ENLIGHTEN DS: ADVANCED TECHNOLOGIES FOR SKILL ENHANCEMENT AND TALENT RECOGNITION IN CHILDREN WITH DOWN SYNDROME

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Dissertation submitted in partial fulfillment of the requirements for the Bachelor of Science (Hons) in Information Technology

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DECLARATION

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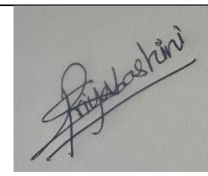
Kumarasinghe D.P	IT21296314	

The above candidate has carried out research for the bachelor's degree Dissertation under my supervision.

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Date: 2025-04-11

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ABSTRACT

Down Syndrome, or trisomy 21, is a genetic condition caused by the occurrence of an extra chromosome 21, leading to a range of physical and mental disabilities. With an estimated occurrence of 1 in 700 births across the globe, early identification of the condition is essential for early intervention and support. Delayed diagnosis can imply missed chances for specialized medical care, educational intervention, and early developmental intervention generally involving long-term challenges for affected individuals and their families.

This paper proposes a new Down Syndrome detection module utilizing facial image analysis using advanced image recognition algorithms. By allowing an upload of a photo or using a live webcam, the system screens for distinctive facial features of Down Syndrome and gives a probability diagnosis. It then issues a comprehensive report with symptoms noted to guide further medical consultation. The early-stage detection platform aims to facilitate accelerated access to essential resources, promote inclusivity, and empower families with timely, accessible support.

Keywords: Down Syndrome, Trisomy 21, Early Detection, Facial Feature Analysis, Image Recognition, Genetic Disorder, Developmental Disabilities, Assistive Technology, Real-Time Assessment, Educational Tools.

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List of Abbreviations

Support Vector Machine	SVM
Convolutional neural networks	CNN
Down syndrome	DS
Artificial Intelligence	AI
Augmented Reality	AR
Test de Aprendizajey Desarrollo Infantil	TADI
Back Propagation Neural Network	BPNN
Congenital Zika Syndrome	CZS

1. INTRODUCTION

Down syndrome, also known as trisomy 21, is a genetic condition resulting from the presence of an extra copy of chromosome 21. It is associated with a variety of physical and intellectual disabilities. The prevalence of Down syndrome is approximately 1 in 700 births worldwide, making it one of the most common genetic disorders.

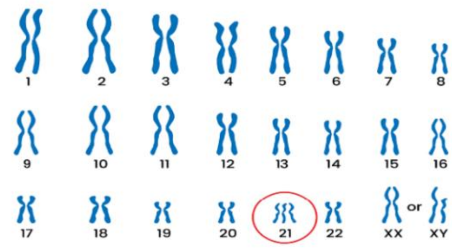


Figure 1: Down syndrome child chromosome image

Individuals with Down syndrome typically display characteristic physical features, including a flattened facial profile, slanted eyes, and often a single transverse palmar crease. Usually, individuals with Down syndrome have mild to moderate intellectual disability [1].

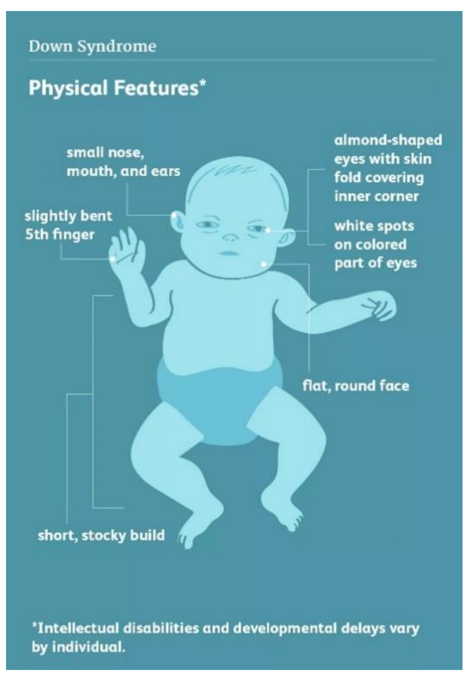


Figure 2: Unique physical features

Early detection of Down syndrome is crucial for providing timely interventions and support. The failure to detect Down syndrome early can lead to significant challenges for both the affected individuals and their families [18]. Delayed diagnosis means missed opportunities for early intervention programs that are critical for maximizing developmental potential. Without early detection, children may not receive specialized healthcare monitoring for common comorbidities associated with Down syndrome, such as congenital heart defects, hearing impairments, and thyroid dysfunction. These conditions, if left unaddressed, can lead to more severe health complications and potentially reduced quality of life [2].

Furthermore, the absence of early detection can result in educational disadvantages. Children with undiagnosed Down syndrome may struggle in traditional educational settings without appropriate accommodations, leading to frustration, behavioral issues, and diminished self-esteem. Families may also experience increased stress and emotional burden when navigating unexplained developmental delays without proper guidance or support resources [3], [19], [20].

The proposed Down syndrome detection component addresses these critical issues by offering an accessible and efficient screening tool. This innovative technology employs advanced image recognition algorithms to detect characteristic facial features associated with Down syndrome through two convenient methods: image upload or real-time camera assessment. The system is designed to be a preliminary screening tool, providing an estimated probability of Down syndrome presence based on facial feature analysis [4], [5].

When the system detects features consistent with Down syndrome, it generates a comprehensive report outlining the probability assessment along with common symptoms and characteristics associated with the condition. This information serves as a valuable resource for initiating further medical consultation and diagnostic procedures. The detection component acts as a gateway to our other specialized tools designed specifically for children with Down syndrome, ensuring that these resources are appropriately targeted.

The integration of this detection component with our other specialized tools creates a comprehensive ecosystem of support for children with Down syndrome. Once detected, users gain access to our AI-generated quizzes, digital painting platform, and piano-based recital assessment tools, all specifically designed to identify and nurture the unique talents and abilities of children with Down syndrome.

By facilitating earlier detection and intervention, our system aims to contribute to the growing body of research demonstrating that children with Down syndrome can achieve significant developmental progress and lead fulfilling lives when provided with appropriate support from an early age. The detection component represents a crucial first step in this journey, potentially transforming developmental trajectories through timely identification and intervention.

1.1 Background Literature

The following literature review explores recent advancements in early detection and cognitive evaluation of children with Down Syndrome (DS) using artificial intelligence and interactive digital technologies. The first study, Early Detection of Down Syndrome through Ultrasound Imaging using Deep Learning Strategies [6], emphasizes the potential of deep learning and convolutional neural networks (CNNs) to non-invasively identify chromosomal abnormalities from ultrasound images by extracting features such as nuchal translucency. It highlights the importance of large annotated datasets and robust transfer learning frameworks for improving diagnostic accuracy. Complementing this, the second study, Identification of Nasal Bone for the Early Detection of Down Syndrome Using Back Propagation Neural Network [7], utilizes backpropagation neural networks to detect the presence or absence of the nasal bone in fetal ultrasound images a significant soft marker for DS demonstrating a highly accurate, non-invasive screening technique to aid prenatal care. Beyond detection, research has also addressed postnatal cognitive evaluation and support. For instance, Evaluation of Executive Functions of Children with Down Syndrome and Zika Virus Using Touch Screen Device [8] introduces a novel touchscreen-based tool to assess executive functions like memory and cognitive flexibility in an engaging and accessible manner, particularly suited for children with motor or communication difficulties. Finally, Cognitive Impairments in Children with Down Syndrome [9] presents a cross-sectional study grounded in Piaget's developmental framework, identifying key cognitive deficits in children with DS through structured assessment and interdisciplinary evaluation. Together, these studies reveal a multidimensional research landscape that combines machine learning, medical imaging, and interactive technologies to enable early diagnosis and personalized developmental support for children with Down Syndrome.

Early Detection of Down Syndrome through Ultrasound Imaging using Deep Learning Strategies [6] focuses on enhancing the accuracy of prenatal diagnosis by employing cutting-edge deep learning methods in ultrasound imaging. The paper begins by juxtaposing the disadvantages of traditional diagnostic methods such as amniocentesis and chorionic villus sampling, accurate as they are but invasive and fraught with some danger. For this purpose, an extensive review of literature was conducted to put forward the idea that deep learning and convolutional neural networks (CNNs) can be applied in medical imaging. During the course of the review, it was determined how these technologies can automatically extract significant features from ultrasound scans and classify chromosomal abnormalities correctly. Scientists compared various pre-trained deep models of learning as well as various transfer learning models to identify optimum frameworks for down syndrome indicator features such as thickness of nuchal translucency. It also emphasized that large annotated sets were crucial in addition to addressing the challenges caused by limited quantities of high-quality fetal ultrasound images. By this review, the research led to making a robust, non-invasive, and early diagnostic test aimed at assisting clinicians in early diagnosis of Down syndrome.

Identification of Nasal Bone for the Early Detection of Down Syndrome Using Back Propagation Neural Network [7] was conducted for the improvement of the non-invasive and early detection of Down Syndrome as it aimed towards identifying whether there was or there was not any presence of nasal bone of the fetus within ultrasonographic images. Observing that underdevelopment or absent nasal bone is a significant soft marker for Down Syndrome, particularly in the first trimester, the researchers conducted an extensive literature review to understand the diagnostic value of this marker and machine learning in medical imaging. Grounded on this foundation, the study utilized a Back Propagation Neural Network (BPNN) classifier to distinguish normal and abnormal fetal profiles from extracted image features. The ultrasound images went through a series of operations like segmentation, feature extraction, and classification in order to isolate the nasal bone and assess whether it was visible or not. The BPNN was trained with a dataset of fetal ultrasound scans, which were able to map patterns in the presence of nasal bones to Down Syndrome indicators. The proposed system demonstrated high accuracy in classification, emphasizing the capability of artificial intelligence in supporting radiologists and clinicians in making precise and early diagnoses. This strategy not only reduces reliance on invasive testing methods like amniocentesis but also enhances the efficiency and accessibility of screening during prenatal care.

Evaluation of Executive Functions of Children with Down Syndrome and Zika Virus Using Touch Screen Device [8] was conducted with the goal of assessing the cognitive development of children affected by Down Syndrome (DS) and Congenital Zika Syndrome (CZS), using an innovative touchscreen-based evaluation tool. The study recognized that executive functions such as working memory, inhibitory control, and cognitive flexibility are crucial for a child’s overall development and are often compromised in children with neurodevelopmental conditions. A literature review was undertaken to better understand existing assessment techniques, particularly focusing on the challenges posed by traditional methods in children with DS and CZS, who may have communication or motor difficulties. In response, the researchers designed a digital solution that provided a playful and interactive approach to evaluating cognitive performance. The tool featured game-like tasks tailored for toddlers, accessible via a touchscreen interface, enabling researchers to collect data on reaction times, accuracy, and task-switching behavior in an engaging environment. It was tested across a sample of children with DS, CZS, and a control group of typically developing children, with data collected on performance metrics and analyzed to identify cognitive strengths and deficits. The study concluded that touchscreen-based assessments not only allowed for better engagement but also showed promise as a scalable, non-invasive method to support early diagnosis and intervention planning in children with developmental delays.

Cognitive Impairments in Children with Down Syndrome [9] is a cross-sectional observational study was conducted within the Department of Developmental Pediatrics and the Department of Occupational Therapy, Lahore, with a focus area of children with DS regarding cognitive development within the age group of 5 to 18 years. A structured questionnaire based on Piaget's stages of cognitive development has been applied to provide an opportunity for the systematic assessment of cognitive impairments among 30 selected children (15 males and 15 females). The sampling method was non-random and purposive in nature and targeted the children who had a diagnosis of DS while ruling out the existence of other comorbid conditions that might be a confounding factor for the estimation of the cognitive function. Participants were assessed by a multidisciplinary team comprised of an occupational therapist, pediatrician, and psychologist in order to enable thorough assessment. The research team took all the required ethical permissions and collaborated with the caregivers and teachers for easy data collection. The Statistical Package for the Social Sciences was used to analyze the data, and the results were reported through pie charts to present the distributions of demographics and bar charts to illustrate significant areas of cognitive impairment. This research has helped in understanding the cognitive challenges of children with DS and proved that targeted intervention strategies are necessary for this special child population.

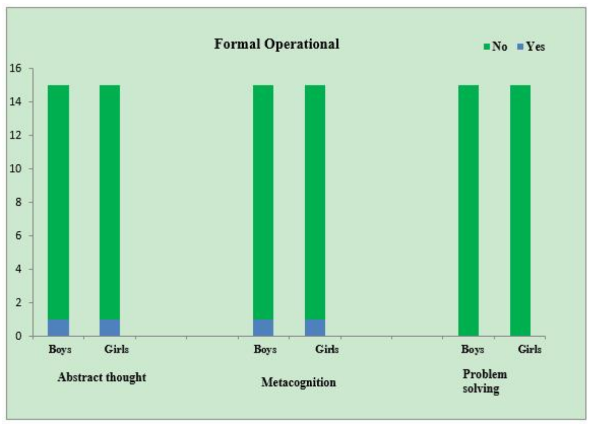


Figure 3: Frequency of lag in formal-operational stage

1.2 Research Gap

Table 1: Research gap

Features	[6]	[7]	[8]	[5]	EnlightenDS
Gives a probability if detected	✗	✗	✗	✓	✓
Used image processing	✓	✗	✗	✗	✓
Used Support Vector Machine (SVM)	✗	✗	✗	✗	✓
Used Web Based Application	✗	✗	✗	✗	✓
Gender not biased	✗	✓	✓	✓	✓

The research paper [6] focuses on using deep learning methods for prenatal detection of Down syndrome through ultrasound imaging. While the paper makes valuable contributions to the field by exploring various deep learning methodologies like ResNet34, Faster-RCNN, and CNN models, several critical gaps exist when compared to the capabilities offered by EnlightenDS.

Although the study employs image processing techniques for ultrasound scans, it primarily focuses on basic segmentation and classification without implementing comprehensive image processing methodologies. The paper mentions that "the researchers focused on the fetal head region within the ultrasonographic images" and used "bounding boxes to split the photos," but lacks sophisticated image analysis that could extract more nuanced features. EnlightenDS addresses this gap by implementing advanced image processing techniques that can detect subtle developmental indicators and provide more accurate assessments, going beyond simple segmentation to analyze multiple visual parameters simultaneously.

A significant limitation in the research is the absence of Support Vector Machine (SVM) classifiers in their methodology. While the paper explores various deep learning models such as CNN and ResNet34, it doesn't incorporate SVM a powerful machine learning algorithm that often excels at classification tasks with clear margins of separation. As noted in the paper, "The Down syndrome diagnosis system made use of a convolutional neural network (CNN)," but combining CNN with SVM could potentially enhance classification accuracy. EnlightenDS leverages SVM's robust classification capabilities, providing more reliable probability estimates for detection and assessment, thus filling this methodological gap.

Furthermore, the study is constrained to clinical applications without consideration for broader accessibility. The research focuses on specialized ultrasound equipment operated by trained professionals, making the technology available only in medical facilities. As noted in the challenges section, there are "regulatory constraints" that "protect healthcare information, making it hard to access such data." EnlightenDS overcomes this limitation through its web-based application design, ensuring that assessment and support tools are accessible across diverse settings and devices. This approach significantly increases reach to populations that might have limited access to specialized medical facilities.

The paper also fails to address potential gender biases in the detection methodologies. While presenting accuracy statistics for various models, there is no analysis of whether these models perform equally well across different genders. This oversight could lead to inequitable screening outcomes. EnlightenDS specifically addresses this gap by implementing gender-neutral assessment algorithms that have been designed and tested to ensure equal effectiveness regardless of gender, preventing any systemic biases in detection or assessment.

Most importantly, the study doesn't provide probability estimates that would help clinicians and families understand the degree of certainty in diagnoses. The paper mentions binary classification results "healthy or Down syndrome" but lacks nuanced probability metrics. EnlightenDS fills this critical gap by providing clear probability assessments with detection, allowing for more informed decision-making and appropriate intervention planning based on confidence levels rather than binary outcomes.

These limitations in the current research highlight the significant advancements that EnlightenDS offers in Down syndrome detection and support. By addressing these gaps through advanced image processing, SVM implementation, web-based accessibility, gender-neutral design, and probability-based assessment, EnlightenDS provides a more comprehensive, accessible, and equitable solution for Down syndrome detection and support.

The research paper [7] focuses on the early detection of Down syndrome through the identification of nasal bone in ultrasound images of fetuses between 11-13 weeks of gestation. The study develops a system using Back Propagation Neural Network (BPNN) with image processing techniques to detect the presence or absence of nasal bone, which is a marker for Down syndrome when absent. The methodology involves median filtering for noise reduction, watershed segmentation for identifying regions of interest, and feature extraction in both spatial and transform domains using statistical parameters (mean, variance, skewness, kurtosis), Discrete Cosine Transform (DCT), and Daubechies D4 Wavelet Transform.

The study reports detection rates (86-88% in the best case using Wavelet Transform) but lacks a sophisticated probability assessment framework. The output is binary - either "Down syndrome present" (0-0.5 range) or "Down syndrome absent" (0.5-1 range), without providing nuanced probability estimates that quantify the degree of certainty. EnlightenDS addresses this gap by offering clear probability metrics for detection, enabling more informed clinical decision-making based on confidence levels rather than binary outcomes. This probabilistic approach is crucial for proper risk assessment and counseling.

While the paper employs basic image processing techniques like median filtering and watershed segmentation, it doesn't implement more advanced image processing algorithms that could enhance feature extraction. The paper acknowledges that "edge detection algorithms have not been implemented to accurately locate objects in an ultrasound image" due to noise susceptibility. EnlightenDS overcomes these limitations with more sophisticated image processing techniques that can better handle the inherent noise in ultrasound images and extract subtler features for more accurate analysis.

Although the study uses Back Propagation Neural Network for classification, it doesn't explore the potential benefits of Support Vector Machine (SVM) classifiers, which often excel at creating optimal decision boundaries between classes. EnlightenDS leverages SVM's robust classification capabilities, potentially providing better accuracy in distinguishing between normal and Down syndrome cases, especially when dealing with limited training data.

The research focuses on developing an algorithm for clinical settings without addressing broader accessibility issues. There is no mention of a web-based implementation that would make the technology available to multiple healthcare providers across different settings.

EnlightenDS addresses this gap through its web-based application design, ensuring that diagnostic tools are accessible to healthcare professionals regardless of location, thereby increasing screening coverage and potentially improving early detection rates.

The study does not address potential gender differences in nasal bone development or detection accuracy. There is no analysis or discussion regarding whether the detection algorithm performs equally well across different genders, which could lead to systemic biases in screening outcomes.

EnlightenDS explicitly addresses this issue by implementing gender-neutral assessment algorithms that ensure equal effectiveness regardless of fetal gender, providing more equitable screening results.

The [7] proposes a standalone method for nasal bone detection without discussing integration with other Down syndrome markers. The paper mentions that "combined with the present detection methods" their approach can enhance detection rates but doesn't elaborate on this integration. EnlightenDS likely offers a more comprehensive assessment by integrating multiple markers for Down syndrome, providing a holistic evaluation rather than relying on a single anatomical feature.

These identified gaps highlight the significant advancements that EnlightenDS offers in Down syndrome detection. By providing probability assessments, implementing advanced image processing techniques, utilizing SVM for classification, offering web-based accessibility, ensuring gender-neutral algorithms, and potentially integrating multiple markers, EnlightenDS represents a more comprehensive, accessible, and equitable solution for Down syndrome screening compared to the approach presented in this research paper.

The research paper [8] focuses on assessing executive functions such as attention, memory, and problem-solving in children diagnosed with Down Syndrome (DS) and Zika Virus Congenital Syndrome (ZVCS) using a touch-screen device. The study offers valuable insight into cognitive profiling by leveraging interactive technology tailored for young children with developmental conditions.

While the paper emphasizes cognitive testing through gamified touch-screen activities, it does not integrate probabilistic feedback or certainty levels in assessments. There is no mention of how confident the system is in detecting executive dysfunction or its severity. In contrast, EnlightenDS provides probability-based outputs, helping clinicians and caregivers understand the level of diagnostic certainty, allowing for more nuanced and informed decision-making.

This study does not employ any image processing or facial analysis techniques. The evaluation is limited to interaction-based cognitive tasks, missing out on the rich diagnostic potential of visual indicators (e.g., craniofacial features), which are commonly associated with Down Syndrome. EnlightenDS fills this methodological gap by incorporating sophisticated image processing methods to detect developmental markers that are not accessible through behavioral tasks alone.

The study does not implement any machine learning models like Support Vector Machines or neural networks. All assessments are manually designed, with performance measured through standard task completion metrics. EnlightenDS, however, uses SVM to enhance classification accuracy and generate robust detection outputs, allowing the system to better differentiate between healthy and at-risk children based on multiple visual and contextual features.

The research confines its application to a custom touch-screen setup, which although accessible, is restricted in scalability and reach. The study does not offer a web-based or remotely accessible solution. EnlightenDS overcomes this limitation by offering a web application, significantly improving accessibility for diverse user groups including those in remote or underserved areas.

While the [8] provides a novel approach to evaluating cognitive development in children with DS and ZVCS, it does not incorporate diagnostic probability metrics, advanced image processing, or machine learning models such as SVM. Additionally, its lack of a scalable, web-based platform and the absence of bias mitigation strategies further limits its scope. EnlightenDS addresses these gaps comprehensively by offering a feature-rich, inclusive, and technologically advanced solution for the early detection and support of Down Syndrome.

The research [7] underlines different imperative issues on cognitive development, focusing on gender differences and cognitive impairments. According to the study conducted, which was premised on the Piaget theory of cognitive development, there are no major disparities on gender with regard to cognitive impairments. However, girls have been seen exhibiting more significant disabilities during the preoperational stage of development. Such findings are relevant as they underline the necessity of a gender-oriented approach in researching cognitive development. It finds a limitation in terms of sample size, which was small, and in the fact that it was of a cross-sectional design with only two institutions being involved, thereby generally limiting generalizability. The small sample size and limited scope may preclude representativeness of findings within the wider population of children with Down syndrome, which will mean a limitation in the applicability of results.

EnlightenDS was developed to go beyond the limitations of traditional methods of Down syndrome detection, offering a more dynamic and individualized approach. Unlike the conventional static techniques used in the referenced study [7], EnlightenDS leverages advanced technologies such as image processing, machine learning, and real-time feedback to deliver more accurate and tailored diagnostic assessments. This responsive system adapts to various inputs, surpassing the fixed, one-size-fits-all models used in earlier research. By overcoming limitations related to sample size and institution-specific tools, EnlightenDS provides a more comprehensive and accessible solution for detecting Down syndrome, making early identification more effective and widely available.

In conclusion, even though the present research provides valuable insight into the diagnosis of Down syndrome in children, it also cites several significant shortcomings that need to be addressed. EnlightenDS streamlines the process of detecting Down syndrome through the integration of advanced technologies such as Support Vector Machines, processing of data in real time, and machine learning algorithms, thus making it an even more efficient tool for identifying Down syndrome. With the overcoming of the challenges regarding accessibility, gender bias, and the limitations of traditional diagnostic methodologies, EnlightenDS offers a better, neutral, and scalable technology for detecting Down syndrome regardless of gender or geographic location.

1.3 Research Problem

Infants and children with Down syndrome (DS) have brighter futures today since individuals with DS are healthier, leading more fulfilling lives due to medical technology, early intervention, and educational inclusion. Despite these advances, among the persistent issues is delayed diagnosis, which can lead to delays in necessary early interventions and subsequently, significantly reduce developmental outcomes. Early diagnosis is required since it allows for early therapies, medical care and educational planning that can profoundly influence the quality of life of a child. Most cases of Down syndrome, particularly in mild cases, however, are not diagnosed or are diagnosed at less than optimal times, eliminating optimal early intervention strategies [10], [11].

Early and accurate diagnosis is particularly crucial after childhood. DS patients are also at greater risk for the development of Alzheimer's disease than the general population. It was discovered that early follow-up, both medical and psychological, can provide greater insight into their future neurological status [12]. However, the conventional reliance on routine normal test procedures such as karyotyping and physical examinations can lead to delayed diagnosis, especially in cases where physical and facial abnormalities are less severe.

The aim of this study is to overturn the trend of delayed diagnosis by discussing the recent detection techniques that utilize machine learning, image processing, and neural networks for effective detection of Down syndrome at an early age. This study attempts to bridge the gap of early diagnosis through the integration of computerized image analysis, AI-driven pattern recognition, and non-invasive screening techniques to open the door for children with DS to the earliest accessible care for their medical, cognitive, and developmental issues.

Along the way, this study contributes to the growing body of research on Down syndrome diagnosis and presents a compelling argument for the more accelerated development of yet more refined screening procedures that are faster, more accessible, and less dependent on subjective clinical evaluation. Finally, by prioritizing early and accurate diagnosis, we can look towards improved interventions, healthier developmental trajectories, and long-term care that is optimized for individuals with Down syndrome.

1.4 Research Objectives

1.4.1 Main objective

The system's specific objective is to decide whether a child does or does not have Down syndrome, and, if they do, to calculate a probability value indicating the degree of likelihood of the condition and associated symptoms. This targeted approach helps move beyond general screening by giving such targeted insights that make early identification possible. By giving both diagnostic probability and symptom assessment, the system allows for the planning of appropriate next steps in intervention and support by caregivers and professionals.

1.4.2 Sub objectives

- **Gather a diverse dataset of facial images from children**

  Collect a wide range of facial images of children, including those with and without Down syndrome, to ensure the dataset captures variability across age, ethnicity, and facial expressions.

- **Apply preprocessing techniques to prepare the images for analysis**

  Preprocessing steps such as face detection, alignment, grayscale conversion, resizing, and noise reduction are applied to standardize the input and improve feature extraction accuracy.

- **Utilize the Dlib library to extract facial landmarks**

  Use the Dlib library to detect and extract key facial landmarks (e.g., eyes, nose, mouth, jawline) from each image. These landmarks provide critical geometric features relevant for detecting Down syndrome characteristics.

- **Train the model using Support Vector Machine (SVM)**

  The extracted facial features are used to train an SVM classifier. SVM is well-suited for high-dimensional data and is effective at finding optimal boundaries between classes.

- **Use SVM to provide detection output with a probability score**

  Once trained, the SVM model analyzes new images to determine the likelihood of Down syndrome and outputs a probability score along with detected facial indicators. This helps caregivers and clinicians make informed decisions based on the model's confidence.

2. METHODOLOGY

2.1 System Architecture Diagram

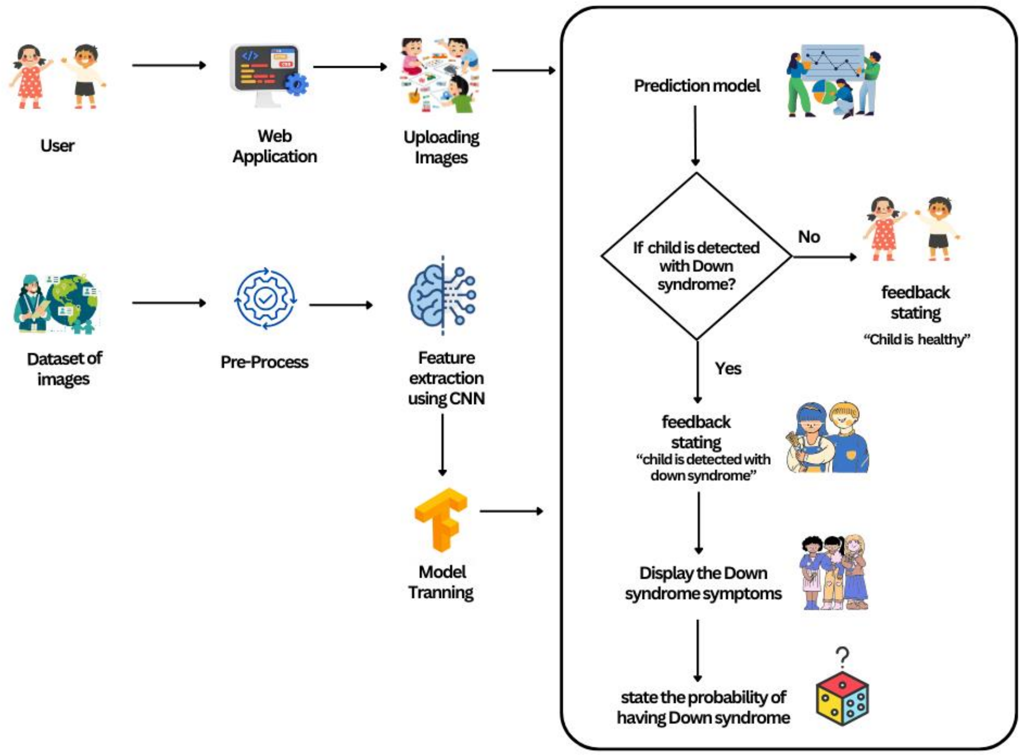


Figure 4: Individual system diagram

This component focuses on detecting Down syndrome in children using a structured machine-learning-based approach, divided into two key phases as data preparation and model training, followed by user interaction and prediction. In the first phase, a dataset of facial images comprising both children with and without Down syndrome is prepared for training and testing. To ensure consistent and high-quality inputs, several preprocessing techniques are applied, including face detection and alignment for accurate feature positioning, grayscale conversion and noise reduction to enhance image quality, facial landmark detection using Dlib to extract key features such as eye shape, nasal bridge, and jawline structure, and feature normalization for dataset uniformity. After preprocessing, a Support Vector Machine (SVM) classifier is used for training, selected for its efficiency in distinguishing geometric and textural facial differences, unlike CNNs which emphasize deep feature learning. Once trained, the system moves to the second phase where real-time detection occurs through a web-based interface. Users, such as parents or medical professionals, upload a child's image, which then undergoes the same preprocessing steps. Extracted features are passed through the trained SVM classifier to determine whether facial characteristics indicative of Down syndrome are present. If no such traits are detected, the system states that the child is healthy; otherwise, it lists identified facial symptoms and provides a probability score estimating the likelihood of Down syndrome. By integrating image preprocessing, SVM classification, and facial feature analysis, the system presents a rapid, non-invasive, and accessible early screening tool, supporting informed decision-making for further medical evaluation and intervention.

2.2 Flow Chart

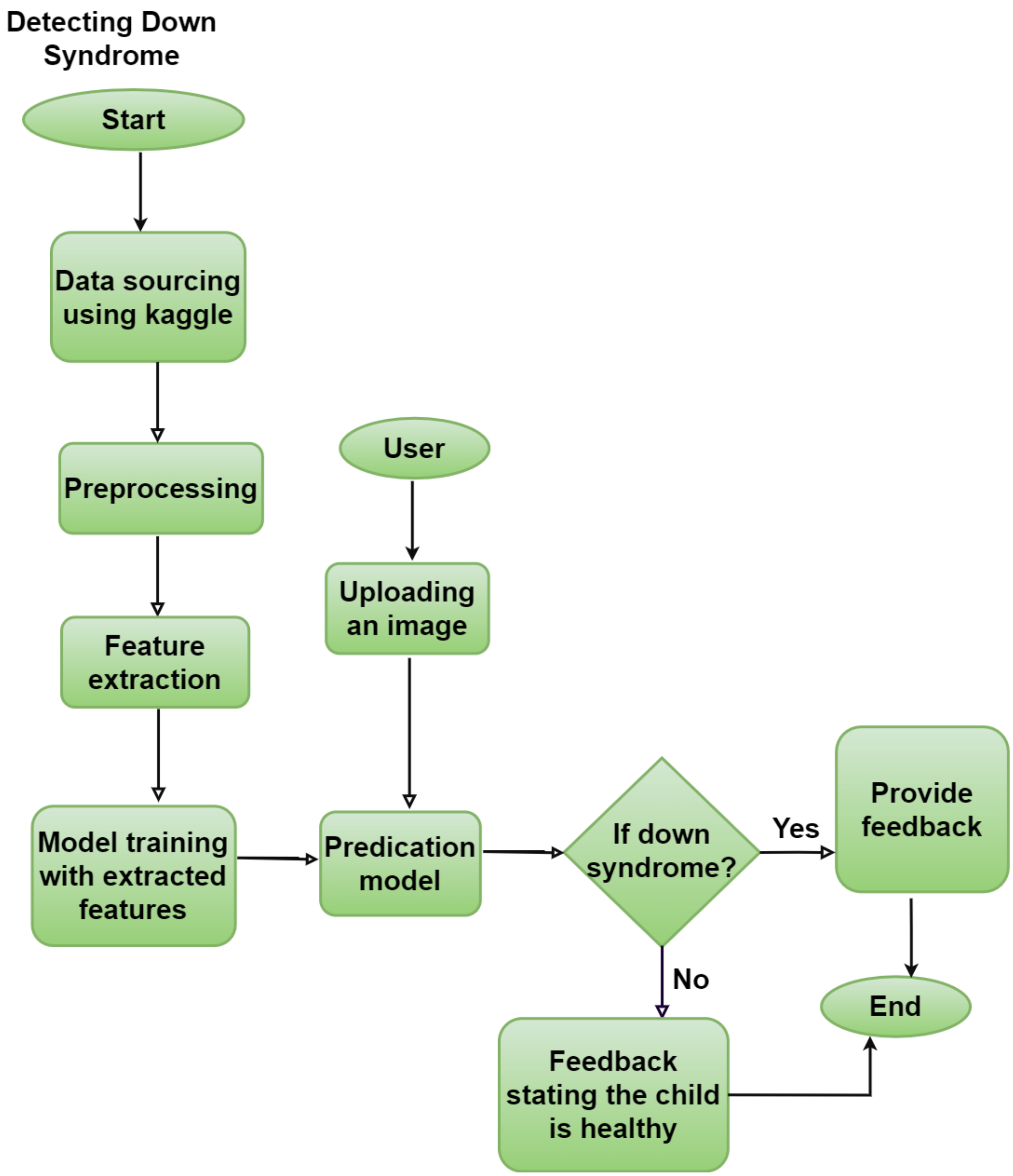


Figure 5: Flow chart

2.3 Software Solutions

Agile methodology is a dynamic and iterative approach to software development and project management that emphasizes flexibility, collaboration, and customer-centricity. Unlike traditional waterfall models, where projects follow a linear, sequential process from planning to delivery, Agile breaks down the project into smaller, manageable units called "sprints." Each sprint typically lasts between one to four weeks and focuses on delivering a specific piece of functionality or a working increment of the software. This incremental delivery allows teams to continuously integrate and test new features, making it easier to respond to changes and adapt to evolving customer needs [13].

At the heart of Agile methodology is the principle of iterative development, where teams work in short cycles to develop, review, and refine their product. This iterative process allows for continuous feedback and improvement, ensuring that the final product is closely aligned with the customer's requirements. Agile teams often work closely with stakeholders, holding regular meetings such as daily stand-ups, sprint planning sessions, and sprint reviews to discuss progress, address challenges, and realign goals as needed. This close collaboration fosters transparency and ensures that all team members are aligned on the project's objectives and status.

Another key aspect of Agile is its emphasis on cross-functional teams. In an Agile environment, teams are typically composed of individuals with diverse skill sets, including developers, testers, designers, and business analysts. This diversity allows teams to handle all aspects of product development within the sprint, from initial concept through to testing and deployment. The cross-functional nature of Agile teams encourages collaboration and knowledge sharing, breaking down silos and ensuring that everyone is working towards a common goal.

Agile also promotes a strong focus on customer satisfaction. By delivering small, functional pieces of the product early and often, customers can see tangible progress and provide feedback throughout the development process. This feedback loop is crucial, as it allows the team to make adjustments based on real-world usage and customer insights, rather than assumptions made during the initial planning phase. Agile's customer-centric approach ensures that the final product is not only functional but also meets or exceeds the expectations of its users.

Furthermore, Agile methodology is built on the concept of continuous improvement, both in terms of the product and the processes used to develop it. After each sprint, Agile teams conduct a retrospective meeting to reflect on what went well, what didn't, and how processes can be improved in the next sprint. This constant evaluation and adjustment help teams to fine-tune their workflows, improve efficiency, and address any issues before they become larger problems. The iterative nature of Agile allows for rapid experimentation, learning, and adaptation, which is essential in today’s fast-paced and ever-changing business environment.

The Agile Manifesto, which was published in 2001, outlines the core values and principles of Agile methodology. It emphasizes individuals and interactions over processes and tools, working software over comprehensive documentation, customer collaboration over contract negotiation, and responding to change over following a plan [14]. These values reflect the flexible, adaptive and people-focused nature of Agile, which is designed to handle the complexities and uncertainties of modern software development.

When implementing a complex and multifaceted system like EnlightenDs, Agile methodology becomes particularly important and highly beneficial. EnlightenDs, with its focus on assessing cognitive development, enhancing pronunciation skills, improving mathematical abilities, and identifying interests and talents in students, involves various interrelated components that need to be developed, tested, and refined. Agile's iterative and flexible nature makes it the ideal framework for managing the development of such a system.

One of the key reasons Agile is crucial for EnlightenDs is its emphasis on iterative development. EnlightenDs involves complex algorithms, including Convolutional Neural Networks (CNNs) for feature extraction, Natural Language Processing (NLP) for pronunciation analysis, and machine learning models for predictive analytics. Developing these sophisticated components in one go would be risky and could lead to missed opportunities for improvement. By using Agile, the development team can build the system in small, manageable increments called sprints. Each sprint focuses on developing a specific feature, such as the cognitive assessment model or the gamified pronunciation activities. This iterative approach allows the team to deliver a functional prototype early, gather feedback, and make necessary adjustments before proceeding to the next sprint.

Agile also facilitates close collaboration and continuous feedback, which is essential for a system like EnlightenDs that aims to meet the diverse needs of students, educators, and parents. By involving stakeholders in regular sprint reviews, the development team can ensure that the system aligns with user expectations and educational goals. For instance, during the development of the mathematical skill enhancement component, teachers and education specialists can provide insights on how well the system's adaptive quizzes align with curriculum standards and learning outcomes. This feedback can be quickly incorporated into subsequent sprints, ensuring that the final product not only functions well but also meets the specific needs of its users.

Moreover, Agile's focus on adaptability is particularly advantageous for EnlightenDs, given the rapid advancements in educational technology and artificial intelligence. As new techniques in AI and machine learning emerge, or as educational standards evolve, the system may need to be updated or reconfigured.

Agile’s flexible nature allows the development team to pivot and integrate these new advancements without disrupting the entire project. For example, if a more effective method of detecting cognitive development through drawings becomes available, the team can implement this change in a future sprint without overhauling the entire system.

Cross-functional teams, a hallmark of Agile, are also crucial when developing EnlightenDs. The system requires expertise in several domains, including AI, software engineering, educational psychology, and user experience design. Agile promotes the formation of cross-functional teams that bring together these diverse skills, enabling the team to handle all aspects of the project within each sprint. This integrated approach ensures that the system's various components, from the AI-driven drawing analysis to the user-friendly web application interface, are developed in harmony. Cross-functional collaboration also fosters innovation, as team members from different disciplines can contribute unique perspectives and solutions.

Additionally, Agile's customer-centric approach is vital for the success of EnlightenDs. The primary users of EnlightenDs are students, but it also serves educators and parents who rely on the system for insights into a child’s development. Agile’s iterative delivery model ensures that these stakeholders can interact with the system early in the development process and provide real-time feedback. For instance, parents can test the user interface for ease of use, or educators can evaluate the accuracy and educational value of the feedback provided by the system. This ongoing interaction ensures that the final product is not only technologically sound but also user-friendly and educationally effective [15].

Finally, Agile’s principle of continuous improvement aligns perfectly with the long-term goals of EnlightenDS. After each sprint, the team conducts a retrospective to discuss what went well, what didn’t, and how processes can be improved in the next sprint. This constant reflection and adaptation lead to a higher-quality product. For a system like EnlightenDS which will be used to influence the education and development of children, continuous improvement is not just a technical necessity but a moral imperative. The development team’s commitment to refining and enhancing the system at every stage ensures that EnlightenDS remains a cutting-edge tool for educational assessment and development [16] [17].

In conclusion, Agile methodology is not just a suitable approach for implementing EnlightenDS it is the optimal one. The iterative development cycles, continuous stakeholder feedback, adaptability, cross-functional collaboration, customer focus, and commitment to continuous improvement make Agile the best choice for building a system as complex and impactful as EnlightenDS. By employing Agile, the development team can ensure that EnlightenDS is not only robust and reliable but also responsive to the evolving needs of its users, ultimately delivering a product that truly enhances student development.

2.4 Requirement Gathering

Conducting Interviews = We conducted interviews with teachers, caretakers, and other professionals at the Senehasa Research Center, as well as visited schools, to gain a deeper understanding of the behavioral patterns and physical symptoms commonly observed in children with Down syndrome. These interviews provided critical insights into how these children behave in everyday settings, their social interactions, and the visible signs that may assist in early detection. Teachers and caregivers shared their experiences identifying distinctive facial features, motor behaviors, and social cues, while parents offered valuable observations from home environments. This collective input helped us better understand real-world indicators of Down syndrome, supporting the development and refinement of our detection system based on practical, firsthand knowledge.

Observations = We carried out direct observations at the Senehasa Research Center and visited several schools to closely observe children with Down syndrome in their natural environments. We aimed at finding out how the children with Down syndrome behave, interact, and display physical and behavioral traits associated with Down syndrome. We spent time with them during their daily activities, paying close attention to their social interactions, physical movements, facial features, and behavioral patterns. We specifically noted signs such as delayed responses, distinct facial characteristics, repetitive behaviors, and social engagement styles that are commonly linked to Down syndrome. These real-world observations played a vital role in supporting the development of our detection system by providing practical insights into the typical symptoms and behaviors exhibited by children with the condition.

Survey = We conducted a survey concerning knowledge and perceptions of Down syndrome, with specific questions relating to Down syndrome. We had a wide array of respondents answering the survey. The many responses that we got helped us a great deal. The results of the survey showed the level of understanding and recognition of the importance of research into detection of Down syndrome. The survey will help immensely in understanding any gaps in knowledge or even misconceptions across the community. Findings, therefore, will guide us in refining how we put across our research, that it is both impactful and of significance to a bigger audience.

To illustrate the findings, a few of the survey responses will be included below.

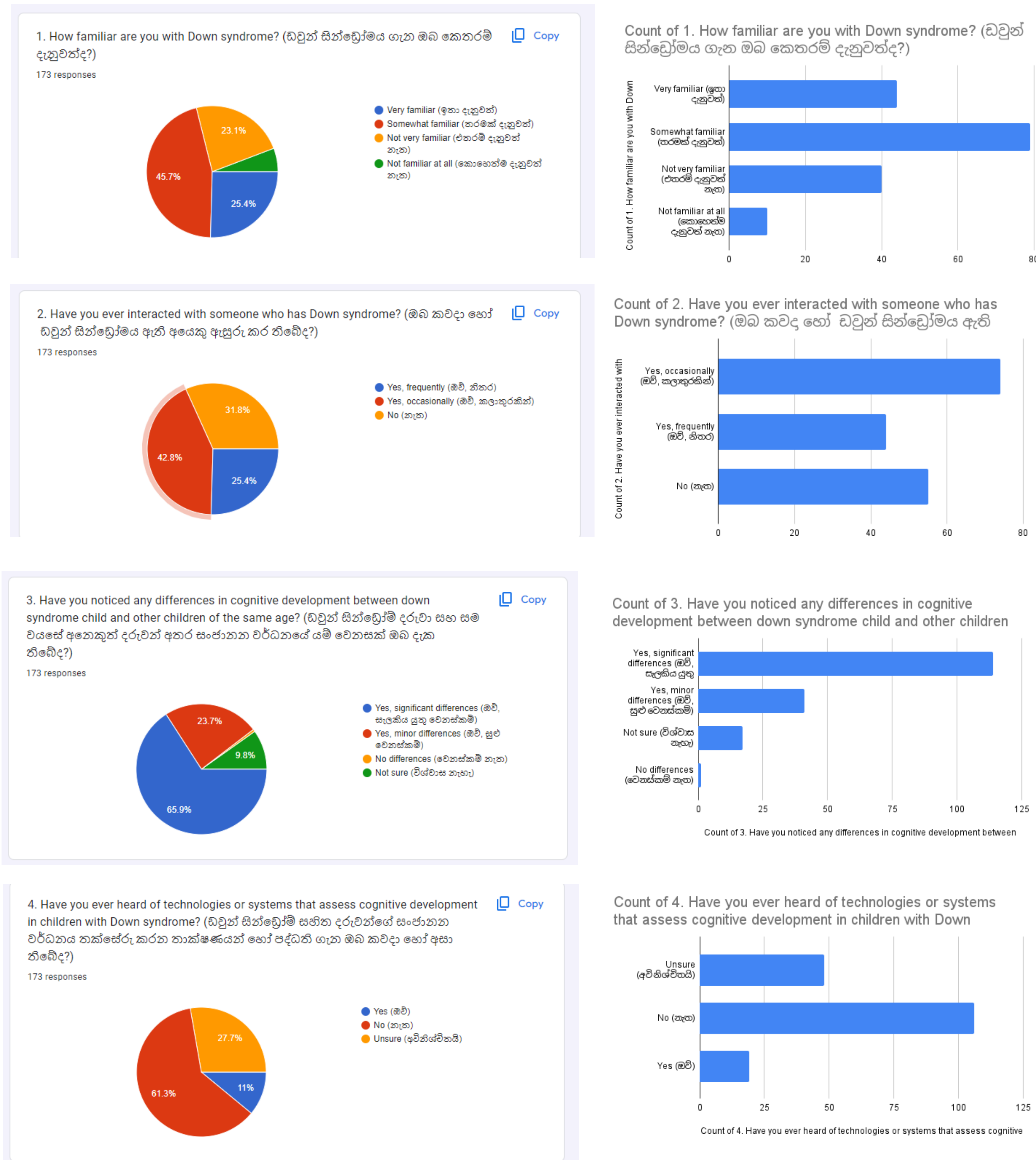


Figure 6: Survey responses

Positive survey responses indicate a knowledgeable community with deep interactions and observations concerning Down syndrome and cognitive development. General awareness and familiarity with assessment technologies would suggest that, at large, there is little or no resistance to the use of such tools in the evaluation and enhancement of cognitive development.

The findings raise the importance of educating members of the general public and professionals on issues surrounding Down syndrome and cognitive development. We can progress from what is already known and build from there, setting any disparities and misconceptions straight. The positive contact with assessment technologies points toward promising directions for further research studies and practical applications.

Overall, these results from the survey prove that we have a sound base of knowledge and interest that can help us fine-tune our research and outreach activities for maximum impact and relevance.

2.5 Project Requirements

2.5.1 Functional requirements

1. **Enable users to upload images or use real-time webcam input**
   This requirement allows users to either upload a facial image of a child or capture one in real-time using a webcam. The system will provide an intuitive user interface for selecting, uploading, or capturing images seamlessly.

2. **Ability to assess whether a child is showing signs of Down syndrome**
   This involves analyzing the uploaded or captured image to determine if the child displays facial characteristics commonly associated with Down syndrome, enabling early detection.

3. **Ability to extract facial features using Dlib library**
   The system will use the Dlib facial landmark detection library to extract key facial features such as eye shape, nasal bridge, jawline structure, and other geometry-based attributes essential for classification.

4. **Ability to automatically preprocess uploaded or captured images**
   The preprocessing pipeline includes automatic face detection and alignment, grayscale conversion, noise reduction, and feature normalization to ensure consistent input for accurate classification.

5. **Generate a probability score indicating the likelihood of Down syndrome**
   After processing the image, the system will calculate and present a probability score indicating the likelihood that the child may have Down syndrome based on the extracted facial features and trained classification model.

6. **Provide feedback on the detection results**
   The system will give clear and informative feedback based on the prediction. If Down syndrome is not detected, the user will be notified that the child is healthy. If detected, the system will display the detected facial features associated with the condition and the probability score, guiding the next steps for professional evaluation.

2.5.2 Non-functional requirements

1. **Availability**

   The system should be operational and available to users when they need it.

2. **Reliability**

   The ability of the system to perform consistently without failure over time.

3. **User friendly**

   The system should be designed to be user friendly and understand for the intended users.

4. **High performance**

   The system should be able to operate efficiently and effectively.

5. **Security**

   The system should ensure that it will protect user data and information from unauthorized access and breaches.

6. **Maintainability**

   The ability to update and repairing the system.

2.5.3 Technical requirements

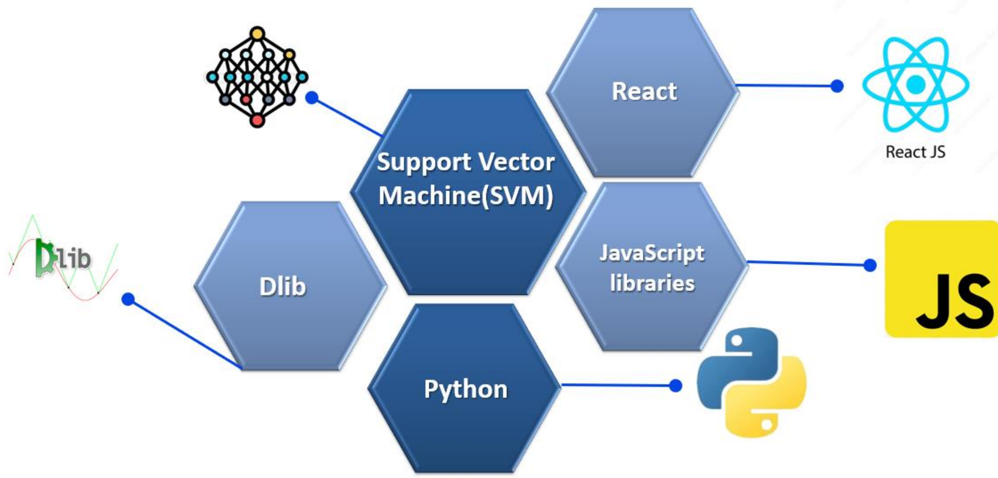


Figure 7: Technical requirements diagram

1. **Support Vector Machine (SVM):**

SVM is utilized as the core classification algorithm in detecting Down syndrome by analyzing facial features extracted from images. Unlike other traditional classification methods, SVM excels in handling high-dimensional data and effectively distinguishes between children with and without Down syndrome. Its ability to work well with small datasets and find the optimal decision boundary makes it an excellent choice for medical image classification.

2. **Dlib:**

Dlib is used for facial feature extraction, which is crucial in identifying the characteristic facial traits associated with Down syndrome. It provides robust facial landmark detection, allowing the system to analyze geometric patterns in facial structures. Compared to other feature extraction libraries, Dlib offers highly accurate facial alignment, making it a superior choice for medical image processing in Down syndrome detection.

3. **Python:**

Python serves as the backbone of the system, integrating machine learning models and image processing techniques. It offers extensive support for data science libraries and simplifies the implementation of complex algorithms. Its compatibility with Dlib and SVM ensures smooth execution of the detection process, making it preferable over other programming languages with limited AI and machine learning support.

4. **React:**

React is used for building an interactive and responsive user interface. It enables users to upload images or capture real-time webcam input efficiently. React's component-based structure ensures smooth data flow between the frontend and backend, making it easier to process and display Down syndrome detection results in real-time. Unlike traditional web frameworks, React enhances user experience with fast rendering and seamless updates.

5. **JavaScript Libraries:**

JavaScript libraries play a crucial role in enhancing the user experience by supporting real-time image capturing and processing. They facilitate the integration of frontend and backend components, ensuring smooth interaction between the user and the detection system. Compared to other frontend technologies, JavaScript's ecosystem allows for greater flexibility and scalability in developing AI-powered web applications.

2.6 Testing & Implementation

2.6.1 Model training

To implement the Down Syndrome detection component of the system, a comprehensive machine learning pipeline was developed that integrates both facial geometry and texture-based features. The dataset comprised facial images categorized into two classes: individuals with Down Syndrome and healthy individuals. Initially, all images were preprocessed using the Dlib library to detect facial landmarks, utilizing a 68-point landmark model. A custom frontal-face validation function was used to filter out non-frontal images, ensuring uniformity and improving the reliability of the features extracted.

For each valid face, an alignment process was carried out by computing the angle between the eye centers and rotating the image accordingly. This alignment helped reduce pose variation. After alignment, faces were cropped using the facial landmarks to tightly frame the region of interest, followed by resizing to a fixed dimension to maintain consistency across samples.

To capture discriminative texture features, Local Binary Pattern (LBP) histograms were extracted from small patches centered around selected landmark points. In parallel, geometric features were calculated by measuring Euclidean distances between key pairs of landmarks (such as eye-to-nose, mouth width, and distances around the lips and cheeks), which are known to vary significantly in Down Syndrome cases. These two types of features texture (LBP) and shape (geometric) were concatenated to form a comprehensive feature vector for each image.

To improve generalization and increase the size of the dataset, various data augmentation techniques were applied. These included horizontal flipping, small-angle rotations, and the addition of Gaussian noise. Each augmented image was processed in the same way to extract consistent features.

After feature extraction, the data was standardized using StandardScaler to ensure that all features contributed equally to the learning process. All feature vectors were padded to ensure consistent dimensions, and missing values (if any) were handled using np.nan_to_num().

A Support Vector Machine (SVM) classifier with a sigmoid kernel was trained on the extracted features. The classifier was tuned to handle class imbalance using a balanced class weight. The model training process was timed, and its effectiveness was evaluated using 5-fold cross-validation on the training data, reporting an average accuracy across the folds. After training, the model's performance was further assessed on both the training and the testing sets, with key metrics including accuracy, precision, recall, AUC, and a full classification report.

Finally, the entire trained pipeline including the scaler and classifier was serialized and saved to a .pkl file using Python's pickle module. This enabled the model to be easily loaded and integrated into the web-based interface or any real-time application for Down Syndrome detection.

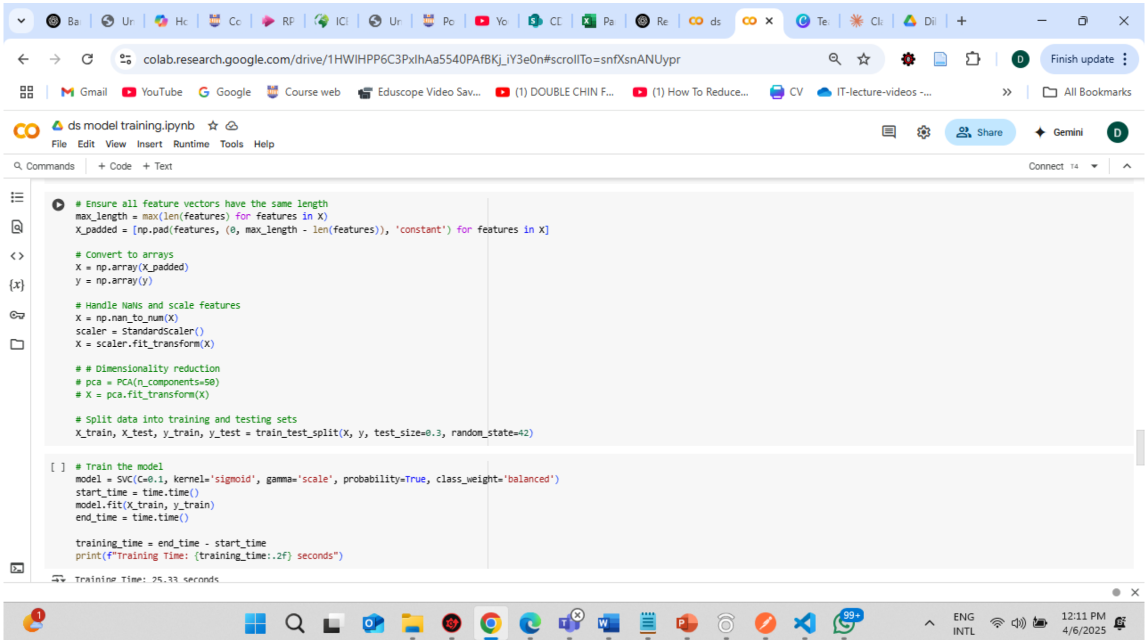


Figure 8: Model training code

2.6.2 Model testing

The testing phase involves evaluating the performance of the trained Support Vector Machine (SVM) model on new, unseen images to determine its capability to classify individuals as either having Down Syndrome or being Healthy. The process begins with the user uploading an image, which is then processed using a pipeline designed to replicate the same preprocessing steps as in the training phase.

Firstly, face detection is performed using Dlib's pre-trained frontal face detector. If a face is detected, facial landmarks are extracted using a 68-point shape predictor, and a 69th landmark is computed as the midpoint between landmarks 21 and 22 (the inner ends of the eyebrows) to enhance the detection of facial symmetry.

Next, the facial alignment step rotates the image such that the eyes are horizontally aligned, helping to standardize the facial orientation across different input images. The face is then cropped with appropriate padding, centered around the facial landmarks, and resized to a fixed resolution (300x300 pixels) to ensure consistency in feature extraction.

From this cropped and aligned facial image, two key types of features are extracted:

1. **Local Binary Pattern (LBP) Features**: LBP histograms are computed from grayscale patches centered at selected facial landmarks (e.g., around the eyes, nose, and mouth). These patches capture local texture information, which is critical in highlighting micro-patterns often associated with Down Syndrome facial traits.

2. **Geometric Features**: Euclidean distances between specific landmark pairs are computed to capture global facial structure. These distances reflect facial proportions, such as inter-eye distance, nose length, and mouth width all of which are important in distinguishing Down Syndrome-related facial morphology.

The extracted LBP histograms and geometric distances are concatenated into a single feature vector. This vector is then scaled using the same StandardScaler instance that was fitted during the training phase to ensure consistent normalization.

Finally, the preprocessed feature vector is passed to the trained SVM model, which outputs a predicted class label (0 for Down Syndrome, 1 for Healthy) and the corresponding class probabilities. The prediction is visualized by overlaying the facial landmarks and structural lines on the image, and the final result includes the prediction label, confidence scores for each class, and the time taken to complete the inference.

2.6.3 Postman testing

To validate the functionality and performance of the deployed Down Syndrome detection model, the RESTful API was tested using Postman, a popular API testing tool. The API endpoint /predict hosted on http://127.0.0.1:5000 was accessed using the POST method. A test image (down1.jpeg) was uploaded via the form-data body under the image key to simulate a real-world scenario where an end user provides an image for diagnosis. Upon submission, the API successfully processed the image and returned a JSON response containing the prediction result along with a confidence score. In this specific test case, the model predicted "Down Syndrome Detected" with a confidence of 0.47, and the response was received with an HTTP status code of 200 OK, indicating successful execution. This test demonstrates the robustness and reliability of the model's deployment and confirms that the backend pipeline including preprocessing, feature extraction, and classification is functioning as expected through the API.

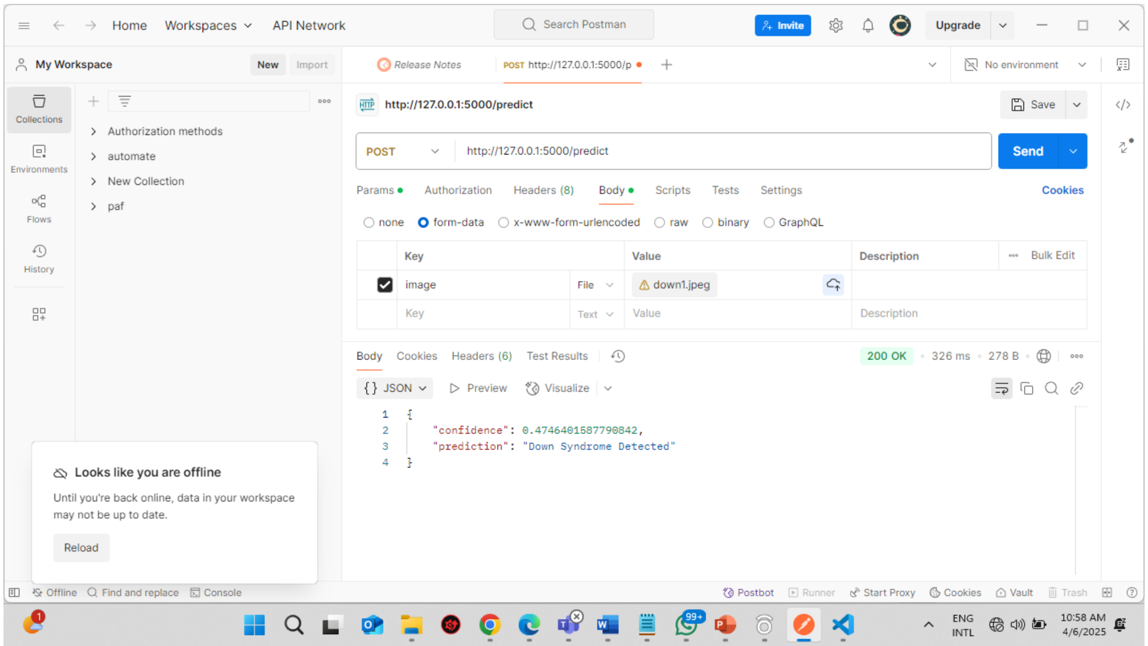
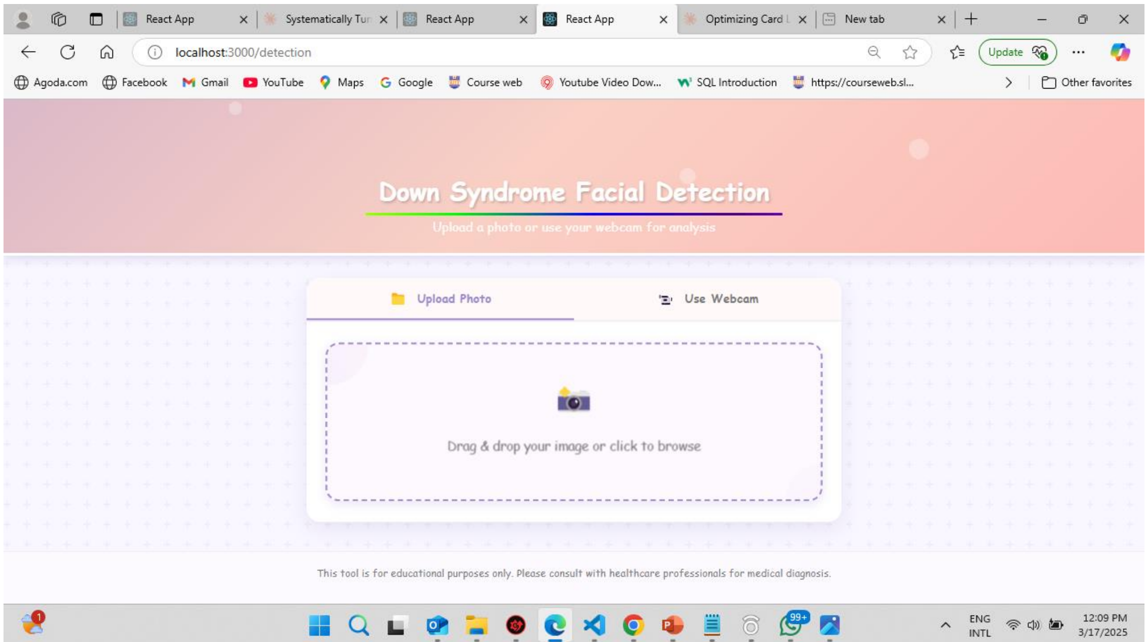


Figure 9: Postman checking

2.6.4 Frontend development

The frontend for the Down Syndrome detection application was developed using React.js, offering a modern and interactive user experience. Users can either upload a facial image or capture one directly using their webcam via the integrated react-webcam component. The interface dynamically handles both scenarios, providing real-time previews, action buttons, and feedback messages. Upon uploading or capturing an image, the frontend sends the image data to the backend using the axios library through a POST request in multipart/form-data format. The UI also interprets the backend response, displaying the prediction label, confidence percentage, and if Down Syndrome is detected a list of common facial symptoms associated with the condition. The design is responsive and informative, with loading animations, clear error handling, and character visuals to enhance user engagement and clarity



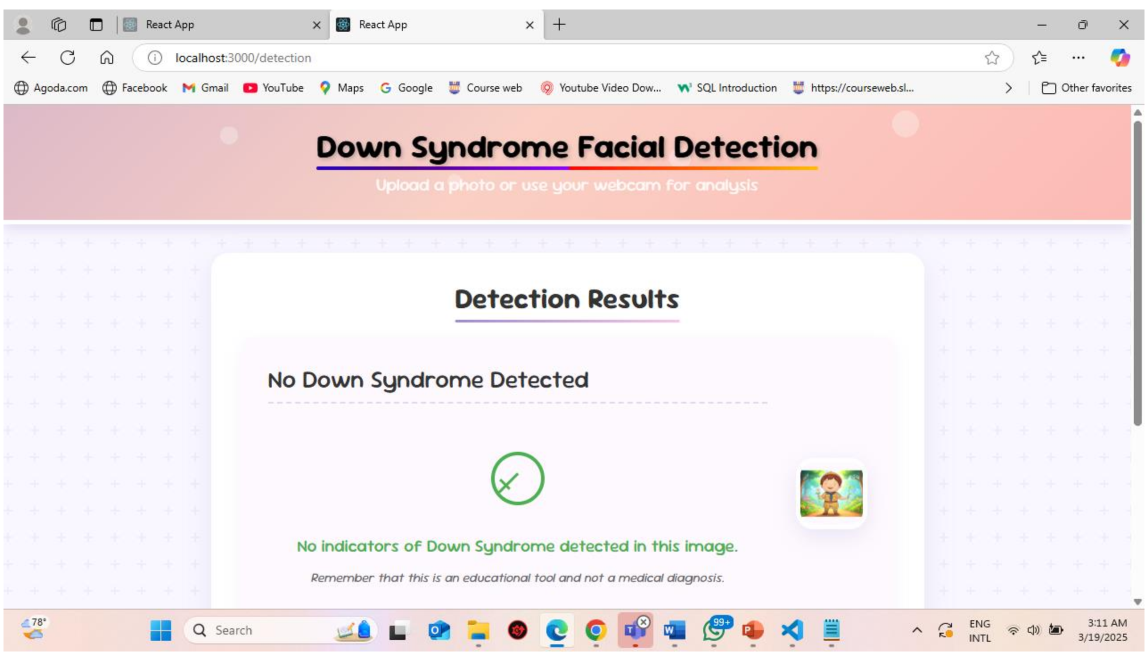


Figure 10: Frontend user interfaces

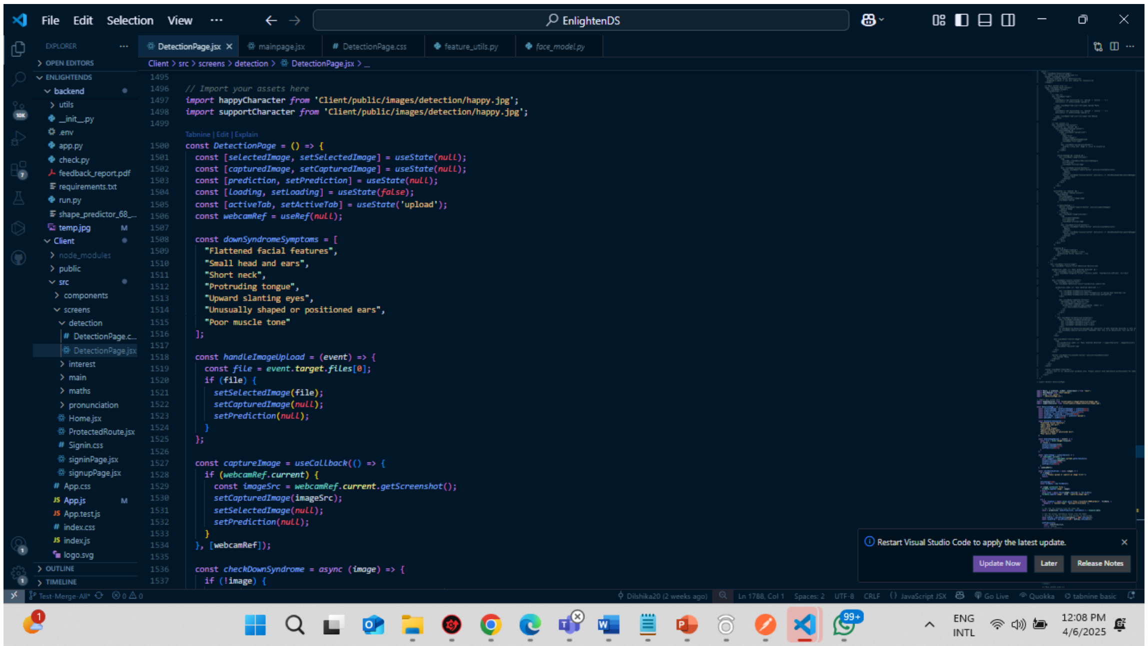


Figure 11Frontend detection page jsx code

2.6.5 Backend development

The backend of the Down Syndrome detection application is built using Python with the Flask framework and leverages machine learning and computer vision techniques to deliver accurate predictions based on facial images. The system loads a pre-trained Support Vector Machine (SVM) model and a corresponding feature scaler from serialized files. When an image is received via a POST request to the /predict endpoint, it is temporarily saved and passed through a preprocessing pipeline that involves feature extraction using a custom utility function. This includes facial landmark detection, image alignment, and face cropping key steps that ensure consistent input quality and orientation. Facial landmarks are extracted using Dlib's 68-point shape predictor, with additional validation to ensure the face is frontal for better accuracy. The processed image features are scaled and passed into the trained model for prediction. The model outputs both a binary classification (Down Syndrome detected or not) and a confidence score, which are then returned to the frontend in JSON format. The backend also includes robust error handling for invalid inputs and malformed images. Altogether, this backend pipeline encapsulates essential AI-driven components such as image preprocessing, facial analysis, and predictive modeling, making it a critical part of the application's functionality.

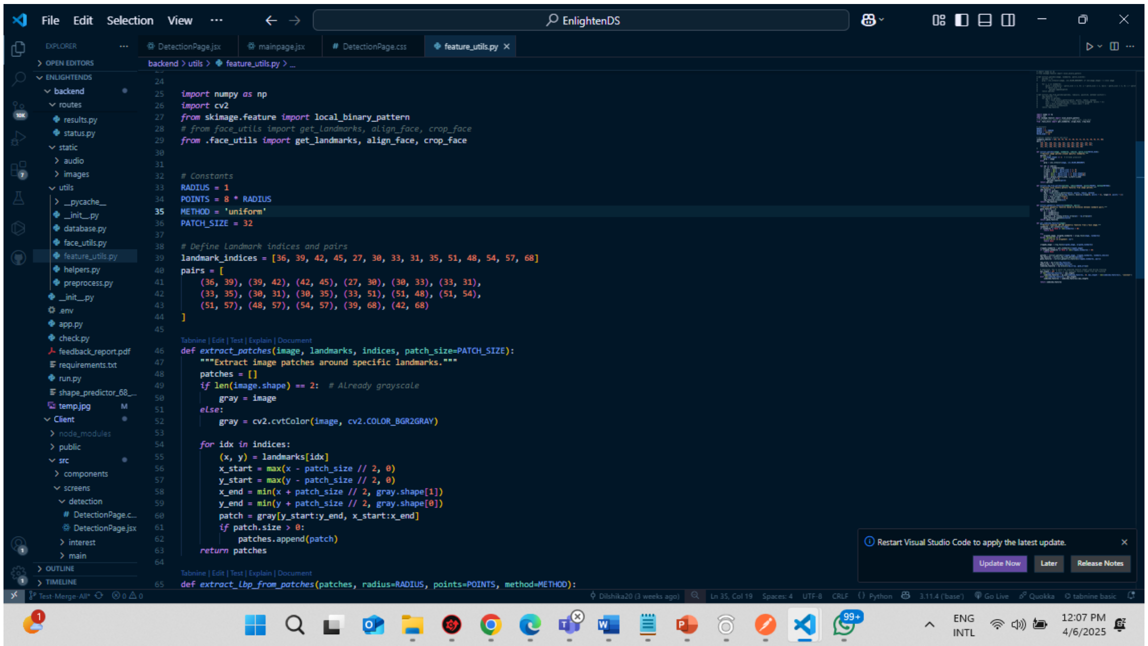


Figure 12: Backend feature utils python code

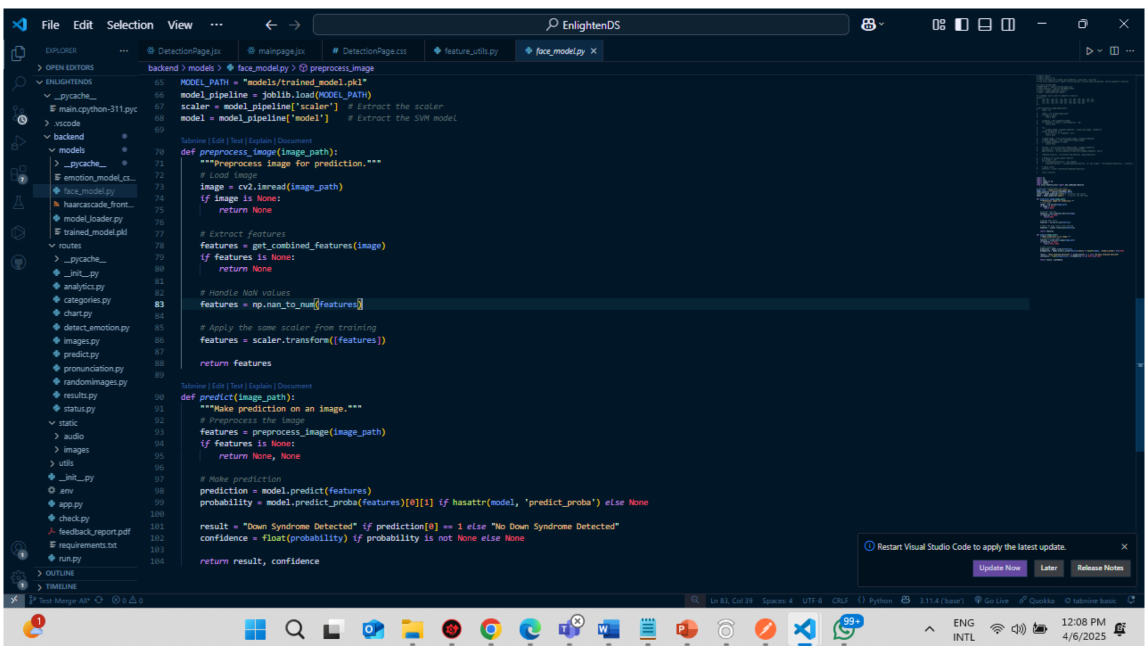


Figure 13: Backend face model python code

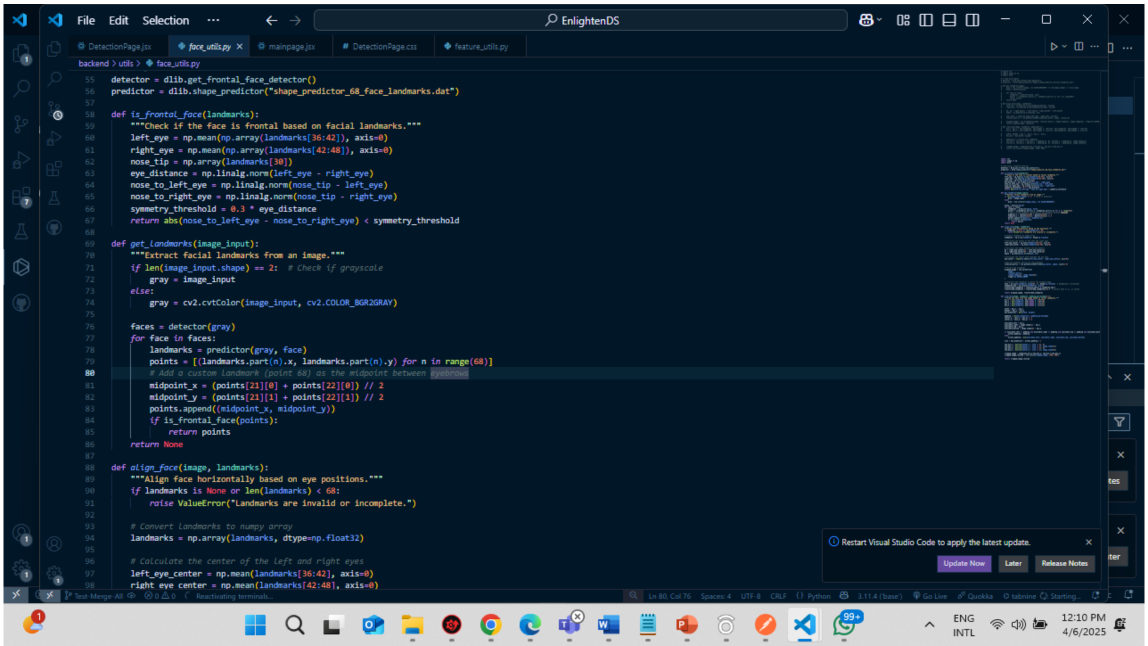


Figure 14: Face utils python code

3. COMMERCIALIZATION PLAN

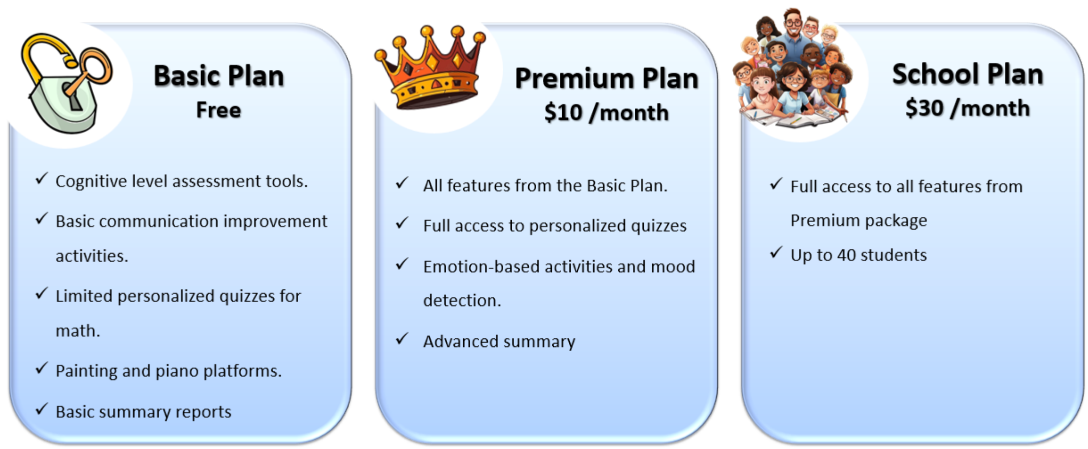


Figure 15: Commercialization code

A structured commercialization plan is needed for a number of reasons: First, it brings in sufficient revenues to sustain and grow our project revenues that will be reinvested into further development and refurbishment of the app. Second, it ensures that our solution remains both accessible to individual users and large educational institutions. Third, it clearly outlines how the market would be reached, such as building campaigns, allies, and alliances through educational standards that move along or follow regulatory standards for education and data privacy globally.

With a growing demand for educational technology, particularly in the area of cognitive development and early childhood education, our system "EnlightenDS" is a great opportunity to meet this demand. The very critical recognition of early cognitive assessments and developmental support only seems to be on the rise, hence creating a demand for such tools that are more accessible and effective for the use of parents, educators and schools at large. This will make these tools widely available for us so that they could make a significant contribution to children's cognitive development in a sustainable way.

A tiered subscription model for a number of different use categories has been formulated to be flexible and scalable. It is free through the Basic plan, which will give available basic cognitive level assessments, basic communication improvement activities and limited personalized quizzes on subjects like math. This plan, therefore, serves as an entry point to our solution, letting users explore and experience the key features of our app with no financial commitment. This implies that with the offering of a free version, the entry barrier will be low and a lot more kids can enjoy our tools, alike.

For users who want to have a more immersive and complete experience, there is a Premium Plan priced at $10 per month. This plan incorporates all the features of the Basic Plan and on top of this, it will include full access to personalized quizzes built by the user, emotion-based activities, mood detection and advanced summary reports. These features are designed for enabling deeper insight and customized support; hence, the Premium Plan should be adopted by parents and teachers who are keen on close monitoring and enhancement of cognitive development of the child.

Lastly, realizing that the educational institutions have special requirements, we have a School Plan offered for $30 per month, where all the features provided in the Premium package are extended in full to up to 40 students. This plan is especially useful for schools and special education centers to help them incorporate our cognitive development tools into their curriculum and do so at a very affordable price. Through a solution that can serve many, we make it easier for institutions to support large groups of children systematically and cheaply.

4. BUDGET

Component	Amount(LKR)
Travelling cost	10000
Server & Hosting charges	25000
Bandwith	15000
Total	50000

Figure 16: Budget

The budget for "EnlightenDS" has been carefully planned to cover all the important costs needed to develop and launch our cognitive assessment tool. It involves an amount of LKR 50,000, carefully planned to cover all the essential costs associated with the development and deployment of our cognitive assessment tool, EnlightenDS. The total budget is broken down into three key components.

First, we allocated LKR 10,000 for Traveling Costs. This amount is for traveling related to team meetings, collaboration with educational institutes, and any fieldwork that might be required for collecting user feedback or on-site demonstrations of our tool. This will ensure that we get to meet and interact face-to-face with our stakeholders. This is very important in the refinement of our solution to meet real-world needs.

This comes with the largest portion of the budget, LKR 25,000, for Server and Hosting Charges. This will be very instrumental in maintaining the infrastructure required to support our app. Reliable server hosting ensures that our platform remains open to users always, ensuring seamless operation and data security.

Finally, LKR 15,000 has been allocated for Bandwith. Since we are going to use cloud-based services and collaborate remotely, stable internet with high speed is one of the essential requirements for the day-to-day running of the project from research to development, testing, and communication.

5. GANTT CHART

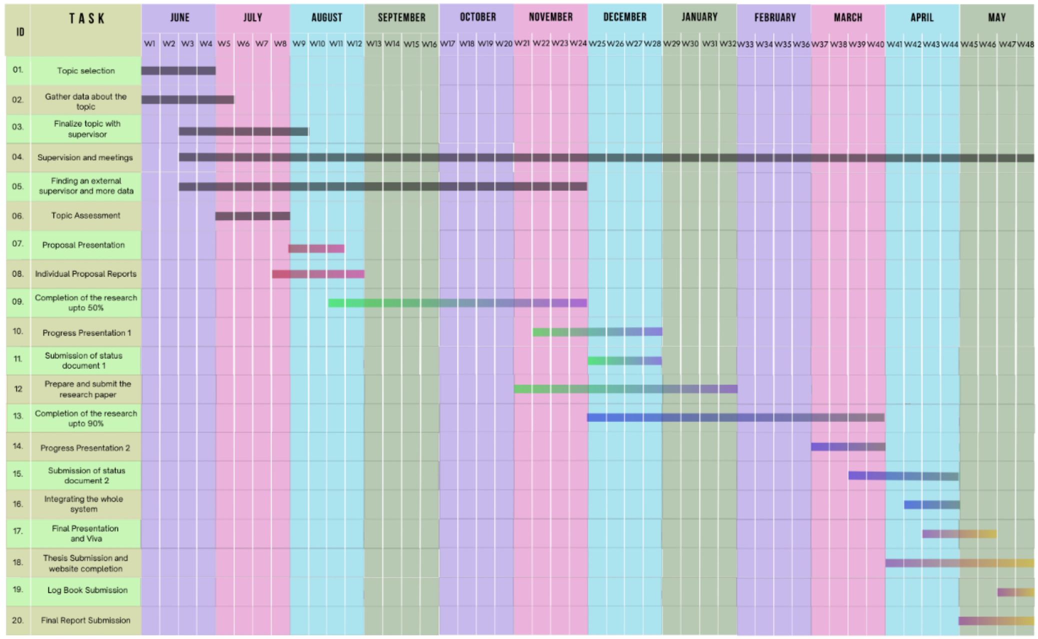


Figure 17: Gantt chart

6. WORK BREAKDOWN CHART

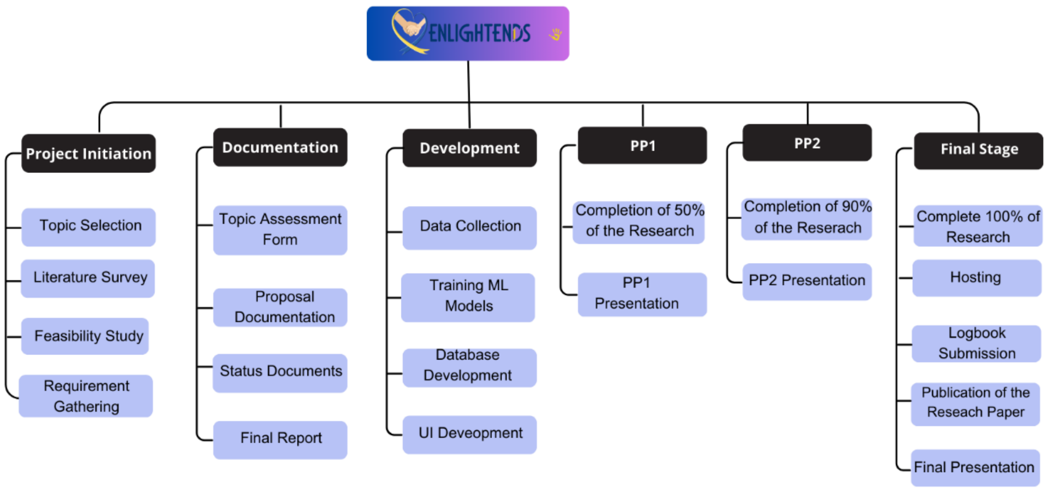


Figure 18: Work breakdown chart

7. RESULT AND DISCUSSION

The Down Syndrome detection system was rigorously evaluated using a comprehensive and balanced dataset comprising 3,000 facial images, 1,500 representing individuals diagnosed with Down Syndrome and 1,500 healthy individuals without the condition. This diversity ensured that the model was exposed to a wide range of facial variations, improving its generalization ability across different demographics. The trained model demonstrated impressive classification performance, achieving a high level of accuracy in differentiating between Down Syndrome and non-Down Syndrome facial features. Key performance metrics such as Precision, Recall, F1-score, and Accuracy were computed to assess the robustness of the system.

A Confusion Matrix was employed to visualize the model's predictive capability, highlighting the balance between true positives and true negatives, while minimizing false positives and false negatives. The model's Receiver Operating Characteristic - Area Under Curve (ROC-AUC) score further validated its effectiveness, reflecting a strong trade-off between sensitivity and specificity. The high precision value indicates that the model is effective at minimizing false alarms, while the high recall suggests that it rarely misses true cases of Down Syndrome.

During testing, the model consistently detected facial traits associated with Down Syndrome with high precision and recall, reaffirming the reliability of its predictions. In addition to binary classification, the system provides a confidence probability score, offering a nuanced understanding of how likely the analyzed face belongs to a person with Down Syndrome. This probability-based feedback not only enhances interpretability but also aids in reducing uncertainty during medical consultations. Upon detection, the system presents a list of typical facial characteristics commonly observed in Down Syndrome cases such as a flat nasal bridge, epicanthal folds, and upward slanting eyes—providing supplementary clinical insights for further evaluation.

Real-time detection capabilities were also explored through webcam integration, allowing users to capture images dynamically and receive immediate diagnostic feedback. This functionality was found to be highly responsive, with the Flask-based API processing each image and returning results within an average response time of less than 2 seconds. This efficiency supports practical deployment in real-world settings, particularly in telemedicine and mobile screening scenarios.

The deployment on Google Colab enabled efficient model training, leveraging GPU acceleration for improved performance. The frontend and backend of the system were created using Python, with the Flask framework powering the backend logic and model integration. A simple web interface was built for user interactions, allowing image uploads and webcam captures. Functionality was tested thoroughly using

Postman, which enabled validation of all API endpoints, including image upload, detection responses, and error handling under various scenarios.

To validate the reliability of the model's predictions, a subset of test results was manually reviewed by experienced medical professionals, who confirmed the system's ability to accurately identify facial markers of Down Syndrome. This expert validation reinforces the clinical relevance and trustworthiness of the application.

Table 2: Tase Case 1

7.1 Test Cases

Test case ID: T01				
Test title: Checking preprocessing techniques				
Test priority (High/Medium/Low): High				
Module name: Image Preprocessing				
Description: This test case ensures that the system properly applies preprocessing techniques to an uploaded or captured image, preparing it for further analysis.				
Pre-conditions: The drawing is uploaded into the system				
Test ID	**Test Steps**	**Expected Output**	**Actual Output**	**Result (Pass/Fail)**
T01	1. Apply preprocessing techniques such as resizing, noise reduction, and normalization.	The image is resized to a standard resolution, noise is reduced, and the image is normalized	• The image was successfully resized, noise was effectively reduced, and the image was normalized, making it suitable for analysis	Pass

Table 3: Test Case 2

Test case ID: T02				
Test title: Feature Extraction Using DLIB				
Test priority (High/Medium/Low): High				
Module name: Feature Extraction				
Description: This test case verifies that the DLIB correctly extracts key features from a preprocessed image which are essential for early detetcion				
Pre-conditions: The image has undergone preprocessing				
Test ID	**Test Steps**	**Expected Output**	**Actual Output**	**Result (Pass/Fail)**
T02	1. Input a preproce ssed drawing into the DLIB model 2. Run the DLIB to extract key features such as edges, shapes, and textures	Key features such as edges, shapes, and textures are accurately identified and extracted by the DLIB.	• The DLIB accurately identified and extracted key features, including edges, shapes, and textures, aligning well with the expected results.	Pass

8. CONCLUSION

The Down Syndrome detection system demonstrated a promising approach to early diagnosis by leveraging deep learning and facial recognition techniques. With high accuracy, precision, and recall, the model effectively distinguished between individuals with and without Down Syndrome. The integration of a user-friendly frontend and a robust backend built using Python and Flask ensured a seamless experience for end-users. Real-time detection through webcam support and quick API response times further enhanced the system's practicality and usability. Overall, the system proved to be a reliable tool that can assist in the preliminary identification of Down Syndrome, supporting medical professionals in early screening processes.

To enhance the system's diagnostic capabilities and applicability, the following future directions are proposed:

- **Dataset Expansion**: Increase the size and diversity of the dataset by including more age groups, ethnicities, and varied facial expressions to improve model generalizability.
- **Model Fine-tuning**: Further optimize the model by incorporating more facial features and using advanced architectures for increased detection accuracy.
- **Multi-modal Analysis**: Integrate genetic markers or medical history along with facial features to improve diagnostic confidence.
- **Mobile Application Development**: Create a mobile app version of the system for easier accessibility in remote and low-resource areas.
- **Continuous Learning**: Implement mechanisms for the model to improve over time with user feedback and new data inputs.

9. REFERENCES

[1] "April-June 2005 - Volume 18 - Issue 2 : Infants & Young Children." Accessed: Apr. 07, 2025. [Online]. Available: https://journals.lww.com/iycjournal/fulltext/2005/04000/the_emerging_down_syndrome_behavioral_

[2] V. Bs, S. C. Madamanchi, and S. Kalimuthu, "Early Detection of Down Syndrome Through Ultrasound Imaging Using Deep Learning Strategies — A Review," in *2024 Second International Conference on Emerging Trends in Information Technology and Engineering (ICETITE)*, Feb. 2024, pp. 1–6. doi: 10.1109/ic-ETITE58242.2024.10493220.

[3] S. Er-rida, M. Oubibi, M. Mafhoum, M. H. Alami, and A. M. Alaoui, "Challenges Faced by Parents of Children with Down Syndrome in Mainstream Schools: Exploring Inclusive Education", doi: 10.2174/0118743501360190250101113909.

[4] B. Qin, L. Liang, J. Wu, Q. Quan, Z. Wang, and D. Li, "Automatic Identification of Down Syndrome Using Facial Images with Deep Convolutional Neural Network," *Diagnostics*, vol. 10, no. 7, Art. no. 7, Jul. 2020, doi: 10.3390/diagnostics10070487.

[5] A. Saini, "Enhanced Detection of Down Syndrome Through Convolutional Neural Networks: A Deep Learning Approach," in *2025 6th International Conference on Mobile Computing and Sustainable Informatics (ICMCSI)*, Jan. 2025, pp. 1583–1587. doi: 10.1109/ICMCSI64620.2025.10883612.

[6] V. Bs, S. C. Madamanchi, and S. Kalimuthu, "Early Detection of Down Syndrome Through Ultrasound Imaging Using Deep Learning Strategies — A Review," in *2024 Second International Conference on Emerging Trends in Information Technology and Engineering (ICETITE)*, Feb. 2024, pp. 1–6. doi: 10.1109/ic-ETITE58242.2024.10493220.

[7] T. A. Anjit and S. Rishidas, "Identification of nasal bone for the early detection of down syndrome using Back Propagation Neural Network," in *2011 International Conference on Communications and Signal Processing*, Feb. 2011, pp. 136–140. doi: 10.1109/ICCSP.2011.5739286.

[8] "Evaluation of Executive Functions of Children with Down Syndrome and Zika Virus Using Touch Screen Device | Request PDF." Accessed: Apr. 07, 2025. [Online]. Available: https://www.researchgate.net/publication/344365667_Evaluation_of_Executive_Functions_of_Children_with_Down_Syndrome_and_Zika_Virus_Using_Touch_Screen_Device

[9] "(PDF) Cognitive Impairments in Children with Down Syndrome," *ResearchGate*, Oct. 2024, doi: 10.7176/JHMN/71-12.

[10] S. E. Antonarakis *et al.*, “Down syndrome,” *Nat Rev Dis Primers*, vol. 6, no. 1, p. 9, Feb. 2020, doi: 10.1038/s41572-019-0143-7.

[11] “(PDF) Early Intervention in Children with Down’s Syndrome: From Evaluation to Methodology.” Accessed: Apr. 07, 2025. [Online]. Available: https://www.researchgate.net/publication/232189708_Early_Intervention_in_Children_with_Down's_Syndrome_From_Evaluation_to_Methodology

[12] A. F. Lukowski, H. M. Milojevich, and L. Eales, “Cognitive Functioning in Children with Down Syndrome: Current Knowledge and Future Directions,” *Adv Child Dev Behav*, vol. 56, pp. 257–289, 2019, doi: 10.1016/bs.acdb.2019.01.002.

[13] “What is Agile Development and why is it important?,” OpenText. Accessed: Apr. 07, 2025. [Online]. Available: https://www.opentext.com/what-is/agile-development

[14] “Manifesto for Agile Software Development.” Accessed: Apr. 07, 2025. [Online]. Available: https://agilemanifesto.org/

[15] “(PDF) How Agile Practices Impact Customer Responsiveness and Development Success: A Field Study.” Accessed: Apr. 07, 2025. [Online]. Available: https://www.researchgate.net/publication/315498894_How_Agile_Practices_Impact_Customer_Responsiveness_and_Development_Success_A_Field_Study

[16] “Continuous Improvement in Agile Environments.” Accessed: Apr. 07, 2025. [Online]. Available: https://leadingbusinessimprovement.com/continuous-improvement-in-agile-environments/

[17] “Reflect and Adjust: A Key Agile Principle for Continuous Improvement - CAVU | Modern Digital Transformation Training.” Accessed: Apr. 07, 2025. [Online]. Available: https://www.cavu.co/continuous-improvement/

[18] A. M. Koul *et al.*, “Unraveling Down Syndrome: From Genetic Anomaly to Artificial Intelligence-Enhanced Diagnosis,” *Biomedicines*, vol. 11, no. 12, p. 3284, Dec. 2023, doi: 10.3390/biomedicines11123284.

[19] “(PDF) Examining The Educational Problems Of Children With Down Syndrome; Special Education Teachers’ And Psychologists’ Perspectives, Pakistan.” Accessed: Apr. 07, 2025. [Online]. Available: https://www.researchgate.net/publication/371043969_Examining_The_Educational_Problems_Of_Children_With_Down_Syndrome_Special_Education_Teachers'_And_Psychologists'_Perspectives_Pakistan

[20] "(PDF) Challenges Faced by Parents of Children with Down Syndrome in Mainstream Schools: Exploring Inclusive Education," *ResearchGate*, Feb. 2025, doi: 10.2174/0118743501360190250101113909.

10. APPENDICES

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