing to start learning Python but this tutorial will solve your query. The latest or the newest version of Python is version 3.7.4 or in other words, it is Python 3.

Note: The python version 3.7.4 cannot be used on Windows XP or earlier devices.

Before you start with the installation process of Python. First, you need to know about your System Requirements. Based on your system type i.e., operating system and based processor, you must download the python version. My system type is a Windows 64-bit operating system. So, the steps below are to install python version 3.7.4 on Windows 7 device or to install Python 3. Download the Python Cheatsheet [here](#). The steps on how to install Python on Windows 10, 8 and 7 are divided into 4 parts to help understand better.

Download the Correct version into the system

Step 1: Go to the official site to download and install python using Google Chrome or any other web browser. OR Click on the following link: <https://www.python.org>



Now, check for the latest and the correct version for your operating system.

Step 2: Click on the Download Tab.



Step 3: You can either select the Download Python for windows 3.7.4 button in Yellow Color or you can scroll further down and click on download with respective to their version. Here, we are downloading the most recent python version for windows 3.7.4

Looking for a specific release?

Python releases by version number:

Release version	Release date	Click for more	
Python 3.7.4	July 8, 2019	Download	Release Notes
Python 3.6.9	July 2, 2019	Download	Release Notes
Python 3.7.3	March 25, 2019	Download	Release Notes
Python 3.4.10	March 18, 2019	Download	Release Notes
Python 3.5.7	March 18, 2019	Download	Release Notes
Python 2.7.16	March 4, 2019	Download	Release Notes
Python 3.7.2	Dec. 24, 2018	Download	Release Notes

Step 4: Scroll down the page until you find the Files option.

Step 5: Here you see a different version of python along with the operating system.

Files

Version	Operating System	Description	MD5 Sum	File Size	GPG
Cropped source tarball	Source release		68111671e5b2db4ae77b9ab01b0f09be	23817663	SiG
XZ compressed source tarball	Source release		d33e4aae66097051c2eca45ee3604803	17131432	SiG
macOS 64-bit/32-bit installer	Mac OS X	for Mac OS X 10.6 and later	6428b4fa75d3da91a442c8a1ce08e6	34898416	SiG
macOS 64-bit installer	Mac OS X	for OS X 10.9 and later	5dd605c38257a45773bf5e4a936b241f	28082845	SiG
Windows help file	Windows		d63999573a2c56b2ac56cade6b47cd2	8131761	SiG
Windows x86-64 embeddable zip file	Windows	for AMD64/EM64/x64	9b00c3cfd29ec0b9abe63184a0729a2	7504391	SiG
Windows x86-64 executable installer	Windows	for AMD64/EM64/x64	a702b4b0aef76debdb35a3a583e563400	26880368	SiG
Windows x86-64 web-based installer	Windows	for AMD64/EM64/x64	28c31c60f8b6d73ae9e53a3bd351b4bd2	1362904	SiG
Windows x86 embeddable zip file	Windows		9fab3b6188a1879fda94133574139d8	6741628	SiG
Windows x86 executable installer	Windows		33cc602942a54446a3d8645147e394789	25663848	SiG
Windows x86 web-based installer	Windows		1b670cfa5d317df82c30983ea371d87c	1324608	SiG

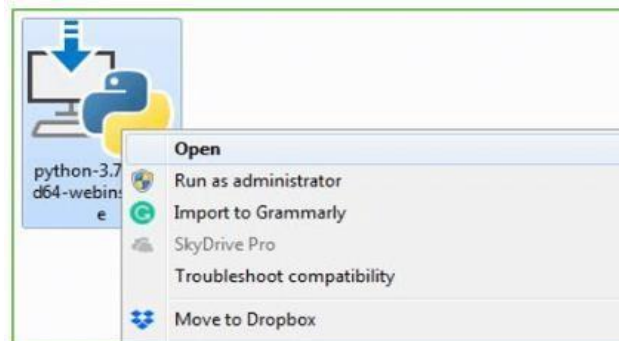
- To download Windows 32-bit python, you can select any one from the three options: Windows x86 embeddable zip file, Windows x86 executable installer or Windows x86 web-based installer.
- To download Windows 64-bit python, you can select any one from the three options: Windows x86-64 embeddable zip file, Windows x86-64 executable installer or Windows x86-64 web-based installer.

Here we will install Windows x86-64 web-based installer. Here your first part regarding which version of python is to be downloaded is completed. Now we move ahead with the second part in installing python i.e., Installation

Note: To know the changes or updates that are made in the version you can click on the Release Note Option.

Installation of Python

Step 1: Go to Download and Open the downloaded python version to carry out the installation process.



Step 2: Before you click on Install Now, make sure to put a tick on Add Python 3.7 to PATH.



Step 3: Click on Install NOW After the installation is successful. Click on Close.



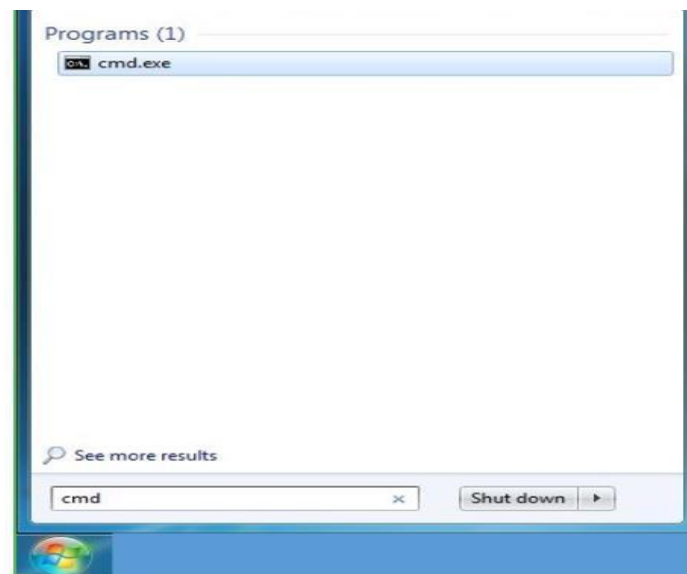
With these above three steps on python installation, you have successfully and correctly installed Python. Now is the time to verify the installation.

Note: The installation process might take a couple of minutes.

Verify the Python Installation

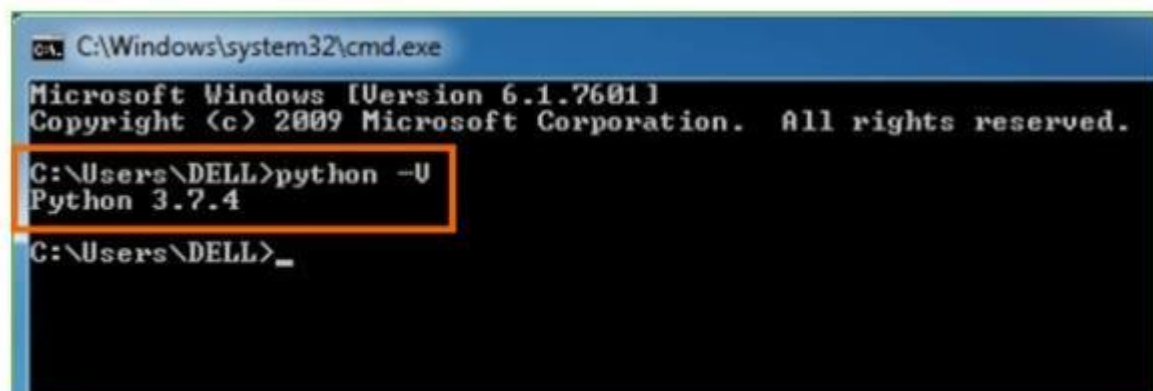
Step 1: Click on Start

Step 2: In the Windows Run Command, type “cmd”.



Step 3: Open the Command prompt option.

Step 4: Let us test whether the python is correctly installed. Type python -V and press Enter.



Step 5: You will get the answer as 3.7.4

Note: If you have any of the earlier versions of Python already installed. You must first uninstall the earlier version and then install the new one.

Check how the Python IDLE works

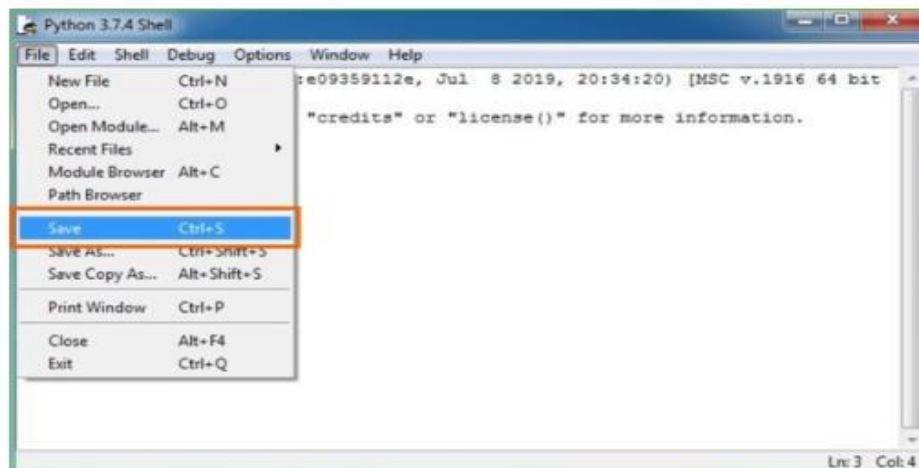
Step 1: Click on Start

Step 2: In the Windows Run command, type “python idle”.



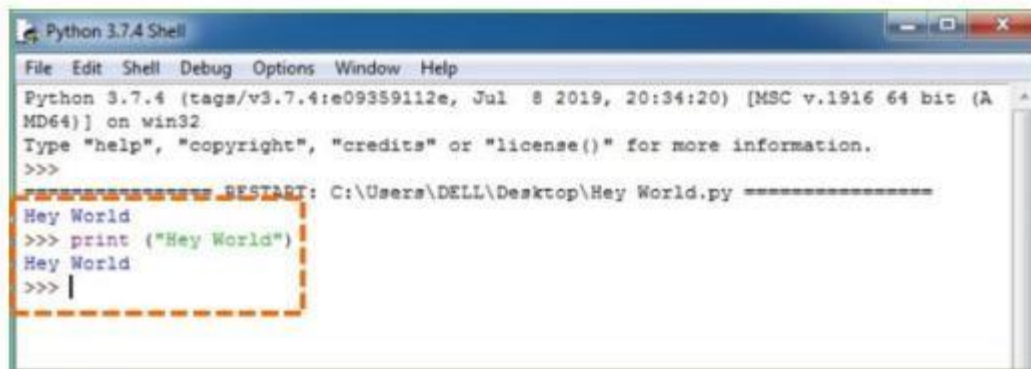
Step 3: Click on IDLE (Python 3.7 64-bit) and launch the program

Step 4: To go ahead with working in IDLE you must first save the file. Click on File > Click on Save



Step 5: Name the file and save as type should be Python files. Click on SAVE. Here I have named the files as Hey World.

Step 6: Now for e.g., enter print (“Hey World”) and Press Enter.

A screenshot of a Python 3.7.4 Shell window. The window has a menu bar with 'File', 'Edit', 'Shell', 'Debug', 'Options', 'Window', and 'Help'. The title bar says 'Python 3.7.4 Shell'. The main text area shows the following: 'Python 3.7.4 (tags/v3.7.4:e09359112e, Jul 8 2019, 20:34:20) [MSC v.1916 64 bit (AMD64)] on win32', 'Type "help", "copyright", "credits" or "license()" for more information.', and a prompt '>>>'. Below this, a dashed orange box highlights the following lines: 'Hey World', '>>> print ("Hey World")', 'Hey World', and '>>> |'. The text '***** START: C:\Users\DELL\Desktop\Hey World.py *****' is also visible in the background.

```
Python 3.7.4 Shell
File Edit Shell Debug Options Window Help
Python 3.7.4 (tags/v3.7.4:e09359112e, Jul 8 2019, 20:34:20) [MSC v.1916 64 bit (AMD64)] on win32
Type "help", "copyright", "credits" or "license()" for more information.
>>>
***** START: C:\Users\DELL\Desktop\Hey World.py *****
Hey World
>>> print ("Hey World")
Hey World
>>> |
```

You will see that the command given is launched. With this, we end our tutorial on how to install Python. You have learned how to download python for windows into your respective operating system.

Note: Unlike Java, Python does not need semicolons at the end of the statements otherwise it won't work.

7. SYSTEM REQUIREMENTS SPECIFICATIONS

7.1 Software Requirements

The functional requirements or the overall description documents include the product perspective and features, operating system and operating environment, graphics requirements, design constraints and user documentation.

The appropriation of requirements and implementation constraints gives the general overview of the project in regard to what the areas of strength and deficit are and how to tackle them.

- Python IDLE 3.7 version (or)
- Anaconda 3.7 (or)
- Jupiter (or)
- Google colab

7.2 Hardware Requirements

Minimum hardware requirements are very dependent on the particular software being developed by a given Enthought Python / Canopy / VS Code user. Applications that need to store large arrays/objects in memory will require more RAM, whereas applications that need to perform numerous calculations or tasks more quickly will require a faster processor.

Operating system : Windows, Linux Processor

Minimum intel : i3

Ram : Minimum 4 GB

Hard disk : Minimum 250GB

8. FUNCTIONAL REQUIREMENTS

8.1 Output Design

Outputs from computer systems are required primarily to communicate the results of processing to users. They are also used to provide a permanent copy of the results for later consultation. The various types of outputs in general are:

- External Outputs, whose destination is outside the organization
- Internal Outputs whose destination is within organization and they are the User's main interface with the computer.
- Operational outputs whose use is purely within the computer department.
- Interface outputs, which involve the user in communicating directly.

Output Definition

The outputs should be defined in terms of the following points:

- Type of the output
- Content of the output
- Format of the output
- Location of the output
- Frequency of the output
- Volume of the output
- Sequence of the output

It is not always desirable to print or display data as it is held on a computer. It should be decided as which form of the output is the most suitable.

8.2 Input Design

Input design is a part of overall system design. The main objective during the input design is as given below:

- To produce a cost-effective method of input.
- To achieve the highest possible level of accuracy.
- To ensure that the input is acceptable and understood by the user.

Input Stages

The main input stages can be listed as below:

- Data recording
- Data transcription
- Data conversion
- Data verification
- Data control
- Data transmission
- Data validation
- Data correction

Input Types

It is necessary to determine the various types of inputs. Inputs can be categorized as follows:

- External inputs, which are prime inputs for the system.
- Internal inputs, which are user communications with the system.
- Operational, which are computer department's communications to the system?
- Interactive, which are inputs entered during a dialogue.

Input Media

At this stage choice has to be made about the input media. To conclude about the input media consideration has to be given to:

- Type of input

- Flexibility of format
- Speed
- Accuracy
- Verification methods
- Rejection rates
- Ease of correction
- Storage and handling requirements
- Security
- Easy to use
- Portability

Keeping in view the above description of the input types and input media, it can be said that most of the inputs are of the form of internal and interactive.

As Input data is to be directly keyed in by the user, the keyboard can be considered to be the most suitable input device.

Error Avoidance

At this stage care is to be taken to ensure that input data remains accurate from the stage at which it is recorded up to the stage in which the data is accepted by the system. This can be achieved only by means of careful control each time the data is handled.

Error Detection

Even though every effort is made to avoid the occurrence of errors, still a small proportion of errors is always likely to occur, these types of errors can be discovered by using validations to check the input data.

Data Validation

Procedures are designed to detect errors in data at a lower level of detail. Data validations have been included in the system in almost every area where there is a possibility for the user to commit errors. The system will not accept invalid data.

8.3 User Interface Design

It is essential to consult the system users and discuss their needs while designing the user interface:

User Interface Systems Can Be Broadly Classified As:

- User initiated interface : the user is in charge, controlling the progress of the user/computer dialogue.
- Computer initiated interfaces : In the computer-initiated interface, the computer selects the next stage in the interaction.

In the computer-initiated interfaces the computer guides the progress of the user/computer dialogue. Information is displayed and the user response of the computer takes action or displays further information.

User Initiated Interfaces :

User initiated interfaces fall into two approximate classes:

- Command driven interfaces: In this type of interface the user inputs commands or queries which are interpreted by the computer.
- Forms oriented interface: The user calls up an image of the form to his/her screen and fills in the form. The forms-oriented interface is chosen because it is the best choice.

Computer-Initiated Interfaces:

The following computer – initiated interfaces were used:

- The menu system for the user is presented with a list of alternatives and the user chooses one; of alternatives.
- Questions – answer type dialog system where the computer asks question and takes action based on the basis of the users reply.

Right from the start the system is going to be menu driven, the opening menu displays the available options. Choosing one option gives another popup menu with more options. In this way every option leads the users to data entry form where the user can key in the data.

Error Message Design

The design of error messages is an important part of the user interface design. As user is bound to commit some errors or other while designing a system the system should be designed to be helpful by providing the user with information regarding the error he/she has committed.

This application must be able to produce output at different modules for different inputs.

8.4 Performance Requirements

Performance is measured in terms of the output provided by the application. Requirement specification plays an important part in the analysis of a system. Only when the requirement specifications are properly given, it is possible to design a system, which will fit into required environment. It rests largely in the part of the users of the existing system to give the requirement specifications because they are the people who finally use the system.

This is because the requirements have to be known during the initial stages so that the system can be designed according to those requirements. It is very difficult to change the system once it has been designed and on the other hand designing a system, which does not cater to the requirements of the user, is of no use.

The requirement specification for any system can be broadly stated as given below:

- The system should be able to interface with the existing system
- The system should be accurate
- The system should be better than the existing system
- The existing system is completely dependent on the user to perform all the duties.

9. SOURCE CODE

```
from tkinter import messagebox

from tkinter import *

from tkinter import simpledialog

import tkinter

import matplotlib.pyplot as plt

import numpy as np

from tkinter import ttk

from tkinter import filedialog

import pandas as pd

from sklearn.model_selection import train_test_split

import os

import cv2

from sklearn.preprocessing import StandardScaler

from sklearn.metrics import accuracy_score

from sklearn import svm

from sklearn.metrics import accuracy_score

from sklearn.metrics import f1_score

from sklearn.metrics import precision_score

from sklearn.metrics import recall_score

import matplotlib.pyplot as plt

import seaborn as sns

import os

from sklearn.metrics import confusion_matrix
```



```

main = Tk()

main.title("Children ADHD Disease Detection using Pose Extimation Technique")

main.geometry("1300x1200")


global filename

global X, Y

global X_train, X_test, y_train, y_test, scaler, svm_cls

global dataset

proto_File = "Models/pose_deploy_linevec.prototxt"

weights_File = "Models/pose_iter_440000.caffemodel"

n_Points = 18

POSE_PAIRS = [
[1,0],[1,2],[1,5],[2,3],[3,4],[5,6],[6,7],[1,8],[8,9],[9,10],[1,11],[11,12],[12,13],[0,14],[0,15],[14,16],[15,17]]

in_Width = 368

in_Height = 368

threshold = 0.1

POSE_NAMES = ["Head", "Neck", "RShoulder", "RElbow", "RWrist", "LShoulder",
"LElbow", "LWrist", "RHip", "RKnee",

"RAnkle", "LHip", "LKnee", "LAnkle", "Chest", "Background"]


net = cv2.dnn.readNetFromCaffe(proto_File, weights_File)

net.setPreferableBackend(cv2.dnn.DNN_TARGET_CPU)


def uploadDataset():

    global filename, dataset

    filename = filedialog.askopenfilename(initialdir="ADHDDataset")

```

```

text.delete('1.0', END)

text.insert(END,filename+" loaded\n\n")

dataset = pd.read_csv(filename)

text.insert(END,str(dataset.head()))

```

```

def processDataset():

```

```

    global dataset, X, Y, scaler

    text.delete('1.0', END)

    data = dataset.values

    X = data[:,0:data.shape[1]-1]

    Y = data[:,data.shape[1]-1]

    indices = np.arange(X.shape[0]) #shuffling dataset values

    np.random.shuffle(indices)

    X = X[indices]

    Y = Y[indices]

    scaler = StandardScaler()

    X = scaler.fit_transform(X)

    text.insert(END,"Dataset Processing, Shuffling & Normalization Completed\n\n")

    text.insert(END,"Normalized Dataset Values = "+str(X))

```

```

def splitDataset():

```

```

    text.delete('1.0', END)

    global X, Y, X_train, X_test, y_train, y_test

    X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2)

    text.insert(END,"Total records found in Dataset : "+str(X.shape[0])+"\n")

    text.insert(END,"Total features found in each record : "+str(X.shape[1])+"\n")

```

```

text.insert(END,"Dataset Train & Test Split\n")

text.insert(END,"80% dataset size used to train algorithms :
"+str(X_train.shape[0])+"\n")

text.insert(END,"20% dataset size used to test algorithms :
"+str(X_test.shape[0])+"\n")

def calculateMetrics(algorithm, predict, y_test):

    label = ['Normal', 'ADHD Disease']

    a = accuracy_score(y_test,predict)*100

    p = precision_score(y_test, predict,average='macro') * 100

    r = recall_score(y_test, predict,average='macro') * 100

    f = f1_score(y_test, predict,average='macro') * 100

    text.insert(END,algorithm+" Accuracy : "+str(a)+"\n")

    text.insert(END,algorithm+" Precision : "+str(p)+"\n")

    text.insert(END,algorithm+" Recall : "+str(r)+"\n")

    text.insert(END,algorithm+" FScore : "+str(f)+"\n")

    conf_matrix = confusion_matrix(y_test, predict)

    plt.figure(figsize =(6, 3))

    ax = sns.heatmap(conf_matrix, xticklabels = label, yticklabels = label, annot = True,
cmap="viridis" ,fmt ="g");

    ax.set_ylim([0,len(label)])

    plt.title(algorithm+" Confusion matrix")

    plt.xticks(rotation=90)

    plt.ylabel('True class')

    plt.xlabel('Predicted class')

    plt.show()

```

```

def trainSVM():

    global svm_cls

    text.delete('1.0', END)

    global X_train, X_test, y_train, y_test

    svm_cls = svm.SVC(kernel="rbf", C = 12, probability=True, gamma="auto")

    svm_cls.fit(X_train, y_train)

    predict = svm_cls.predict(X_test)

    calculateMetrics("SVM", predict, y_test)


def predictADHD(testData):

    values = []

    testData = np.asarray(testData)

    values.append(testData)

    testData = np.asarray(values)

    testData = scaler.transform(testData)

    predict = svm_cls.predict(testData)

    return int(predict[0])


def detectDisease(frame):

    global net

    frame_Width = frame.shape[1]

    frame_Height = frame.shape[0]

    img = np.zeros((frame_Height, frame_Width, 3), dtype=np.uint8)

    inp_Blob = cv2.dnn.blobFromImage(frame, 1.0 / 255, (in_Width, in_Height), (0, 0,
0), swapRB=False, crop=False)

    net.setInput(inp_Blob)

```

```

output = net.forward()

H = output.shape[2]

W = output.shape[3]

points = []

testData = []

for i in range(n_Points):

    probMap = output[0, i, :, :]

    minVal, prob, minLoc, point = cv2.minMaxLoc(probMap)

    x = (frame_Width * point[0]) / W

    y = (frame_Height * point[1]) / H

    if prob > threshold :

        cv2.circle(frame, (int(x), int(y)), 8, (0, 255, 255), thickness=-1,
lineType=cv2.FILLED)

        cv2.putText(frame, "{}".format(i), (int(x), int(y)),
cv2.FONT_HERSHEY_SIMPLEX, 1, (0, 0, 255), 2, lineType=cv2.LINE_AA)

        points.append((int(x), int(y)))

        testData.append(x)

        testData.append(y)

    else :

        points.append(None)

        testData.append(0)

        testData.append(0)

predict = predictADHD(testData)

for pair in POSE_PAIRS:

    partA = pair[0]

    partB = pair[1]

```

```

print(str(pair[0])+" "+str(pair[1])+" "+str(partA)+" "+str(partB))

if points[partA] and points[partB]:

    cv2.line(img, points[partA], points[partB], (0, 255, 255), 3,
lineType=cv2.LINE_AA)

    cv2.line(frame, points[partA], points[partB], (0, 255, 255), 3,
lineType=cv2.LINE_AA)

    cv2.circle(frame, points[partA], 8, (0, 0, 255), thickness=-1,
lineType=cv2.FILLED)

    cv2.circle(frame, points[partB], 8, (0, 0, 255), thickness=-1,
lineType=cv2.FILLED)

return frame, img, predict

```

```

def imageDetect():

```

```

    text.delete('1.0', END)

    global scaler, svm_cls

    filename = filedialog.askopenfilename(initialdir="images")

    frame = cv2.imread(filename)

    frame, img, predict = detectDisease(frame)

    frame = cv2.resize(frame, (400, 400))

    img = cv2.resize(img, (400, 400))

    label = ['Normal', 'ADHD Disease']

    print(predict)

    cv2.putText(frame, 'Predicted As : '+label[predict], (10,
25), cv2.FONT_HERSHEY_SIMPLEX, 0.7, (0, 0, 255), 2)

    cv2.imshow("Pose Estimated Image", frame)

    cv2.imshow("Pose Image", img)

    cv2.waitKey(0)

```

```

def videoDetect():

    text.delete('1.0', END)

    global scaler, svm_cls

    filename = filedialog.askopenfilename(initialdir="videos")

    normal_count = 0

    abnormal_count = 0

    video = cv2.VideoCapture(filename)

    count = 0

    while(True):

        ret, frame = video.read()

        if ret == True:

            filename = "temp.png"

            frame, img, predict = detectDisease(frame)

            if predict == 0:

                normal_count += 1

            else:

                abnormal_count + 1

            cv2.imshow("Estimated Pose", frame)

            if cv2.waitKey(5) & 0xFF == ord('q'):

                break

            count = count + 1

            if count > 20:

                break

        else:

            break

```

```

video.release()

cv2.destroyAllWindows()

if normal_count >= abnormal_count:

    text.insert(END,"Pose in Video Predicted as : NORMAL\n")

else:

    text.insert(END,"Pose in Video Predicted as : ADHD Disease\n")


font = ('times', 15, 'bold')

title = Label(main, text='Children ADHD Disease Detection using Pose Extimation
Technique')

title.config(bg='darkviolet', fg='gold')

title.config(font=font)

title.config(height=3, width=120)

title.place(x=0,y=5)

font1 = ('times', 13, 'bold')

ff = ('times', 12, 'bold')


uploadButton = Button(main, text="Upload ADHD Pose Dataset",
command=uploadDataset)

uploadButton.place(x=20,y=100)

uploadButton.config(font=ff)


processButton = Button(main, text="Preprocess Dataset", command=processDataset)

processButton.place(x=20,y=150)

processButton.config(font=ff)

```



```

splitButton = Button(main, text="Split Dataset Train & Test", command=splitDataset)

splitButton.place(x=20,y=200)

splitButton.config(font=ff)


svmButton = Button(main, text="Train SVM Algorithm", command=trainSVM)

svmButton.place(x=20,y=250)

svmButton.config(font=ff)


imageDetectionButton = Button(main, text="Disease Detection from Test Image",
command=imageDetect)

imageDetectionButton.place(x=20,y=300)

imageDetectionButton.config(font=ff)


videoDetectionButton = Button(main, text="Disease Detection from Video",
command=videoDetect)

videoDetectionButton.place(x=20,y=350)

videoDetectionButton.config(font=ff)

font1 = ('times', 12, 'bold')

text=Text(main,height=30,width=110)

scroll=Scrollbar(text)

text.configure(yscrollcommand=scroll.set)

text.place(x=360,y=100)

text.config(font=font1)

main.config(bg='forestgreen')

main.mainloop()

```

10. RESULTS AND DISCUSSION

Attention Deficit Hyperactivity Disorder (ADHD) disease mostly found in children's and this disease can be detected by analysing children's pose estimation. Currently no such technique exists to detect ADHD automatically and can be detected using manual monitoring but this technique is error prone and difficult to detect.

To overcome from above issue we are employing machine learning SVM algorithm which will get trained on normal and abnormal children's poses and then it will analyse pose from new test images or videos to predict whether children post is normal or contains ADHD abnormal poses.

To train SVM we have used below pose dataset which contains children motions

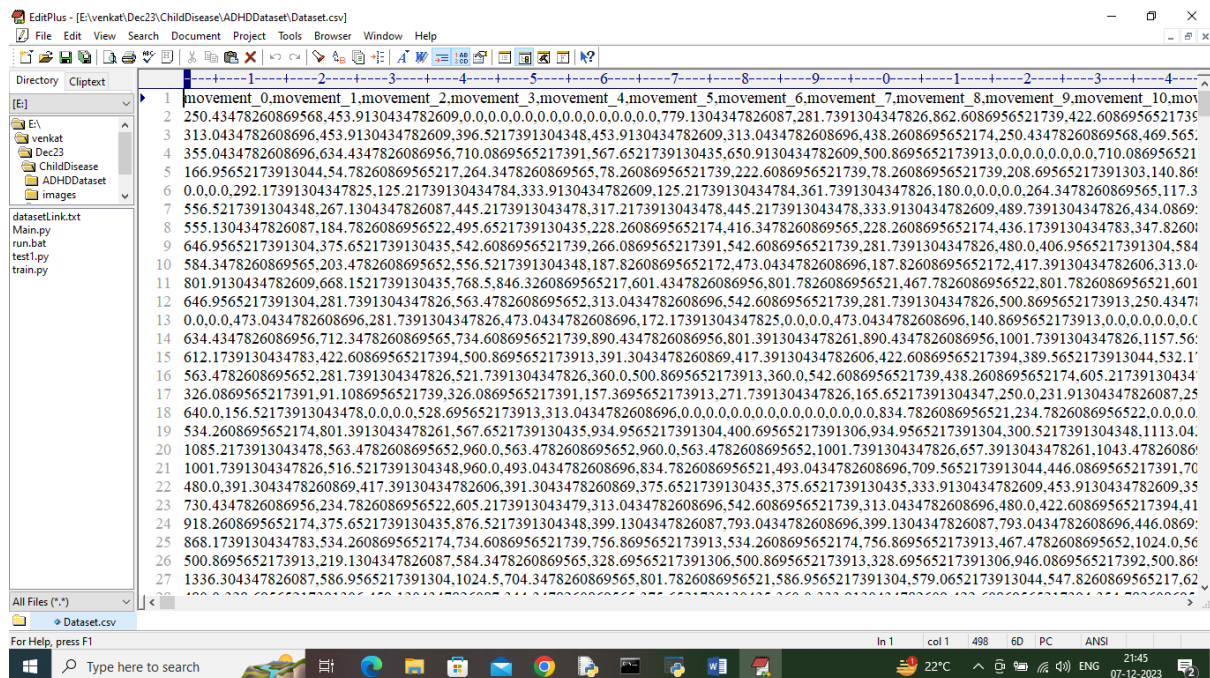


Fig 10.1 Dataset Screens

In above dataset screen first row represents dataset column names and remaining rows represents dataset values and in last column we have class labels as 0 or 1 where 0 represents NORMAL and 1 represents ADHD disease.

To implement this project we have designed following modules

- 1) Upload ADHD Pose Dataset: using this module we will upload dataset and to application and then read all dataset values
- 2) Pre-process Dataset: using this module we will clean, normalized and shuffle dataset values

- 3) Split Dataset Train & Test: using this module dataset will be split into train and test where application using 80% dataset records for training and 20% for testing
- 4) Train SVM Algorithm: 80% dataset will be input to SVM algorithm to train a model and this model will be applied on 20% test data to calculate prediction accuracy
- 5) Disease Detection from Test Image: using this module we will upload test image and then calculate or estimate poses and then applied SVM algorithm to predict whether image is normal or abnormal
- 6) Disease Detection from Video: using this module we can predict ADHD from videos also

SCREEN SHOTS OF OUTPUT:

To run project double click on run.bat file to get below screen

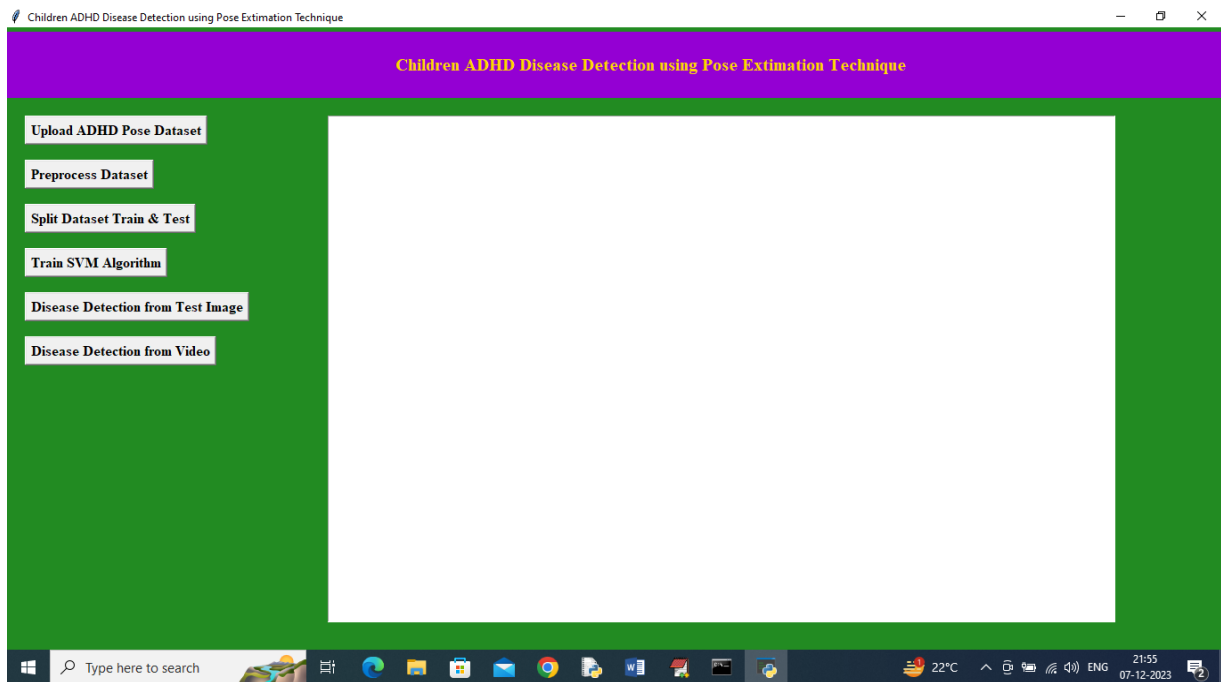


Fig 10.2 Upload ADHD Pose Dataset

In above screen click on 'Upload ADHD Pose Dataset' button to upload dataset and get below output

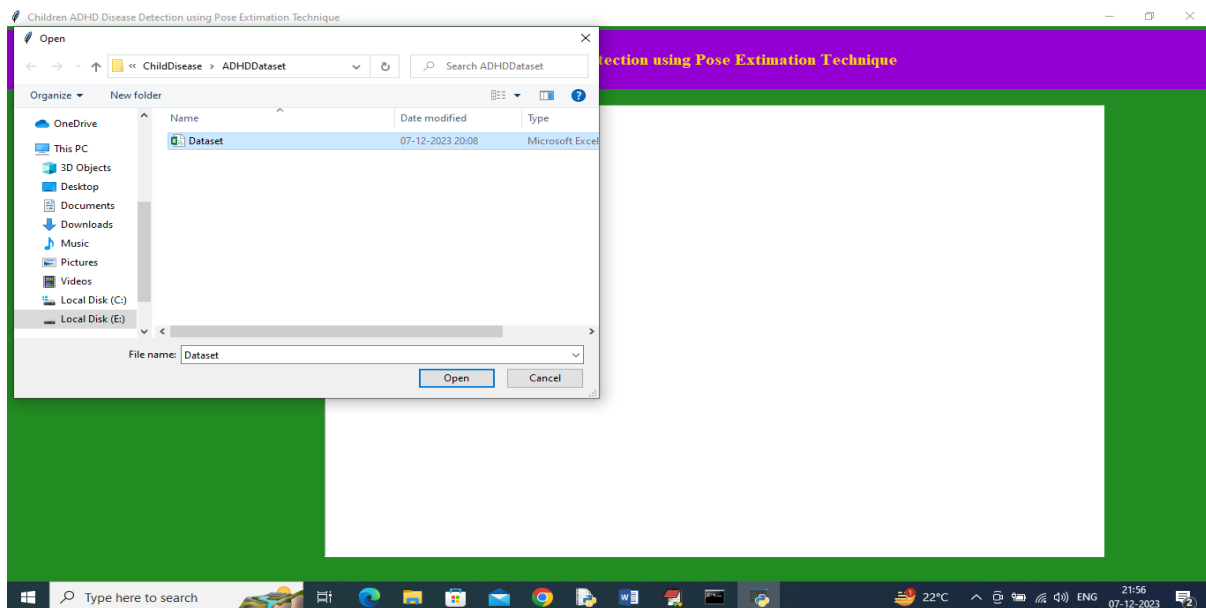


Fig 10.3 Selecting ADHD Dataset

In above screen selecting and uploading dataset and then click on ‘Open’ button to load dataset and get below output

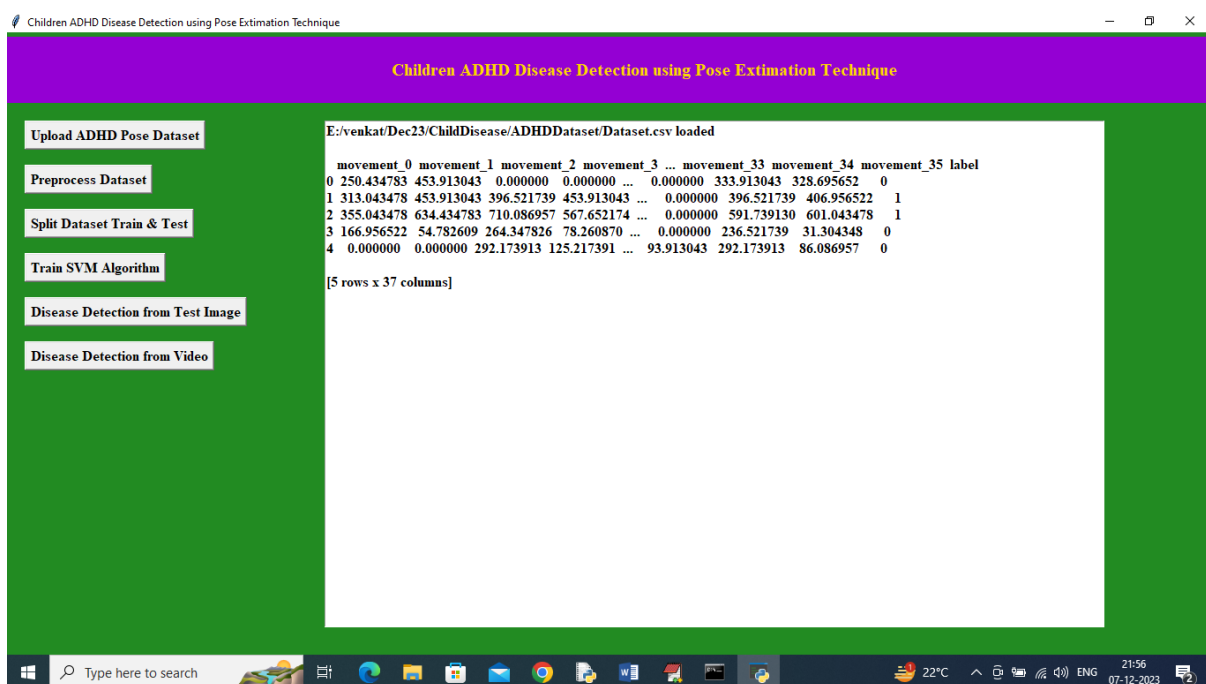


Fig 10.4 Pre-processing Dataset

In above screen dataset loaded and now click on ‘Pre-process Dataset’ button to clean, normalized and shuffle dataset values

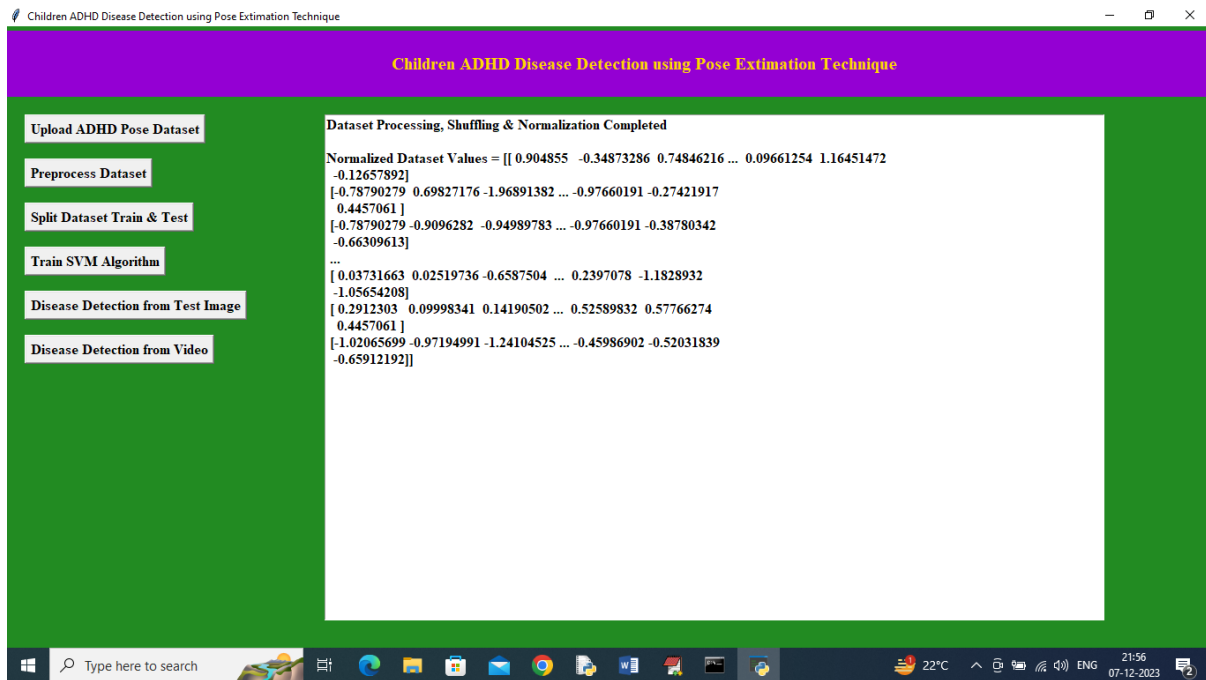


Fig 10.5 Normalization of Data

In above screen we can see dataset is normalized and now click on ‘Split Dataset Train & Test’ button to split dataset into train and test and then will get below output

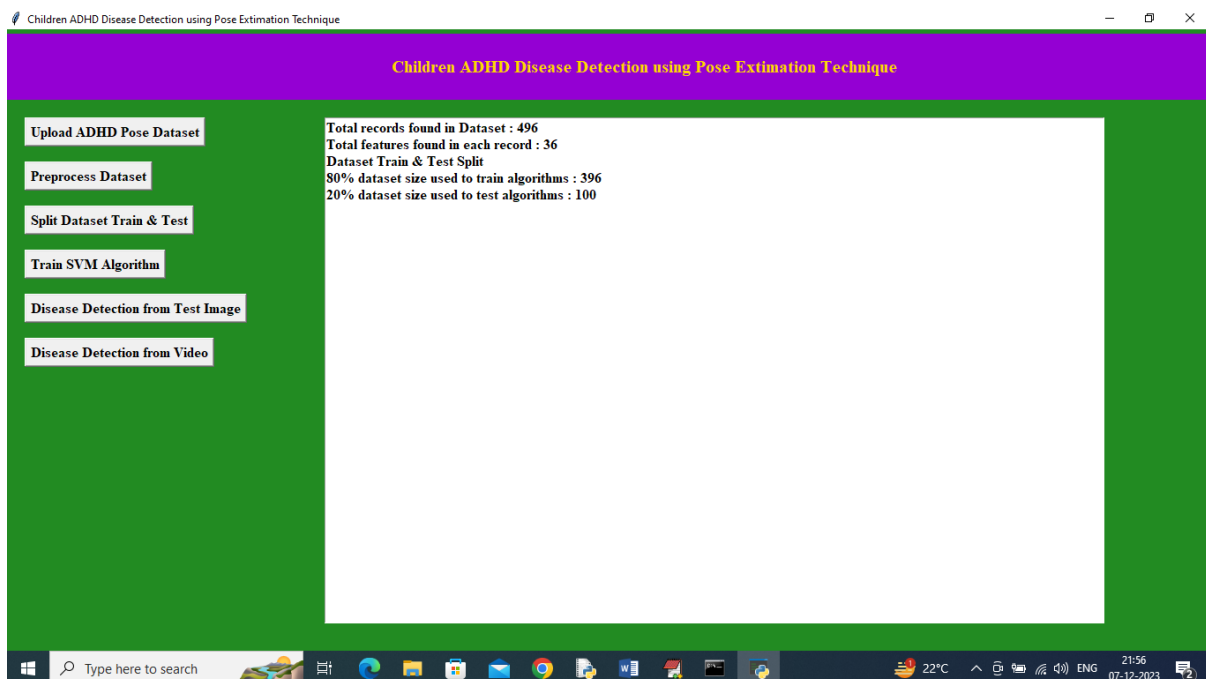


Fig 10.6 Split Dataset to Train & Test

In above screen can see dataset total size and then can see training and testing size and now click on ‘Train SVM Algorithm’ button to train SVM and get below output

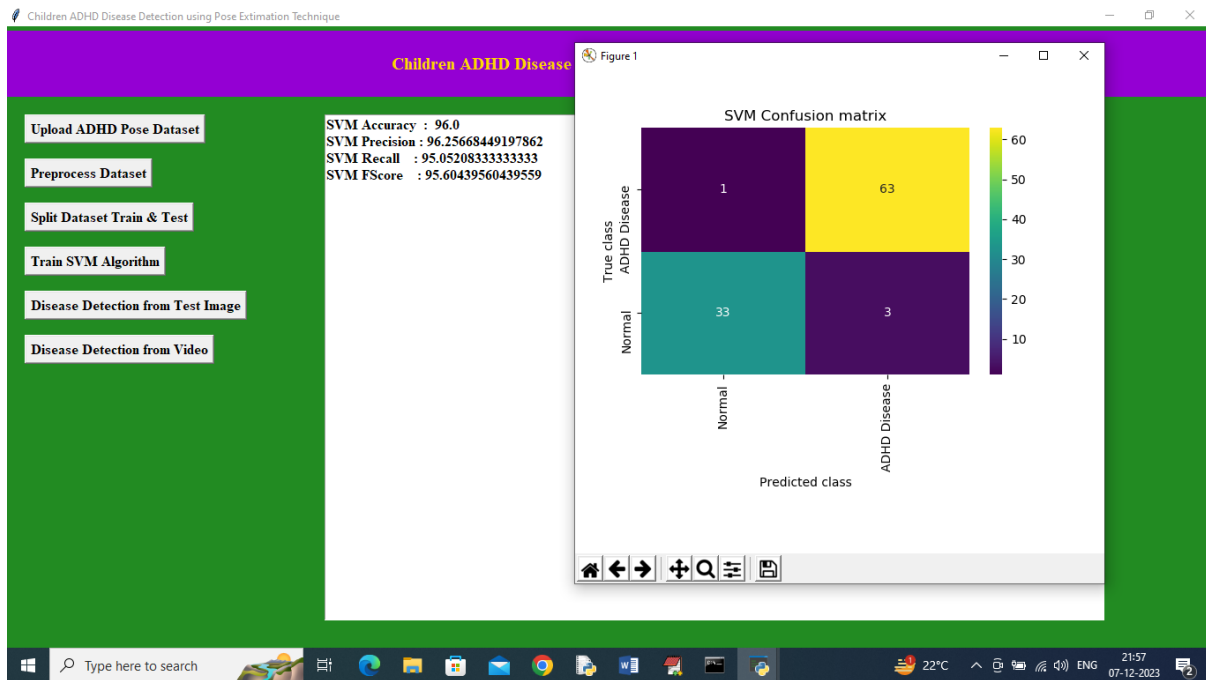


Fig 10.7 Train SVM Algorithm

In above screen SVM training completed and it got 96% accuracy and can see other metrics like precision, recall and FCSORE. In above confusion matrix graph x-axis represents Predicted Labels and y-axis represents True Labels and green and yellow boxes contains correct prediction count and all blue boxes represents incorrect prediction which are very few. Now close above graph and then click on ‘Disease Detection from Test Image’ button to upload test image and get below output

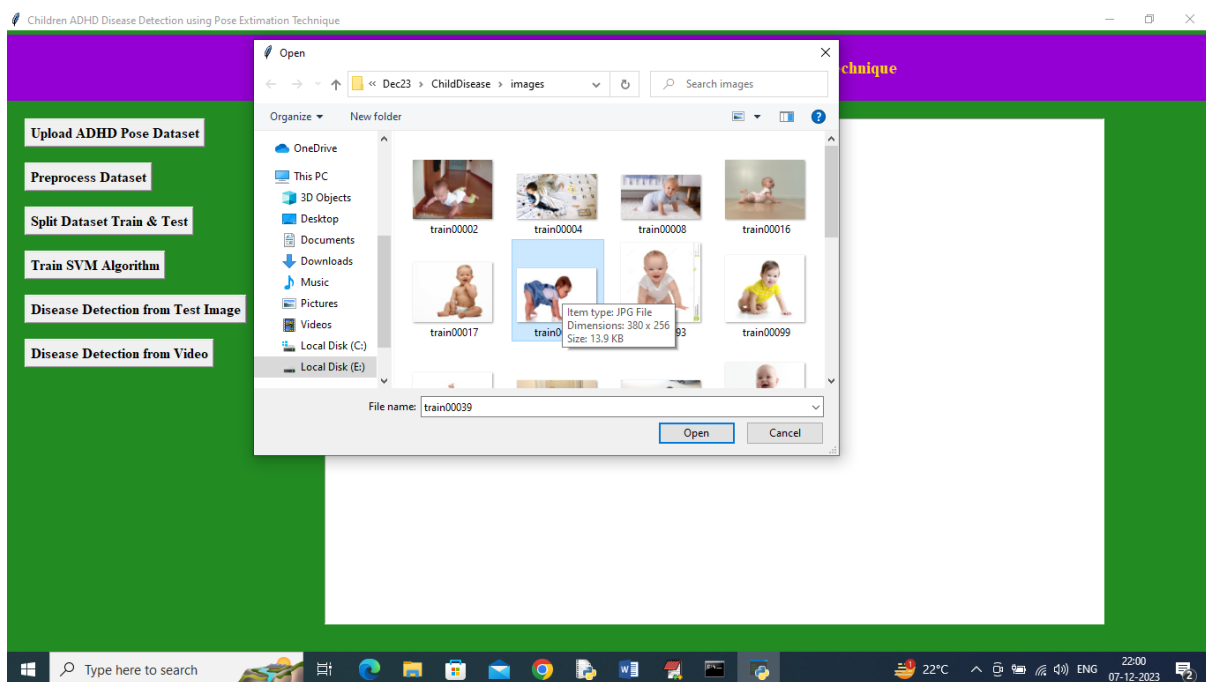


Fig 10.8 Disease Detection from Test Image

In above screen selecting and uploading test image and then click on ‘Open’ button to get below output

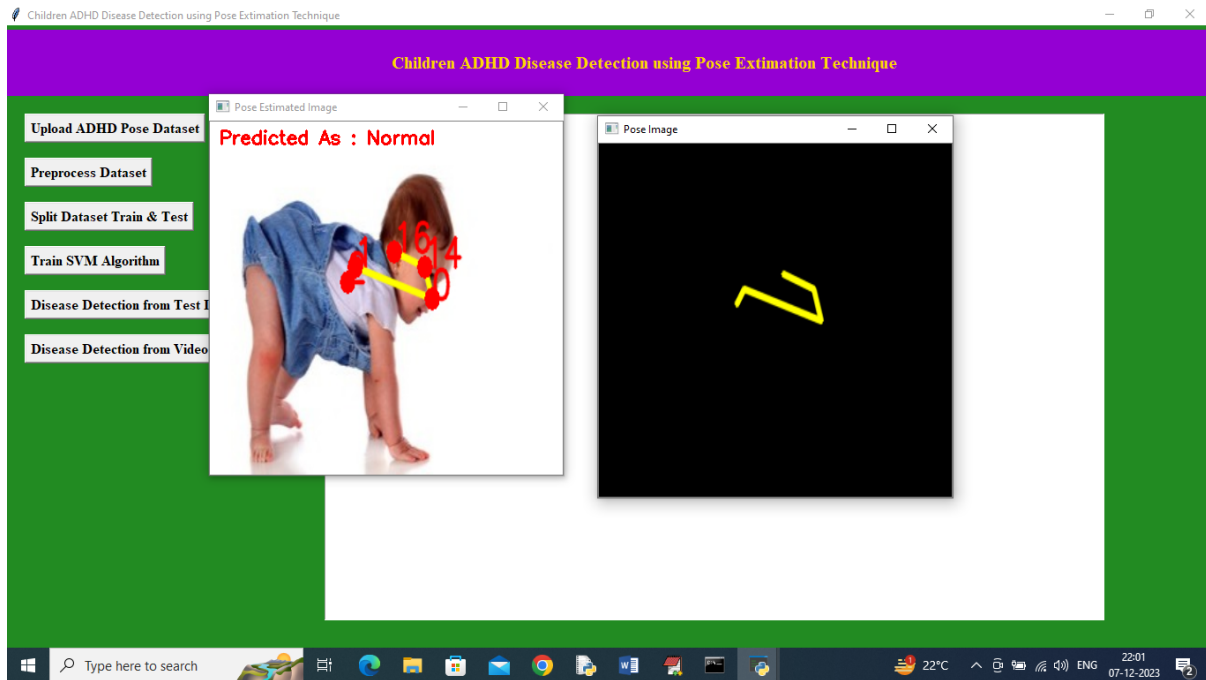


Fig 10.9 Pose Estimation and Prediction

In above screen pose is estimated and that estimated pose drawn in black window also and image predicted as Normal and similarly you can upload and test other images

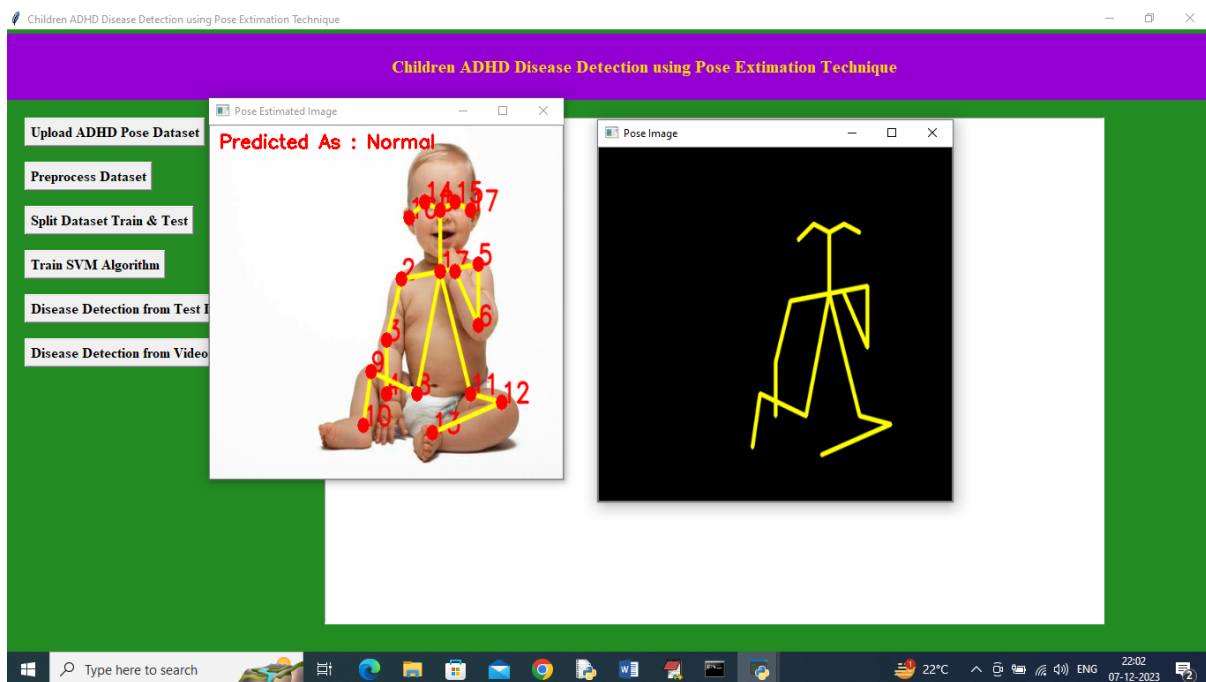


Fig 10.10 Pose Estimation and Prediction

In above screen can see another image output

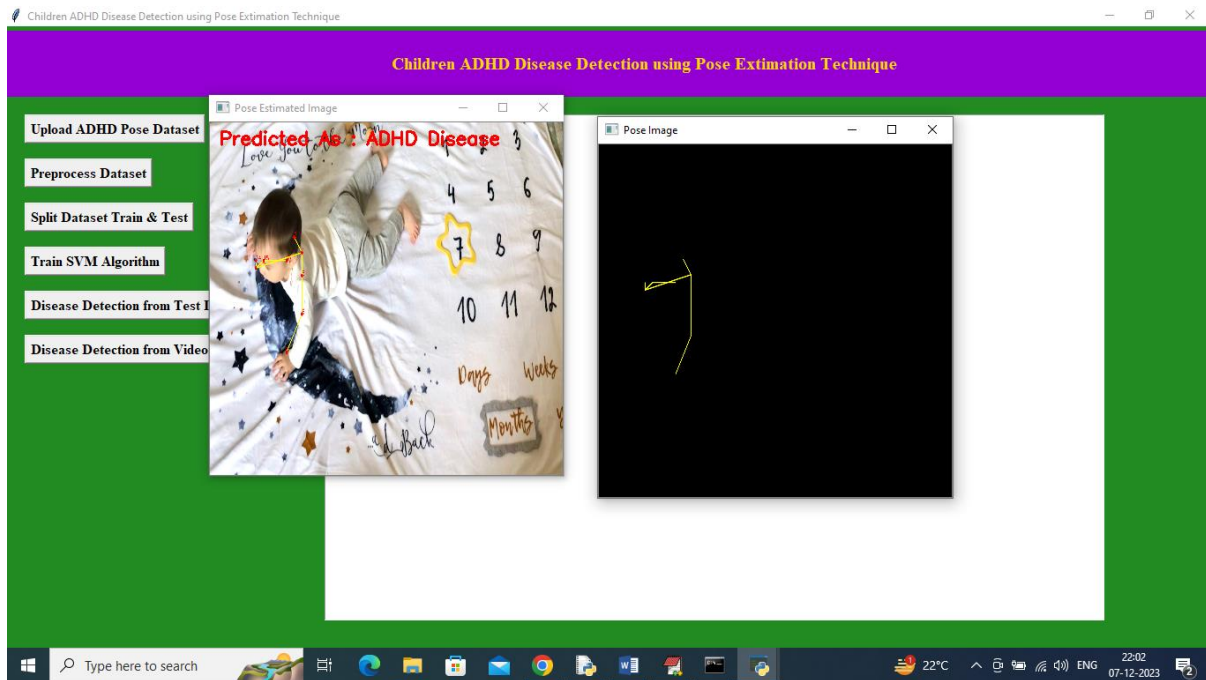


Fig 10.11 Disease Detection from Video

In above screen from pose ADHD disease detected and now click on ‘Disease Detection from Video’ button to upload video and get below output

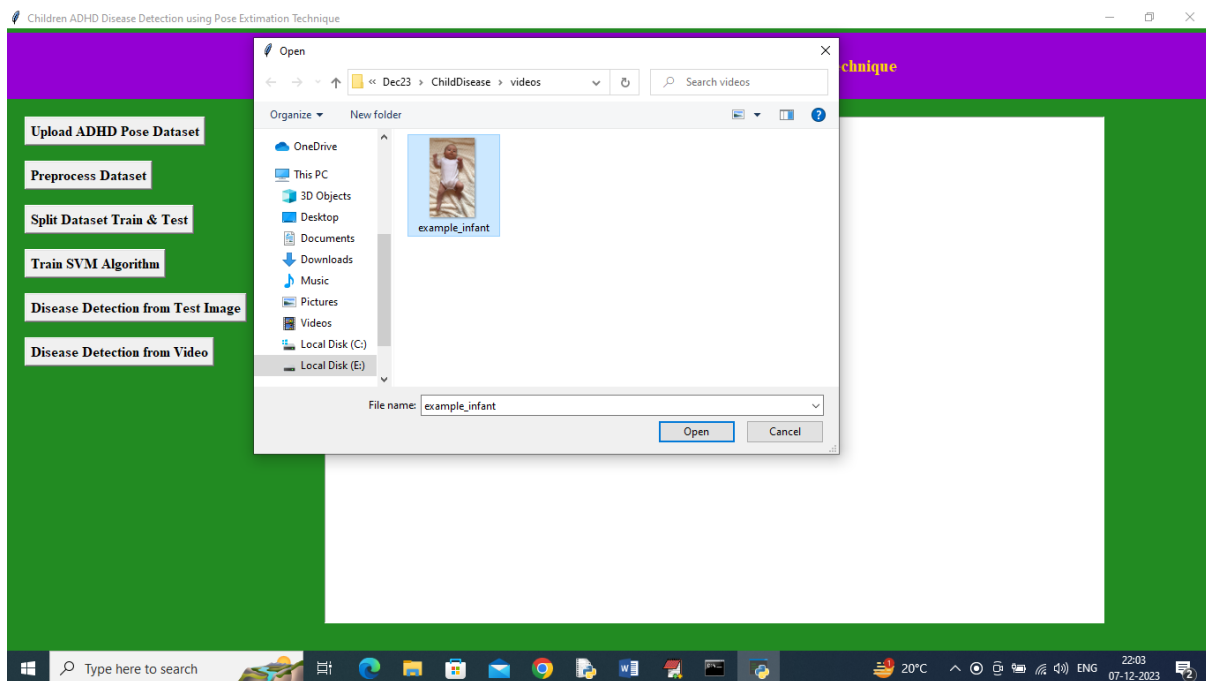


Fig 10.12 Pose Estimation

In above screen uploading video and then application will analyse all poses from video and then give prediction output

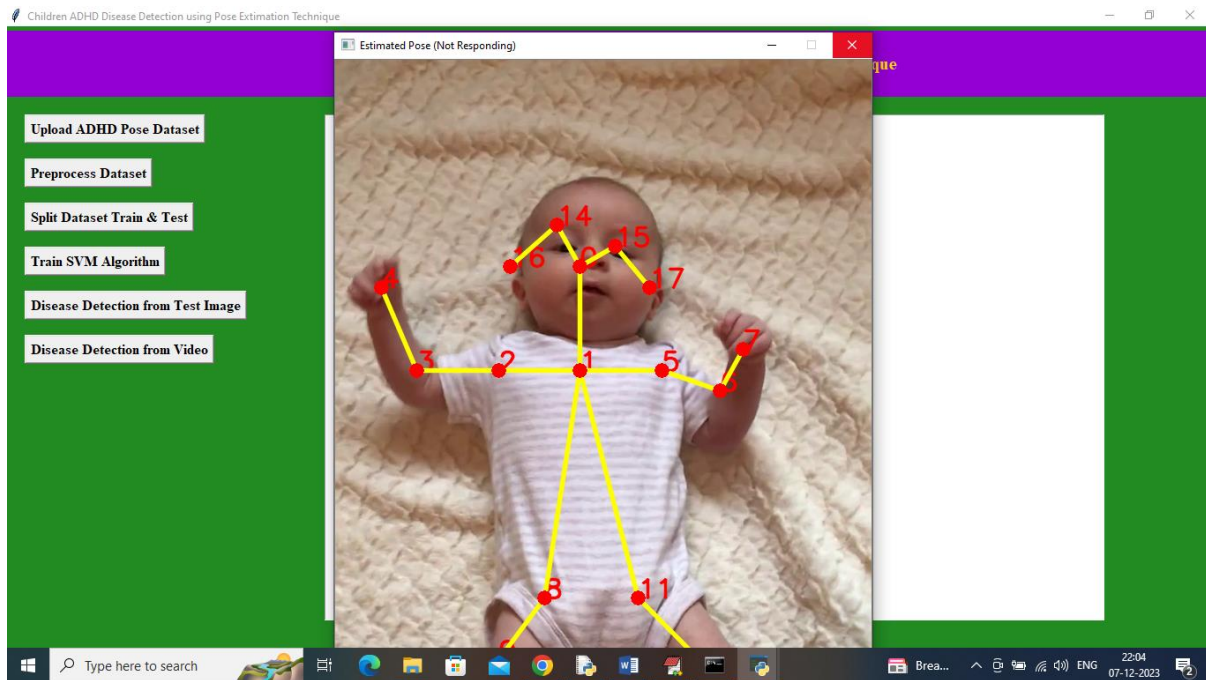


Fig 10.13 Pose Prediction

In above screen can see application start estimating poses from video and after completing video playing will get below output

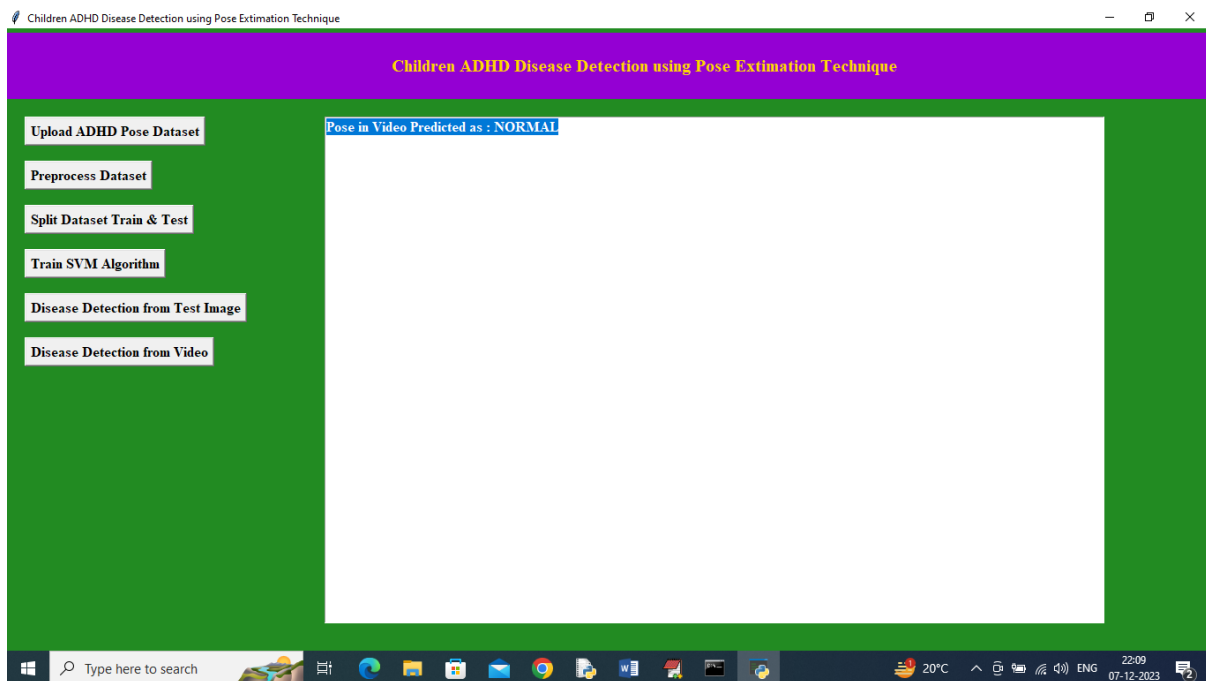


Fig 10.14 Pose Estimation and Prediction Output

In above screen in blue colour text can see estimated poses from video detected as 'Normal'. Similarly by following above screens you can detect ADHD from any child image or video.

11. CONCLUSION AND FUTURE SCOPE

CONCLUSION

In conclusion, the **Children ADHD Disease Detection Using Pose Estimation Techniques** project represents a significant step forward in improving the accuracy and efficiency of ADHD diagnosis. By harnessing the capabilities of artificial intelligence, this system has the potential to augment clinical assessments, leading to more objective evaluations, better intervention strategies, and ultimately, improved outcomes for children. It addresses the limitations of traditional subjective diagnosis, such as observational biases, while also providing access to real-time behavioral analysis, ensuring that medical professionals stay informed with the latest developments in ADHD research. This project underscores the transformative role of AI in pediatric mental health and sets the stage for further innovation in early diagnosis and intervention.

FUTURE SCOPE

Looking to the future, the scope for this application is promising. Firstly, continuous refinement and expansion of the model's dataset will be essential to improve accuracy and adapt to diverse behavioral patterns. Integration with emerging technologies, such as speech and facial recognition, could further enhance the system's diagnostic capabilities. Additionally, the application could be adapted for remote ADHD assessments, enabling telehealth consultations and expanding access to pediatric mental healthcare, particularly in underserved areas. Collaboration with medical professionals and institutions for data validation and ethical compliance will be crucial for the system's ongoing development. Moreover, the principles and techniques developed in this project could serve as a blueprint for similar AI-based diagnostic tools in other neurological disorders, ushering in a new era of intelligent healthcare solutions. Ultimately, the future scope involves not only the continual advancement of this specific application but also its potential to revolutionize pediatric mental health diagnostics.

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