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An Engineering Framework for NDD and NDEVD Identification in the Human Brain: Critical Analysis and its Treatment Through AI Therapy

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Abstract - Stressful daily routine and fast moving lifestyle have resulted in the brain malfunctionality leading to a global healthcare problem. This situation has generated the need to understand the brain structure and its functionalities in the context of health, diseases and disorders.Identification of brain malfunctionality is a critical area of neuroscience and medical diagnostics research. An array of disease identification and advanced methods including neuroimaging, genetic testing, biomarker detection, and machine learning methods have been recognized.Neuroimaging devices offer cross-sectional vision, generating high-resolution structural and functional information regarding brain abnormalities.They speed up the early diagnosis of diseases such as Alzheimers, Parkinsons, and brain tumors. Genetic research identifies mutations, and susceptibility genes to determine neurodegenerative or neuropsychiatry disorders.Molecular and biochemical markers, offer non-invasive diagnostic tools to closely follow disease progression and treatment response.

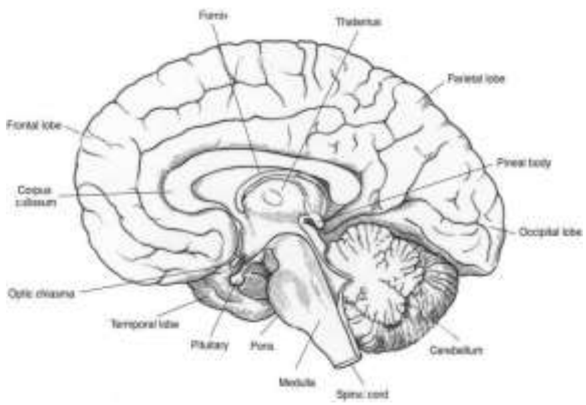
Machine Learning Algorithms, especially Deep-Learning are immensely useful in analyzing large neuroimaging data, enhancing diagnostic accuracy and forecasting patient outcomes.Brought together in synergy, these methods by clinicians, medical scientists, and pedagogues have devised a prototype that can enable early detection, improved diagnostic specificity, by obviating misdiagnosis and providing customized treatments.This kind of framework is helpful in identifying new diseases and their symptoms for improved diagnosis and improved patient care.

Key Words- Brain Disorders, Diseases, Neuro-degeneration, Neurons.

1. INTRODUCTION

Human brain is a centralized controlling center of the Central Nervous System (CNS) filled with millions of nerve cells in the skull.As with all the other body parts that have to be coordinated and controlled, e.g., integration of information by the sense organs, the human body has a center of command in the cerebrum, cerebellum, and medulla oblongata to coordinate such actions.It is a gelatinous mass of tissue that weighs approximately 14kg and is made up of 86 billion nerve cells or neurons.The cerebrum is connected to the stem and the brain stem is connected to the spinal cord.

Brain stem is made up of things like midbrain, pons and medulla oblongata.Aside from the cortex, the brain also has other important structures such as the thalamus, pineal gland, hypothalamus, pituitary gland, amygdala, and the hippocampus.. Every part of the cerebral cortex has a unique cavity where cerebrospinal fluid is generated and circulated. The lateral ventricles are divided by a membrane known as the septum pellucidum, situated beneath the corpus callosum. Cerebrum controls the voluntary movements. This is the biggest region and weighs around twothirds of the brain's weight. In addition, the cerebrum is divided into two parts known as the cerebral hemispheres. The left side of the brain speaks and understands language whereas the right side visually and spatially analyzes information. Both of them are linked together with the help of a bundle of nerve fibers known as the corpus callosum. Each hemisphere is further divided into four sections called lobes, categorically the frontal, temporal, parietal, and occipital lobe. Each of these are specialized in performing various functions. Starting from the frontal lobe, it is responsible for managing emotions , problem solving, memory retrieval, language judgement and actions. On the other hand, the temporal lobe is responsible for perception like speech and hearing. This helps to receive audio sensations which can be processed verbally through spoken or written words. The parietal lobe is responsible for processing information that pertains to movement, touch, taste, and temperature. The occipital lobe performs visionary activities and also controls the activities of human-body, like processing, integrating and coordinating the information received. Fig.1 shows different parts labelled for a human brain.



2. LITERACTURE SURVEY

Early dyslexia and neurodevelopmental disorder detection has evolved significantly with advances in artificial intelligence and multimodal data analytics. Recent studies highlight handwriting, speech patterns, neuroimaging, and eye-tracking signals as potential biomarkers to predict dyslexia risk at an early stage.
Rangasrinivasan et al. [1] introduced an AI-enhanced handwriting analysis framework using tablet-based digital input to extract stroke-level features such as pressure, tilt, velocity, and formation consistency. Their findings demonstrated that handwriting-based features strongly correlate with dysgraphia and dyslexia, forming a foundation for handwriting-driven assessment models. Similarly, Drotár et al. [4] applied machine learning algorithms to classify dysgraphia using pen kinematics and achieved an accuracy close to 80%, showing that motion-level features provide higher diagnostic reliability than traditional paper-based screening.
Alkhurayyif and Sait contributed two key studies in this domain. Their first work [2] reviewed state-of-the-art dyslexia detection methods and concluded that multimodal AI systems outperform single-modality approaches due to richer cognitive representation. Their second study [3] developed a deep learning model integrating MRI, EEG, and behavioural features, achieving high diagnostic precision and demonstrating the strong neurobiological basis of dyslexia.
Kunhoth et al. [5] reviewed automated dysgraphia assessment systems and reported limitations such as small datasets, lack of standardization, and poor model generalization across writing styles and languages. These insights highlight the need for larger and more diverse datasets to improve real-world usability.
Beyond handwriting and neuroimaging, gaze-based analytics have emerged as another critical dimension. Toki et al. [6] performed a systematic review of eye-tracking studies and reported that dyslexic readers exhibit slower saccades, increased fixation duration, and more frequent regression eye movements during reading tasks. These findings suggest that eye-movement characteristics may serve as additional cognitive markers for screening.
In support of intervention research, Barua et al. [7] emphasized the role of AI-based assistive learning tools, showing improved user engagement, reading fluency, and comprehension when adaptive digital interventions are combined with early detection systems. Furthermore, Liyakathunisa et al. [8] applied supervised machine learning for early risk prediction using behavioural and educational features and demonstrated that early screening can detect dyslexia risk before formal diagnosis.

Some widespread NPD include movements, seizures, anger, migraine headaches, various types of addictions, eating disorders, depression, and anxiety. The individual suffering from NPD shows violence, aggression, criminal and antisocial behavior, impulse control disorder and episodic dis-control. These disorders have a relatively high and rapid incidence and manifest early childhood Autism and adult Schizophrenia .

Genes, nutrition and other external factors contribute significantly to the escalation of the neurological disease/disorder. The CNS is considered damaged when all relevant activity ceases and the cells essentially perish. Disorders change the normal activities of the brain, leading to engraved, progressive or sudden decline in the functions of brain such as sensory, motor and cognitive functions.

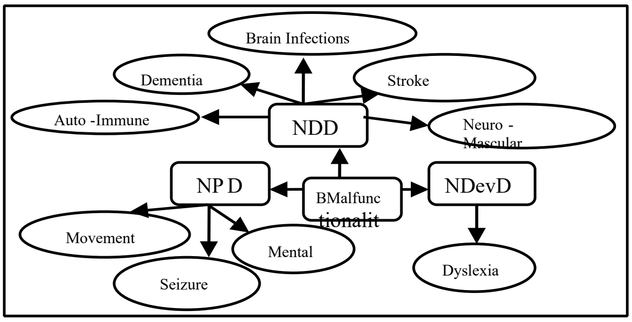


Fig.3. NDD Categories

Some of the major classes of brain diseases are reflected in figure 3. Some of the NDD are associated with abnormal deposits of tau protein, amyloid neurofibrillary tangles and other misfolded proteins in the brain, which are classified as autoimmune diseases. These diseases range from Alzheimer's and Huntington's to Parkinson's and Prion . According to some studies, it is believed that genetic mutations fall under the umbrella of deposition of misfolded proteins in Prion.

It results in loss of coordination of body movements and even cognitive processes. At the same time physio-cognitive impairments and in extreme situations dementia are induced by cell death, inflammation, and synaptic deficits in the brain. NDD is incurable. Cell transplant therapy is successful in the late stages of the disease with symptomatic relief. Heritability of depression increased from 38% to 75 percent .

One in every 4 persons who are over 55 years of age have Dementia . It is a syndrome that defines the advanced stages of NDD. The terminal stages severely compromise the ability to perform cognitively normal daily activities. It is also marked by impairments of memory and cognition, visual disturbances, disturbed attention and behavioural disturbances. Epigenetic effects augment symptoms. Certain metals have been reported to induce acceleration of AD and PD like lead (Pb), Mercury (Hg), Arsenic (As), Cadmium (Cd), and Aluminium (Al). Some pesticides also have an important role in the etymology of neurological disorders, such as Paraquat (PQ) and 1-methyl-4phenyl-1,2,3,6-tetrahydropyridine (MPTP).Rotenone,like Trichloroethylene (TCE) and other toxic nanoparticles also cause neuronal cell death and malfunctionality of the CNS.

Table 1 and 2 is a detailed study about the NDD, categories from figure 3 with the parts of the brain affected leading to malfunction and its treatment respectively. Critical analysis of tables 1 and 2 resulted in the selection of Dyslexia disease that affects productivity of children thereby affecting productivity of the nation at large.

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TABLE 1: CRITICALLY ENGINEERED HYBRIDIZED CATEGORICAL ANALYSIS OF ND DISEASES (NDD)

Region Affected		Leading to		Treatment (Therapy, Drugs)
1. Brain cells / Brain	10. Temporal lobe	1. Aggression	10. Paralysis	1. Immunomodulators / B/ Passive immunity
2.Blood vessels	11. Frontal lobe	2. Seizures	11. Uncontrolled Bowel / Bladder	2. Anti-Inflammatory / immunosuppressive
3.Venules/Veins in Brainstem	12. Cortex	3. Falling Tendency / Imbalance	12. Headache / Drowsiness / Fever	3. Speech / Sensory / Physical therapy
4.Eye / Optical Nerve	13. Brain Functioning	4. Vision / Speech/ Sleep Difficulties		4. Chemotherapy
5. Hypothalamus	14. Axon	5. Nausea/Irritability / Fatigue		5. Anti-sense
6.Brainstem	15. Nerve cell / Neuron	6. Hearing Problems		6. Antibiotic
7.Hippocampus	16. Spinal cord	7. Behavioral Issues		7. Anti-Psychotics/Depressant/ Convulsants/ Seizure/Anxiety
8. Amygdala		8. Cognitive Issues		8. Cognitive Enhancer / Inhibitors
9. Cerebrum		9. Neurological Issues		

		Region Affected																Leading to												Treatment (Therapy, Drugs)							
	D	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8
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	19	✓																			✓	✓	✓			✓			✓			✓	✓				
NMD	20	✓														✓	✓			✓	✓	✓		✓		✓						✓					
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TABLE 2: CRITICALLY ENGINEERED HYBRIDIZED CATEGORICAL ANALYSIS OF NEURO-DEVELOPMENTAL DISORDERS (NDevD)

SC	D	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6	7
Dyslexia	1	✓	✓								✓				✓		✓		✓	✓	✓	✓	✓	✓	✓			✓	✓		✓	✓	✓			✓	

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4. MODELS TO STUDY BRAIN DISORDERS

To interpret the different molecular paths corresponding to several categories of brain disorders, organism models such as the house fly, zebra fish, pig and primates along with Caenorhabditis elegans and Drosophila melanogaster are incorporated. In the last three decades, several studies have shown an increasing amount of evidence pointing towards the existence of highly developed similarities in the structure and the organization of the brain of monkeys and humans. Nerve cells are equally important in further understanding the differences of molecular structures in the progression of brain diseases or disorders.

Age-related and other NDD like AD, PD and HD are highly attributed to the model conserved in the counterparts Advancements in transgenic technologies have allowed the use of Drosophila as a model for various NDD such as AD, PD, Amyotrohic Scleros, Hereditary Spastic Paraplegia and other Polyglutamine diseases. The pathogenesis of other NDD such as PD, HD and AD occurring in humans have been preserved ontology in Zebrafish and vice versa. More recently, transgenic zebrafish that express Green Flourescent Protein (GFP) were created. The larvae of the Zebrafish display measurable Neuro-Pathological and behavioral phenotypes similar to humans. Also, transgenic technologies are used in the building of Mice models and Rats have been genetically altered to investigate the Pathophysiology of Autism, Fragile X syndrome, and other NPD.The pig's cerebral cortex, unlike that of the mice or rat, possesses a cerebral convolution comparable to the human neo-cortex and so it is expected to have high translational value. Lind et al. reviewed the use of pig in neuroscience to model human brain diseases. Pigs are anatomically, physiologically, and genetically closer to humans than mice, and so genetically modified pigs are being used to model different neurological disorders. Similar studies were done in transgenic monkeys. Monkeys are the most preferred animals for studying the nature of disease progression in PD, microcephaly, AD and sleep disorders because they are the closest animals to humans.

There is no regenerative potential in the brain neurons, thus age-related degeneration results in severe brain malfunctions. NDD/D in the brain are associated with these characteristics and have a slow progression initially. These diseases are more prevalent in rural population particularly in the developed nations where average longevity is greater. The diseases include PD, progressive supra-nuclear palsy, multi-system atrophy, Alzheimer's Dementia, Front-temporal dementia.

PD is an illness which leads to trouble with movement and stiffness and behaves as an ongoing degenerative process of the nervous system. It is linked with the death of neurons in the Substantia Nigra and other areas of the brain. And it is also related to the development of intracellular protein aggregates called Lewy bodies (LB's) in the neurons.

Studies help to effectively devise measures to improve people with certain brain disorders. The use of nanoparticles for transporting drugs across the BBB is one of the most advanced applications of nanotechnology in clinical neuroscience. Nanoparticles can possibly perform several different actions in a specific order, which could be beneficial for drug delivery across the BBB.

Dyslexia is a learning disorder that affects an individual's ability to read, write, and spell. It is characterized by difficulties with phonemic awareness, decoding, fluency, and comprehension. Dyslexia is not a disease, but rather a difference in how the brain processes written language. Dyslexia is not associated with progressive brain damage or degeneration. Research has proved that persons with Dyslexia have variations in brain structure and functionality, specifically in the regions where spoken language processing is carried out. These differences comprise of 1. Reduced Gray material in the left Occipto-Temporal region, 2. Abnormal white matter traces, affecting communication between brain regions, 3. Differences in brain activity patterns in the regions of phonological processing. Research has shown that brain is capable of reorganizing itself in response to targeted interventions. This concept, known as neuroplasticity, suggests that individuals with dyslexia can benefit from evidence-based interventions, such as phonics-based instruction, to improve reading and writing skills.

III. SYSTEM ARCHITECTURE

Fig.4 shows the system architecture of the Dyslexia Identification System (DIS), where the data of more than 100 children were given as input to the system. The system detects the presence or absence of the ailment and provides customized learning mechanisms for different Dyslexia profiles.

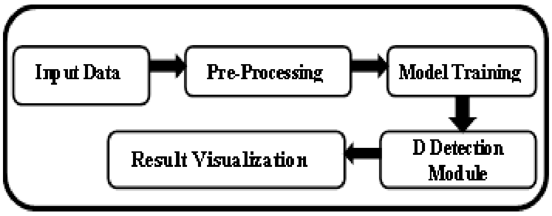

Fig.4:System Architecture.

Step 1: Dataset Collection and Preparation (Input data)

Machine learning models solely depend upon the quantity, quality and variety of the data set used for training testing and evaluation. The prototype, aims to create and curate a comprehensive dataset that incorporates text, audio and behavioral data from both impaired and non-impaired children to ensure a robust model performance.

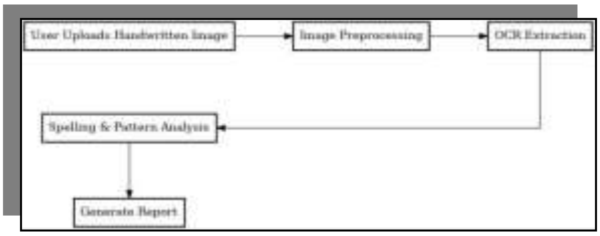

Fig 5: Handwriting Assessment Flowchart.

The flowchart fig 5 illustrates the sequential process of a handwriting assessment system. It begins with the user uploading a handwritten image, which then undergoes image preprocessing steps such as grayscale conversion, resizing, and noise removal to enhance quality. Next, the OCR extraction phase uses tools like Tesseract or Google Vision to convert handwriting into machine-readable text. The extracted text is analyzed in the spelling and pattern analysis stage to detect common indicators of writing disorders, including letter reversals, omissions, and irregular spacing. Finally, the system compiles the findings and produces a report summarizing error types, providing a score, and suggesting potential improvements or further evaluations.

The data sources consisted of publicly available dataset like "Kaggle" that included both textual and speech samples from children, categorized into affected and non-affected groups, and customized Collection where data is gathered through collaborations with schools, educational institutions and therapy centers having affected children. The collection strictly adheres to ethical guidelines by obtaining informed consent from the participants.

The types of data collected are textual data that includes samples of reading, writing exercises, focusing on errors, grammar and reading speed referred to as viewing senses, audible data that captures speech patterns to assess phonological skills and pronunciation accuracy referred to as hearing, vocalizing senses and behavioral data that captures eye movements, mouse pointer behavior and touch interactions during learning activities referred to as motion senses. *Step 2: Pre-processing*

Textual data is normalized by removing unnecessary symbols and formatting errors. Audio data undergoes noise removal and segmentation to isolate relevant speech segments. Behavioral data is cleaned to remove outliers and structured accordingly for machine learning compatibility. This step ensures that the raw data is transformed into structured, clean and meaningful formats suitable for training the models. It consists of data cleaning, extracting key speech features and normalization of textual data to ensure consistency.

Step 3: Model Training

Training phase consists of utilizing several ML methodologies like Convolutional (CNN), Recurrent (RNN) Neural Networks, Natural Language Processing (NLP), Deep Learning and the Random Forest Algorithm (RFA), to build a hybrid classification model with added advantages. After training, the model outputs a prediction that identifies whether a child is Dyslexia affected or not.

Step 4: Dyslexia Detection Module (DDM)

Dyslexia identification calls for the need to design a machine learning model capable of processing multimodal data inputs like text, speech, and behavioral patterns. Figure 2 shows the detailed block diagram of Dyslexia Detection Module.

Step5: Result Visualization

The output obtained is displayed in the form of graphs: A bar graph to visualize the child's score categorized into no, mild, moderate or severe Dyslexia and comparative visualization where the child's score can be compared to an average of their age group, allowing parents or teachers to better assess the child's performance.

IMPLEMENTATION AND RESULTS

This section outlines how the system is implemented to achieve the above mentioned objectives, focusing on the core architecture and technologies to detect Dyslexia by evaluating reading and speech patterns, followed by personalized learning paths. At the core of the system, DDM uses advanced algorithms like NLP for reading assessments and speech recognition models to evaluate speech accuracy. This model helps classify whether the child might have dyslexia based on reading speed, errors, and phonological awareness. Upon detecting potential signs of Dyslexia, the system provides personalized, gamified learning tasks designed to improve reading skills and speech accuracy, following a multisensory approach. Real-time feedback is given to the child during learning sessions, with a dashboard available for educators and parents to track progress and offer support. The proposed system mandates the need to couple Machine Learning, WebDevelopment and Gaming technologies for a better identification, assessment and diagnosis of Dyslexia.

Figure 6,7,8 show Neuro Nurture Landing Window, Login page, Tailored quiz for varying age group children and mathematical analysis of Dyslexia Risk Identification respectively.s

Fig.6: screen short of CognitiveLens Assessment Platform

CognitiveLens Fig 6 is a comprehensive digital tool designed to support early identification of learning differences in children and adults. By analyzing handwriting, cognitive abilities, and speech patterns, the platform offers detailed assessments to detect potential indicators of dyslexia, attention difficulties, memory challenges, and speech-related issues. It empowers educators, therapists, and parents with actionable insights through interactive evaluations and automated reports. With features like handwriting analysis, cognitive testing, and speech evaluation, CognitiveLens aims to personalize learning interventions and promote academic success through science-backed data and targeted support strategies.

Fig.7: Handwriting Assessment

The Handwriting Assessment tool from CognitiveLens allows users to draw or upload handwriting samples for analysis. It evaluates spelling accuracy, letter formation, and patterns that may indicate dyslexia. In this example, the user wrote the words "apple," "banana," "cat," and "dog." The system analyzed 18 strokes and identified minor inconsistencies in letter spacing and height, but detected no significant dyslexia indicators. The typed and handwritten words matched correctly, and the analysis provided insights into writing clarity and formation, offering valuable feedback for early learning assessments.

Correct Letter	Dyslexic Form	Error Type
b	d	Letter reversal
d	b	Mirror confusion
p	q	Reversed shape
q	p	Direction error
m	w	Upside-down confusion
n	u	Rotation mistake
s	z	Similar shape mix up
E	3	Mirror image

Fig 8: Dyslexia Handwriting Errors examples

This table fig 8 lists common errors seen in dyslexic handwriting. These include letter reversals like writing 'b' as 'd', or mirror confusions such as 'd' written as 'b'. Other examples are shape reversals, where 'p' becomes 'q', and directional mistakes like 'q' as 'p'. Some children might swrite 'm' as 'w', which is an upside-down confusion, or 'n' as 'u', showing a rotation error. Letters like 's' and 'z' may be confused due to their similar shapes. Capital letters also pose challenges; 'E' may appear as '3', a mirror image, or
'R' as 'Я', which is reversed. Lastly, a child might write 'h' as 'n', showing confusion in vertical strokes. These patterns help identify the types and frequency of dyslexic handwriting errors.

Fig.9: Cognitive Assessment

The Attention Span Assessment in the CognitiveLens platform provides insights into an individual's ability to sustain focus and respond quickly to stimuli. In this instance, the user achieved a 66.7% hit rate (4 out of 6 targets) with an average reaction time of 1126 milliseconds, indicating average response speed but slight challenges in sustained attention. The analysis detected moderate dyslexia risk (40%), suggesting some cognitive patterns commonly linked with learning difficulties. Detailed findings highlight that while the user's reaction time falls within a normal range, difficulties in maintaining attention were observed. Recommendations include engaging in attention-training exercises, incorporating activities that promote cognitive speed, and taking regular breaks during focused tasks. The dyslexia assessment also advises professional evaluation to validate preliminary findings and guide appropriate support. This cognitive evaluation is designed to help identify potential learning needs early, supporting more effective and personalized educational strategies.

This table fig 9 categorizes the results of a handwriting assessment based on a percentage score. A score between 0% to 20% indicates no risk, meaning the handwriting appears normal.

A score in the range of 21% to 40% is considered low risk, suggesting some minor writing issues. Scores from 41% to 60% fall under moderate risk, which could indicate possible dyslexia.

A high risk is flagged for scores between 61% and 80%, meaning the writing shows clear signs of dyslexia. Finally, scores from 81% to 100% indicate a very high risk, suggesting strong symptoms of dyslexia in the handwriting patterns

Score Range	Risk Level	Result
0 - 20%	No Risk	Normal
21 - 40%	Low Risk	Minor issues
41 - 60%	Moderate Risk	Possible dyslexia
61 - 80%	High Risk	Likely dyslexia
81 - 100%	Very High Risk	Strong signs of dyslexia

Fig 10:Dyslexia score analysis

CONCLUSION

The framework for D and D identification in the human brain offers a technical approach for diagnosing neurological conditions with higher accuracy and precision. Due to the existence of non-genetic factors in the human brain, the research is more focused on the study of epigenetic factors i.e the study of changes in genes as interpreted by cells without changing DNA sequence. Databases developed for NDD have proven a great boon in this area. Although there are several models to study NDD but still there is a need for specialized technique to identify NPD with overlapping symptoms. By integrating advanced neuroimaging, genetic analysis, biomarkers and machine learning techniques, this framework enhances early detection, customizes personalized treatment, by refining diagnostic and therapeutic capabilities to improve patient outcomes. The developed prototype not only supports clinical practice but also acts as a benchmark for AI and NLP researchers to better understand brain diseases, disorders and diagnosis, benefiting all the stakeholders like patients, health workers, educationists, medical researchers and software developers. Prototype has a good potential to identify True Positives, True Negatives, False Positives and False Negatives as a future enhancement.

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