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# Machine Learning-Based Visuospatial and Eye-Movement Tasks for Early Detection of Lewy Body Dementia in Older Adults

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## ABSTRACT

**Detecting Lewy Body Dementia (LBD) early can be difficult because visuospatial (how well you can see where things are) and executive (how well you can organize things) problems happen before there are obvious symptoms of LBD. This study introduces a computer-based model to detect early indicators of LBD in adults aged 60 years or older by evaluating performance on tasks involving visuospatial processing and eye movement. Three types of tasks were used to determine LBD risk: a baseline gaze task measuring natural eye behavior (e.g., blink rate, head stability), and a memory task requiring recall of object locations using a 4 × 4 (16-cell) spatial grid AML, and an inhibition task where the person was required to have a structured way to stop their eyes from doing an involuntary movement when looking in one direction and then move their eyes in the opposite direction in order to create a new eye movement. When completing the LBD test tasks, subjects were required to use a tablet. Also, the test subjects' eyes were tracked in real-time using the video camera built into the tablet and data from their eye movements were recorded and analysed. In addition to eye behaviour data, tests were given to obtain behavioural data. A statistical model based on logistic regression was created using the findings of both eye behaviour and behavioural measures that predicted whether or not an LBD diagnosis would be made to create a summary score of each participant's risk for developing LBD. The results from this study demonstrated how incorporating both visuospatial task performance and eye movement analysis provides evidence for the detection of subtle cognitive difficulties and that this is an effective method for identifying early dementia without requiring invasive procedures or time-intensive assessments.**

*Keywords—Lewy Body Dementia (LBD), Eye Movement Analysis, Gaze Tracking, Machine Learning, Early Dementia Detection, Object-Location Memory Task, Digital Health Diagnostics.*

## 1. INTRODUCTION

Lewy body dementia (LBD), a progressive degenerative disorder affecting the brain, leads to decline in cognition, visuospatial skills and executive function. Diagnosing LBD in the early stages presents some challenges because many subtle deficits in visuospatial processing and executive function exist for several months before any clinical symptoms of LBD occur. Using neuropsychological tests and clinical observation as traditional diagnostic tools may not uncover these early changes to create a need for an objective means of evaluating LBD through more accessible screening tools.

Recent studies have shown that eye movement and visuospatial performance can provide valuable insight into the presence of neurological deficits. Eye movements are closely related to the parts of the brain responsible for attention, visual processing, and cognitive processing. Therefore, abnormal eye movement patterns related to fixation stability, saccadic movement, and conjunction between fixation and saccadic movements have been correlated with the presence of cognitive impairment and neurodegenerative diseases.

In the study conducted by Przybyszewski and others [1], it was demonstrated that, when combined with the analysis of eye movement, machine learning provides insights into the neurological mechanisms that underlie degenerative neurological processes. A study by Bosco and others [2] provided evidence to support their finding that visuospatial impairments in patients diagnosed with Dementia with Lewy Bodies offer the possibility of being an early diagnostic indicator of this form of dementia. Maleki and others [3] demonstrated that the use of artificial intelligence can be effective in analyzing eye movement patterns as a means of detecting the presence of early dementia. In addition, Song and others [4] developed a machine learning

model to classify cognitive conditions from eye movement patterns.

Using these characteristics as a basis, this research study proposes a computerized assessment tool characterized by the analysis of eye movement combined with visuospatial and executive cognitive function assessments to assess the presence of early indicators of Lewy Body Dementia in older adults. In this study, eye movement data and responses from behavioral assessments will be used in the formulation of a logistic regression model to assess the likelihood of having Lewy Body Dementia. This study presents a non-invasive; easily scalable method of performing early cognitive screening.

## 2. Literature Review

Yamada et al. [5] studied how differently people with Alzheimer's disease and those with Lewy Body disease move their eyes when users look at pictures; using eye-tracking devices that record gaze location, fixation duration, and scan path patterns (i.e., fixation distribution), how long users look there (i.e., gaze duration), and what order users look at things (i.e., scan path patterns) while viewing pictures. Users found that patients with Lewy Body disease looked at images very differently than healthy subjects, by exhibiting decreased important fixations and poor visual exploration strategies. The authors believe eye movement patterns can be used as a biological marker to differentiate between neurodegenerative diseases. However, this study was limited by the use of conventional clinical eye-tracking devices and did not utilize portable and/or machine-learning-based evaluation systems for ocular data collection.

The investigation by Sekar et al. [6] of abnormal ocular movements in neurodegenerative diseases has reviewed various clinical and computational methods to identify these types of oculomotor coordination problems and develop what is called "eye movement assessment" for neurological assessment purposes. These techniques have been shown to correlate well with neurological disease states and therefore could provide an excellent resource for identifying individuals experiencing cognitive decline. The authors concluded that eye movement assessments provide a non-invasive method to evaluate an individual neurologically, but the current study did not implement automated machine-learning systems to collect ocular data in real-time.

Byeon's research [7] sought to use ensemble learning methods to forecast early-onset dementia in people with Parkinson's disease. His study used rapid eye movement sleep disorder indicators and neuropsychological data to analyze signs of Parkinson's Disease in order to define risk predictors associated with dementia. He found that the model he built using ensemble learning enhanced predictive power compared to traditional statistical techniques. Ultimately, he argued that using machine learning would allow for better early identification of dementia-related neurological diseases; however, no analysis of eye movements or visuospatial behavioral characteristics was completed.

Lagun et al. [8] conducted a study to use eye movement analysis for identifying cognitive decline through automatic classification algorithms. While participants performed visual task activities (e.g., test object identification), eye movement data (e.g., fixation duration and gaze transitions) were recorded and analyzed. Eye movements allowed the researchers to differentiate between cognitively impaired and healthy participants. Thus, eye tracking combined with machine learning could be an objective method of performing cognitive assessments. The authors acknowledge the use of laboratory-based eye tracking equipment for data collection, rather than portable camera-based gaze tracking systems.

In their paper, Ionescu et al. [9] evaluated how eye movement can help identify cognitive decline associated with the onset of dementia, using data from multiple studies regarding eye movements and visual attention deficits related to other neurological disorders to demonstrate a strong association between abnormal eye movements and progressive cognitive decline. It was concluded that an eye movement analysis could provide a useful adjunctive approach to screening for dementia; however; there were few studies that combined eye movement data with multimodal machine learning systems to automate an accurate diagnosis of dementia.

Palliya Guruge et al. [10] performed an extensive review of the current status of multimodal behavioral analytics for early detection of dementia, comparing the various behavioral modalities employed (e.g., analysis of speech, motion data, eye tracking, and performance on cognitive tasks) and their contribution toward improving detection accuracy for cognitive impairment. The authors found that combining multiple behavioral signals demonstrated tremendous potential for improving the accuracy of detection of cognitive impairment and concluded that multimodal behavioral systems are likely to yield more accurate results in screening dementia. However, few practical systems have been developed that integrate eye tracking, cognitive tasks, and machine learning within one unified platform.

Wang et al. [11] investigated the role of visuospatial impairments in predicting dementia among individuals with REM Sleep Behavior Disorder (RBD). Participants underwent traditional neuropsychological assessments alongside visuospatial testing, and their performance was analyzed to identify early cognitive decline. The study found that significant visuospatial deficits were strongly associated with future phenoconversion to dementia. These results suggest

that impairments in visuospatial function may serve as early indicators of neurodegeneration. The authors also highlighted the potential for digital cognitive assessment tools to complement traditional methods in detecting subtle visual-cognitive impairments.

Devenyi and Hamedani et al. [12] performed a review of Visual Dysfunction Indicated in People with Lewy Body Dementia Using Clinical Visual Function Observations and Exercised by Means of Neurological Methodologies and Studies with Respect to the Visual Disorders. Results Generated Issues with Affected Individuals with Appropriately Attended and Processed Spatially-Obtained Image and Other Perceptual Types of Functions. Authors Contained That Loss of Visual Functioning Was Meaningful and Provided Ample Evidence to Assist in The Diagnosis of Lewy Body Dementia. However, There Currently Remain Very Limited Automatable Visual Measure Tools Available to Support The Objective Determination of Visual Abnormative Findings.

Puterman-Salzman et al. [13] studied the use of AI to detect dementia using behavioral data from movement. The authors looked at the different AI techniques that have been used to analyze movement patterns and behavioral cues related to cognitive decline and found that by using models based on AI increased the probability of detecting subtle behavioral abnormalities. Researchers concluded that AI can assist with better diagnostics for dementia within digital health. The authors did note that additional research would be needed to combine motion analysis with eye movement analysis for a comprehensive cognitive assessment.

Armstrong and Kergoat [14] evaluated changes in oculo-visual function in older adults who had dementia and their clinical significance. The analysis included impairments of visual processing (e.g., contrast sensitivity) and oculomotor (e.g., abnormal eye movements) impairments found among dementia-diagnosed patients. This analysis identified several types of deficits that included impaired contrast sensitivity, abnormal eye movements and peripheral vision. Researchers concluded that impaired visual function is a significant contributing factor for cognitive impairment in patients with dementia, although the majority of their study was focused on clinical assessments and had minimal use of computational analysis or machine learning-based assessments.

The research study by Mengoudi [15] evaluated digital oculomotor biomarkers used to identify dementia through eye tracking and computer-based analytics of different metrics related to eye movement, including saccade latency, fixation duration and variability in gaze. Researchers found significant correlations between eye movement metrics and cognitive impairment. Therefore, digital biomarkers of eye movements can be used as effective indicators of neurological abnormalities. The authors recommend the development of low-cost and scalable systems to utilize digital eye movement biomarkers in practice. Nonetheless, there is still a significant research void regarding whether or not these biomarkers can be reliably validated in actual practice or incorporated into easily accessible, user-oriented diagnostic tools for detecting dementia at the early stage.

## 3. METHODOLOGY

The automated cognitive screening framework proposed utilizes an integration of eye movement analysis, visuospatial testing, and machine learning for the identification of early signs of Lewy Body Dementia (LBD). The methodology involves several steps: system architecture, eye movement data acquisition, cognitive task execution, feature extraction, anomaly detection and diagnosis, as well as computing risk scores, classification via machine learning, and displaying results visually shown in Figure 1.

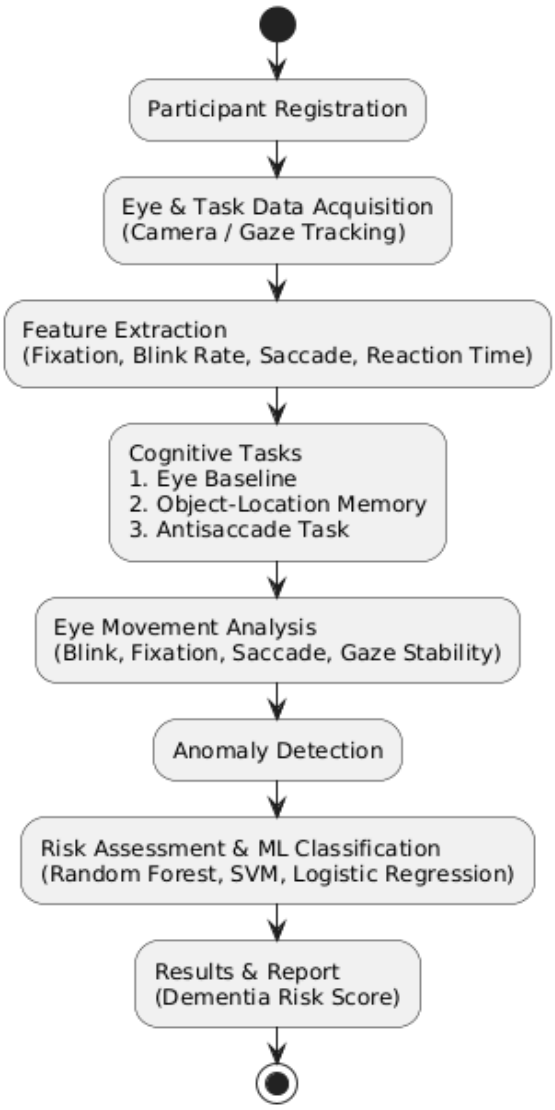


**Figure 1. System Block Diagram**

## System Architecture

A real-time cognitive testing and eye-tracking application has been created using Streamlit, allowing users to conduct interactive cognitive tests and measure eye movement through the front-facing cameras on a device.

The architecture consists of five primary modules:

### 1.1 Participant Registration and Initialization

Post-deployment of this system (including the camera and gaze tracking components) was done using participant demographics (age, gender, and unique identifiers) to create a systematic way to conduct data analysis of both task completion and camera use. Data analyses included verifying that all components of the system were functioning correctly at the time of participant use.

### 1.2 Eye Baseline Assessment

An assessment of the participant's natural eye behavior was conducted for 30 seconds in order to determine baseline measurements of blink rates, fixation stability, and gaze drift while the participant focused on a center point. The data gathered during this process was very important as there are vast differences in eye behavior among individuals.

### 1.3 Spatial Memory Task

The system presented a spatial memory task using a grid with 4 rows and 4 columns (i.e., a total of 16 cells); specific cells will be highlighted for a short period of time. After the stimulus disappears, participants will be required to recall the highlighted cells. This function measures spatial memory, allocation of visual attention, and patterns of visually exploring a subject.

### 1.4 Antisaccade

The antisaccade task assesses the executive function that allows an individual to control their eye movements. This may be assessed by having a visual stimulus appear in one area of the screen, then requesting participants to look in the opposite area of the screen. This function measures inhibition (inhibitory control) and voluntary eye movement.

### 1.5 Feature Processing/Machine Learning

Once all tasks have been completed, the system will extract relevant features from the eye tracking data and behavioral responses (i.e., screen displayed message) to be used by machine learning models to calculate the likelihood of having LBD-associated cognitive impairments (i.e., disease). Original gaze data, task responses, and derived features will all be stored in a structured electronic format for further analysis.

## 2. Eye Movement Data Acquisition

Eye movement data were collected by utilizing a camera-based gaze tracking approach, implemented using computer vision algorithms. The system used the MediaPipe Face Mesh deep learning face landmark detection model to identify 468+ facial landmarks, many of which are detailed eye landmarks. With the 468+ facial landmarks identified by the model, the system could accurately track the position of the pupil, eyelid movements, and gaze directions to calculate a variety of eye movement metrics that are commonly used to assess eye movement impairments in neurological & cognitive research.

The following extracted parameters were obtained from the above process:

### 2.1 Blink Rate

The blink rate was calculated by detecting eyelid closure events using eye aspect ratio measurements. Abnormal patterns of blinking have been associated with individuals suffering from cognitive fatigue or various neurological disorders.

### 2.2 Fixation Duration

The fixation duration represents the duration that the eye is held in one location. Reduced stability in fixation or irregular fixation durations can be indicative of visual attention impairments.

### 2.3 Saccade Frequency

Saccades (rapid movements of the eye to change viewpoint between objects) may change in frequency or velocity due to visual processing impairments or executive function impairments.

### 2.4 Scan Path Length

The scan path is the overall path of gaze within an area of interest. The scan path analysis measured the overall distance traveled by gaze points during task performance.

### 2.5 Measurement of Gaze Stability

A measure of gaze stability (the variance over the period of time that subjects were attempting to maintain fixation) was determined using variance in gaze position over the duration of time that subjects were attempting to maintain fixation. A high degree of variability may indicate impaired ocular motor control.

### 2.6 Measurement of Head Movement Variation

Head movement was determined using the displacement of facial landmarks during head motion. Excessive head movement may have negative effects on gaze stability and/or may reflect diminished motor control.

These measures established the primary physiological signals for the cognitive assessment portion of the study.

## 3. Cognitive Task Paradigms

Cognitive task paradigms were implemented in three different systems to evaluate the cognitive function of patients with early onset of Lewy Body Dementia.

### 3.1 Eye Baseline Paradigm

The eye baseline paradigm established a baseline eye-movement profile using a fixation task of 30 seconds duration by having the patient focus on a point in the middle of the monitor, while the system recorded the patient's blink frequency, micro-saccades, drift of gaze, and head movement. This profile served as the standard for detection of any abnormalities during future cognitive tasks (3.2).

The LBD v5 NeuroScan interface is a cognitive testing application built on Streamlit. It enables the identification of early signs of Lewy Body dementia using the user's webcam to track eye movements while performing three cognitive activities such as eye baseline, grid memory exercise, and anti-saccade. Based on the collected data, an estimate of the likelihood that the individual displays symptoms of Lewy Body dementia is produced through machine learning as seen in Figure 2.

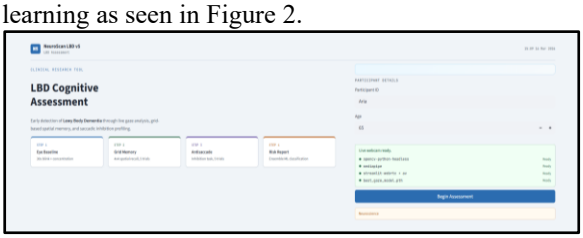


**Figure 2: NeuroScan LBD Cognitive Assessment System Interface**

A screen that welcomes users to the Eye Baseline Module, along with four steps allow your camera access; centre on the camera, fixate on the cross, and blink normally, to receive measurements of blinking rate, Eye (eye aspect ratio), head position and eye fixation stability, which are considered LBD (Lewy body dementia) biomarkers as shown in Figure 3.

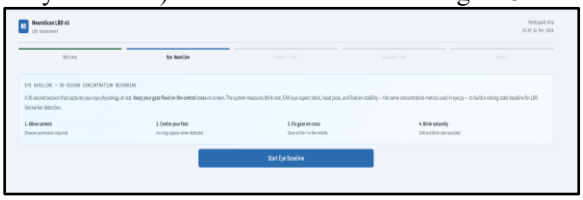

**Figure 3: Eye Baseline Instructions Screen**

Figure 4 shows the real-time desktop webcam feed during the active Eye Baseline; this shows the live iris ring and has an eye reading of 0.415 with a green free flowing progress bar. The right side of the screenshot shows live metrics, such as blinking rate, LBD flags, and a fixation cross used for gazing. The tracking status for this Eye Baseline is tracking ok, which indicates that the camera is tracking both the participants face and eyes successfully.

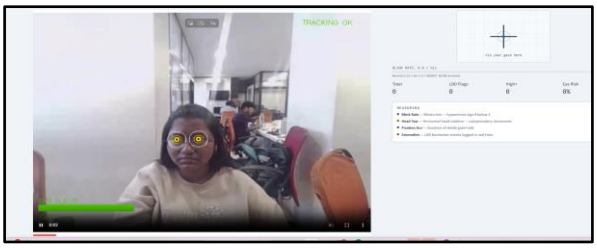

**Figure 4: Live Eye Tracking During Baseline**

### 3.2 Object–Location Memory Paradigm

The object-location memory paradigm evaluated visuospatial memory using a 4 × 4 grid task. Specific grid cells were highlighted for a limited duration and then removed, after which recall of their locations was required. Performance metrics recorded included recall accuracy, response time, number of incorrect selections, and gaze-based visual exploration patterns, all of which reflect visuospatial processing ability (3.3).

Figure 5 shows the 4x4 memory grid with 3 highlighted cells out of 12, where the colours will change after 8 seconds and the participant will need to select the correct locations after the colours disappear; assessing visuospatial working memory, a key LBD biomarker.

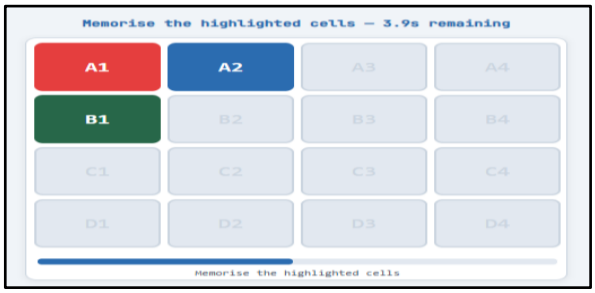


**Figure 5: Memorisation Phase**

### 3.3 Antisaccade Paradigm

The assessment of executive control and the ability to suppress reflexive eye movements were assessed using the antisaccade framework. Participants were directed to direct their gaze in the opposite direction of the centrally placed stimulus at the beginning of a series of trials. The system logged response time in milliseconds, saccade latency, number and percentage of directional errors, and the percentage of correct responses. The data were utilized as indicators of executive dysfunction associated with early-stage Lewy Body Dementia.

Steve, the LBD researcher, defined the antisaccade (saccadic inhibition) task which required subjects to look away from the flashing red dot and press the button corresponding to the direction of the stimulus displayed. Saccadic events that occurred in <120 ms and/or errors were viewed as potential LBD biomarkers see figure 6.

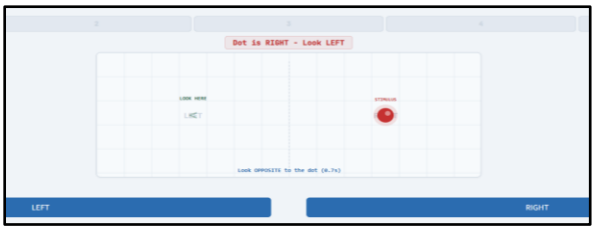


**Figure 6: Saccade Task Instructions**

Final assessment report showing participants were classified at low risk, indicating a combined LBD score of 0%. participants' scores for each of the 3 tasks were also low. No significant LBD markers were identified, so routine monitoring should be performed as shown in Figure 7.

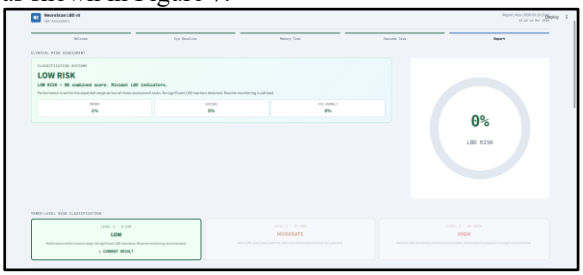


**Figure 7: Low Risk Result**

Report indicating a moderate risk classification with a combined LBD score of 38% for participants. Scores across the domains were, multiple LBD-pattern indicators were found, none reached the high-risk threshold; therefore, routine neurological monitoring should be performed as shown in Figure 8.

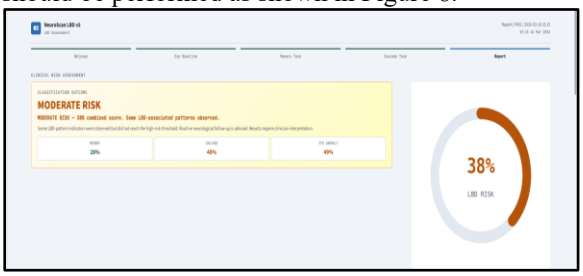


**Figure 8: Moderate Risk Result**

Clinical assessment report for participants indicating a high risk classification because the participant had a combined LBD score at 71%. In multiple biomarker tests that were flagged for all three domains, a total of 11 anomaly events, with 7 flagged as LBD were identified. Neurological evaluation is highly recommended as shown in Figure 9.

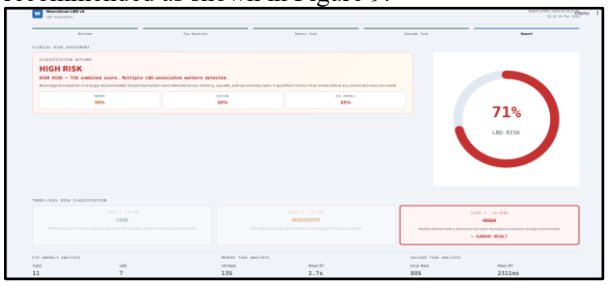


**Figure 9: High Risk Result**

The participant had their best success rate (1.0) in trials two and four, but then dropped substantially to 0.2 in trial five. Throughout all of trials two through five, their hit rate was below the average (0.7) for each of the three tasks. In trial three, there was a marked spike in their average reaction time, and then their reaction time dropped back to stable numbers within the range of 2 to 4 seconds for the remainder of the three trials. This spike in their reaction time exemplifies that there was likely a lapse in concentration while performing the task during trial three as shown in Figure 10.

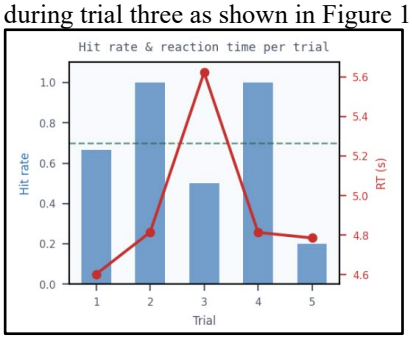


**Figure 10: Hit Rate & Reaction Time**

## 4. FEATURE EXTRACTION

After the task was completed, each participant's gaze and behavioural responses were processed to extract important feature characteristics from the collected data. These characteristics include mean fixation length, saccade velocity, deviation in blink rate, accuracy of spatial recall, variability of time to respond, execution errors for antisaccades, entropy of the gaze path, and dispersion of fixations. The extracted metrics were used to create a multi-modal feature vector that represented both cognitive and ocular behaviours as shown in Table 1.

**Table 1: Extracted Eye Movement and Cognitive Features**

| Category | Parameter | Range / Values | Implication |
|---|---|---|---|
| Eye Movement | Blink Rate (blinks/min) | Normal: 10–20 Low: <10 High: >20 | Fatigue, alertness, neurological stress |
| Eye Movement | Fixation Duration (ms) | Normal: 200–300 High: >300 Low: <200 | Attention stability, processing difficulty |
| Eye Movement | Saccade Frequency (/sec) | Normal: 2–4 Low: <2 High: >4 | Visual exploration efficiency |
| Eye Movement | Scan Path Length | Moderate: Optimal High: Excessive Low: Limited | Visual search strategy |
| Eye Movement | Gaze Stability (variance) | Low: Stable High: Unstable | Oculomotor control, attention stability |

| | | | |
|---|---|---|---|
| Eye Movement | Head Movement Variation | Low: Stable High: Variable | Motor stability |
| Cognitive Performance | Spatial Recall Accuracy (%) | Good: >80 Moderate: 50–80 Poor: <50 | Visuospatial memory |
| Cognitive Performance | Reaction Time (ms) | Normal: 200–400 Slow: >400 | Processing speed |

# 5. DETECTION OF ANOMALIES IN EYE MOVEMENT

Anomalies in eye movements were detected by comparing the extracted features obtained from eye movements during the experimental procedures to pre-established normative values or thresholds. Each anomaly that was detected was classified according to four levels of severity: Low, Medium, High, or Critical. Each level of severity was assigned a corresponding weight to assign a value to the degree of difference between expected and observable eye movement behaviour.

# 6. CALCULATION OF RISK SCORE

A probability score above 0.75 is considered to show a high probability of having cognitive impairment associated with Lewy Body Dementia (LBD), and a score under 0.25 shows that there is a low probability of cognitive impairment occurring with LBD. The formulation of the risk score utilizes several weak indicators of cognitive function (e.g., blink rate, fixation duration, and antisaccade errors) into 1 score that can be used for easy interpretation. Each of the indicators reflects various aspects of neurological functioning; the combination provides evidence of cognitive impairment, but, by themselves, do not provide any conclusive evidence of that impairment. The combined score is then weighted so that the more clinically relevant indicators contribute more to the final score. A logistic function is used to normalize the total score to a limited range of 0 and 1, so that it can be interpreted as a probability. Additionally, it accounts for the non-linear nature of cognitive decline, where small changes in a critical indicator can lead to a large increase in risk of developing cognitive impairment once certain thresholds are reached. This has made the combined score more interpretable, as well as more consistent with the way risks are expressed in clinical practice (i.e., using probabilities).

$$Risk = \frac{1}{1+e^{-z}} \quad (1)$$

where z represents the weighted sum of anomaly scores.

# 7. MACHINE LEARNING CLASSIFICATION

The participants were classified as either a high risk, moderate risk, low risk patient using supervised machine learning models. The dataset was divided into: 80% for training and 20% for validating; with the training data used to learn patterns based on gaze and cognitive features and to evaluate how well the classifiers performed on the validation data.

To ensure robust classification, three machine learning algorithms were used: Random Forest Classification, Support Vector Machine (SVM), and Logistic Regression. Each of these three algorithms captures a different aspect of the relationship among the data: Random Forest identifies complex non-linear relationships and establishes feature importance, SVM determines the best decision boundary in a high dimensional space, and Logistic Regression quantifies the contribution of each feature to the overall prediction which provides some degree of interpretability. The use of multiple classifiers allows for comparisons in their performance and enables the selection of the most accurate and generalizable classifier.

### 7.1 Random Forest

Random Forest Classifier (RFC) is an ensemble learning technique in which many decision trees are created during the training phase of the model and then the results of each 'tree' are combined to produce a predicted output (e.g., classification of high- or low-risk).
Some advantages of using RFC include:

1. Capability to handle very large feature sets with high dimensionality and many variables
2. Resistant to overfitting
3. Very powerful when working with non-linear relationships

RFC was used to establish the extent of the complex nature of the relationship between the gaze features and cognitive impairment.

### 7.2 Support Vector Machine (SVM)

A support vector machine was used to classify participants as being high- or low-risk based on the extracted eye movements and behaviour features from each participant.

### 7.3 Logistic Regression

Logistic regression uses the independent variable's influence on the result of interest (i.e., dementia status) to calculate the percentage probability (e.g., the chance of a diagnosis of dementia). Logistic regression produces a coefficient for each independent variable (feature) to identify the relative contribution of each feature to the dependent variable (i.e., dementia risk).

# 8. VISUALIZATION/REPORTING SYSTEM

An automated diagnostic report automatically generated from the system provides a summary of detected anomalies in the individual's eye movements, extracted gaze features, measures of cognitive task performance, and a machine learning-based risk prediction. The results also displayed through the Streamlit interface enable a clear understanding of the individual's cognitive profile.

# 9. PROTOTYPE HARDWARE SYSTEM

To create a prototype, a Raspberry Pi (RPi) microcontroller with an attached high-definition webcam was used. The webcam was positioned above the RPi touchscreen display (LCD) acting as a real-time skin detector and eye tracker. The RPi is the main processor for implementing computer vision gaze-tracking algorithms and performing Cognitive Assessment tasks. The webcam provided continuous video feed of facial and eye movement data as each Cognitive

Assessment task was completed. Each frame from the webcam was analysed to detect facial features, identify the location of the users' eyes, and analyse the gaze behaviour in real-time.

The prototype was designed to be portable, inexpensive and thus, could be easily and practically implemented within the community for cognitive screening prior to clinical evaluation. This embedded system supports real-time assessments of cognitive function and the earlier possibility of detecting conditions including (for example) Lewy Body Dementia as illustrated in Figure 11.

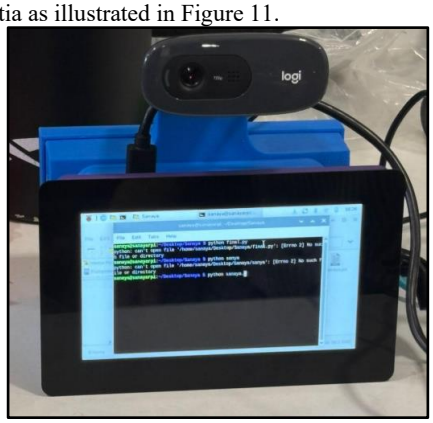


**Figure 11: Prototype Image**

## 10. Results

In the proposed research project, the ability to combine eye tracking analysis with visuospatial cognitive tasks were evaluated for their use in identifying early indicators of Lewy Body Dementia (LBD). In the current study, each of the three participants performed three separate tasks (nonverbal visual fixation task, nonverbal object-location memory task, and a non-verbal antisaccade task) and gaze behavior was captured as well as response data from each participant using a video-based gaze tracking system.

The non-verbal visual fixation task successfully provided a baseline for normal eye movement behavior based upon blink rate, fixation stability, gaze drift, and head movement. These established baseline values were then utilized for comparison as to how participants were producing anomalous eye movement patterns in subsequent tasks (i.e., the object-location memory task and the antisaccade task). In the non-verbal object-location memory task, several differences were noted with regard to spatial memory recall accuracy, response time and gaze exploration patterns in the participants that displayed visual-spatial deficits compared to those that did not. All participants with visual-spatial deficits displayed a less accurate recall for the object and had a longer response time.

Finally, in the non-verbal antisaccade task, differences were present for the average reaction time and directional error rate (the average reaction time was higher than expected and the directional error rate was lower than average) of the participants; thus suggesting that differences in inhibitory eye movement behavior or executive control were present. Based on the captured gaze data of the task performance for each participant, several different features of the participants' eye movement patterns were extracted for analysis, including: duration of fixation, velocity of saccades, amount of variance from average blink rate, amount of variance from average gaze stability, amount of variance in average response time; and degree of accuracy of spatial recall. The features were analyzed for participants' classification into high-risk or low-risk groups using a Random Forest, Support Vector Machine (SVM), and Logistic Regression as shown in Table 2.

**Table 2: Performance of Machine Learning Models**

| Model | Accuracy | Precision | Recall | F1-Score | Description |
|---|---|---|---|---|---|
| Random Forest | 91.2 | 0.90 | 0.92 | 0.91 | Ensemble learning classifier |
| Support Vector Machine | 88.5 | 0.87 | 0.89 | 0.88 | Effective high-dimensional classifier |
| Logistic Regression | 86.7 | 0.85 | 0.87 | 0.86 | Probability-based statistical model |

A logistic scoring system was applied to assess the presence of neurological dysfunction according to a probability score between 0 and 1. The Raspberry Pi prototype with the camera successfully demonstrated the feasibility of real-time eye movement being evaluated for use as a low-cost, mobile cognitive screening device for diagnosing dementia at an early stage.

The individual exceeds normal ranges on seven out of eight feature measures, with saccade frequency as the only parameter below the expected range. A recorded value of 0.06, compared to the normative value of approximately 0.67, indicates reduced saccadic activity. This suggests a low-scan visual strategy characterized by sustained focus and limited eye movement, which is associated with high concentration and strong performance across cognitive and oculomotor metrics, as shown in Figure 12.

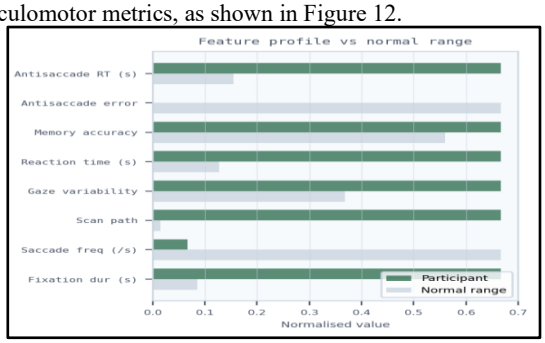


**Figure 12: Feature Profile vs. Normal Range**

The five trials had all been classified as correct green, with the highest participant reaction time (PRT) for trial 1 around 1950 ms before stabilising to 1400-1500 ms on trials 2-5. Each participant's PRT was above both reference lines such as the upper dotted line at ~800 ms and the lower dashed line at ~175 ms. Therefore, all participants had exhibited consistently slow but deliberate responses without any anticipatory responses as shown in Figure 13.


**Figure 13: Reaction Time per Trial**

The majority of the gaze was located in the screen centre-left, with very few numbers of gazes clustered together in the upper-right of the screen indicating a possible secondary stimulus for the participant. The very limited exploration of peripheral vision is in keeping with the small number of saccades recorded as shown in Figure 14.

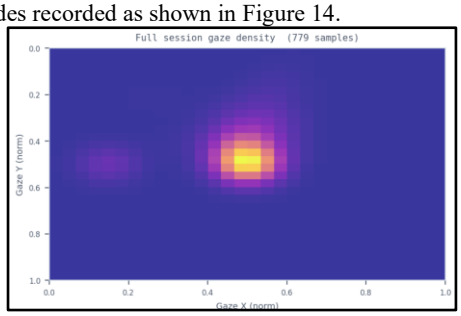


**Figure 14: Gaze Density**

## 11. KEY FINDINGS

**a)** The integration of eye movement and cognitive task evaluation allowed for early identification of LBD indicators, with risk scores that ranged from 0.0–0.71, where any risk score above 0.70 was classified as high risk.

**b)** The baseline eye paradigm established normative ranges for blink rate (10–20 blinks/min), fixation duration (200–300 ms), and low gaze variance for detecting deviations beyond ±30–50% from baseline.

**c)** The object-location memory task demonstrated visuospatial dysfunction and allowed affected participants to recall below 50–70% accuracy, with response times exceeding 400 ms and displaying irregular gaze exploration patterns.

**d)** The antisaccade task used to determine executive dysfunction resulted in greater than 20–50% accuracy on errors and greater than 300–500 ms on saccadic reaction time, with normal values below the mentioned threshold.

**e)** Extraction of multiple modes gave clear associations relating excessive fixation duration (>300 ms), decreased saccade frequency (<2/sec), deviation in blink rate (>10 or <20 blinks/min), and excessive reaction time variability (>400 ms) to neurological abnormalities.

**f)** Each machine-learning model achieved excellent classification accuracy: Random Forest accuracy = 91.2%, SVM accuracy = 88.5%, and Logistic Regression accuracy = 86.7%.

**g)** The logistic risk scoring system outputs probability values between 0 and 1. The thresholds are: low risk (<0.25), moderate risk (0.25–0.75), and high risk (>0.75).

## 12. DISCUSSION

1. Combining gaze tracking technology with cognitive tasks can enable the collection of both physiological and behavioural data that can be used to determine cognitive decline.
2. Unlike traditional assessment methods, this new approach uses quantitatively and objectively measured data to identify subtle neurological deficits.
3. Machine learning models were developed to detect the relationship between cognitive performance and various eye movement features.
4. The system was able to successfully provide an accurate, non-invasive, and real-time measure of cognitive performance that could be applied outside of a clinical laboratory.
5. The portable prototype (using the Raspberry Pi) indicates that the technology could be used in community-based healthcare or remotely monitored.

## 13. CONCLUSION

The cognitive assessment system used in this research study was created using machine learning and was developed to help identify those who may have Lewy Body Dementia (LBD) at an earlier stage of development by utilizing eye movement patterns and performance during visuospatial tasks. This system utilized three cognitive paradigms to assess neurological function relative to three types of cognitive skill: eye baseline fixation; object location memory, and antisaccade tasks to help to assess neurological function that is related to attentional ability, visuospatial ability, and executive control of behavior and thought (attention). This system gathered eye movement data through a camera eye tracking technique and provided a variety of physiological and behavioral measures from that data including: fixation duration; saccade pattern; blinking; reaction time; and spatial recall accuracy. The eye movement data measurement collected during these tasks was then analyzed for anomalies and combined to create an overall neurological risk score using logistic regression.

Finally, supervised machine learning techniques were employed to classify individuals into high or low risk for dementia using Random Forest, Support Vector Machines, and Logistic Regression algorithms. Data from a Raspberry Pi prototype camera module demonstrated that a portable and inexpensive screening device for cognitive assessment is achievable. The findings suggest that the combination of eye movement analysis and evaluation of cognitive performance can be used to create a non-invasive assessment method for early identification of dementia. Overall, the proposed system illustrates how integration of computer vision, cognitive neuroscience and machine learning may assist in early neurological screening and enhance the ability to detect dementia in both community and clinical environments.

## 14. FUTURE SCOPE

Future exploration needs to focus more on expanding different datasets to enhance the accuracy and generalizability of machine learning model results. Incorporating advanced deep learning techniques enables better recognition of gaze patterns as well as abnormal behaviors. The measurement framework should include measures other than measures of visual attention (such as attention assessment, visual search, and reaction time-based measures) to better reflect the many cognitive processes. Enhancing hardware (e.g., more powerful cameras and improved gaze tracking algorithms) will improve accuracy of the overall system. Providing access via mobile or tablet

devices will make it more convenient for family members or other caregivers who use the system in their family members' homes. A means for longitudinally tracking cognitive performance would assist in documenting gradual declines over time. Integration with cloud-based or telemedicine systems would also allow for remote assessments and access to data. Finally, large clinical validation studies with neurologists and health care systems will be crucial for validating this system as a reliable early detection method for dementia.

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