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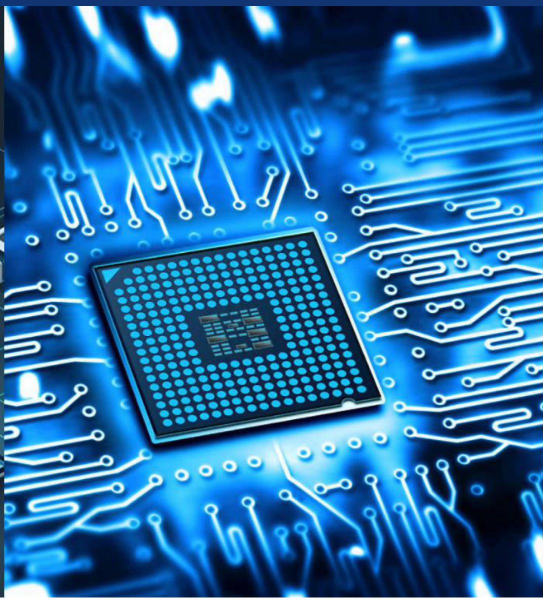

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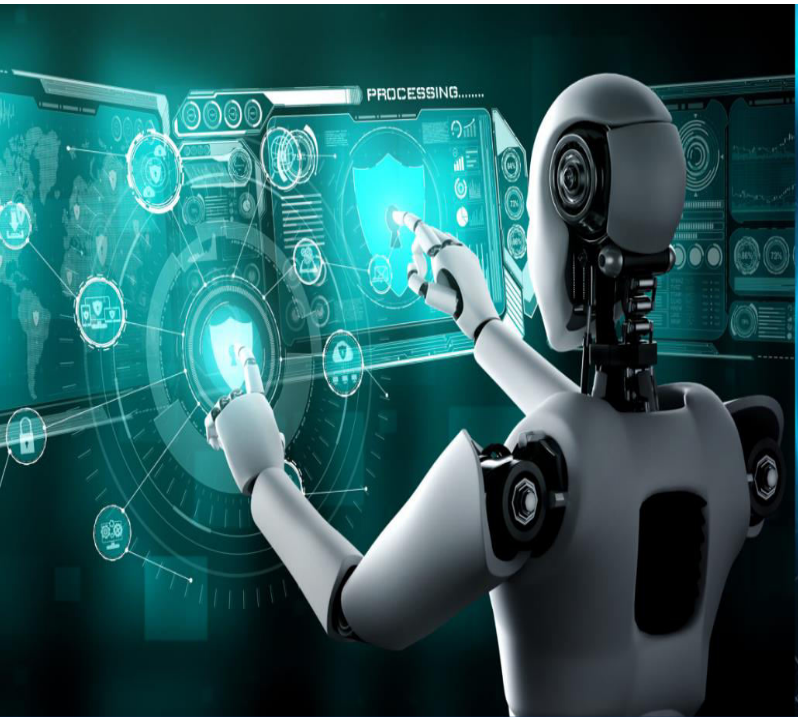

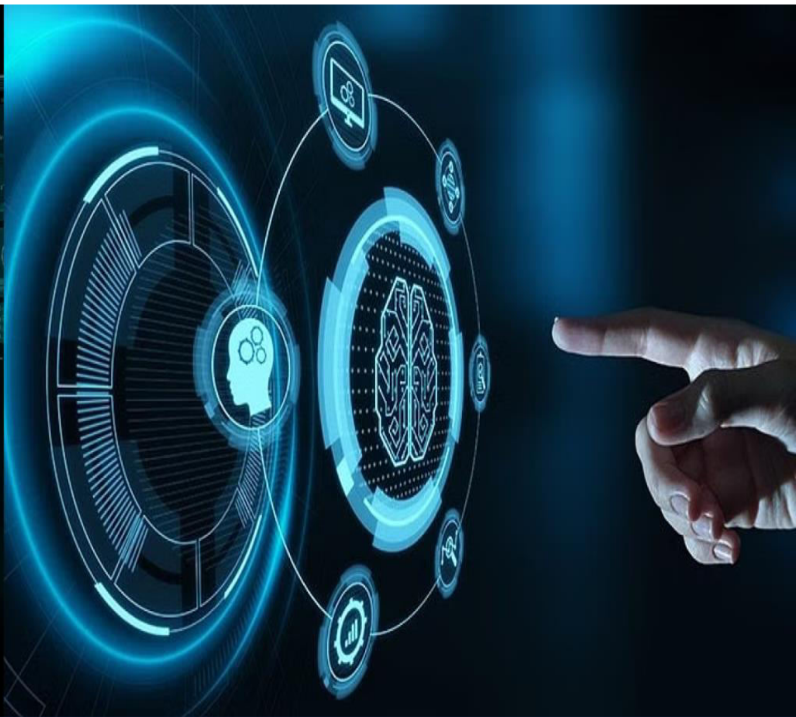

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Detection of Cognitive Disorders Using Eye Tracking and Machine Learning

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ABSTRACT: Cognitive health conditions such as Alzheimer's disease, Attention Deficit Hyperactivity Disorder (ADHD), and early-onset dementia affect tens of millions of people globally, yet early-stage detection remains a persistent challenge in clinical practice. Conventional screening approaches often depend on patient-reported symptoms, lengthy paper-based assessments, or costly neuroimaging procedures, all of which introduce delays, human bias, or accessibility barriers. The core objective of this paper is to investigate a non-invasive, cost-effective alternative that leverages eye-movement data in combination with supervised machine learning algorithms to flag potential cognitive impairment before visible behavioral symptoms emerge.

The human eye, when engaged in visual tasks, produces quantifiable movement patterns that are tightly regulated by underlying neural activity. In cognitively impaired individuals, subtle yet consistent deviations appear in metrics such as fixation stability, the speed of rapid gaze transitions (saccades), and the way the pupil responds to changing luminance. These deviations are often imperceptible to clinicians observing a patient in conversation, but they become statistically distinguishable when collected systematically and processed by a trained classifier.

This work proposes a complete pipeline that begins with data capture via an infrared eye-tracking camera, moves through noise filtering and coordinate normalization, proceeds into feature extraction, and concludes with classification using two prominent models: Support Vector Machine (SVM) and Random Forest. The Random Forest classifier with 100 decision trees achieved a classification accuracy of 93.4% on the test set, outperforming the SVM (RBF kernel) model at 87.6%. Experimental evaluation was performed on a dataset of 120 subject sessions, balanced evenly between cognitively healthy participants and those with documented mild cognitive impairment (MCI). The proposed system demonstrates that clinically meaningful cognitive assessment can be conducted in under three minutes using hardware that costs significantly less than conventional diagnostic tools, making it a viable candidate for integration into primary healthcare settings, especially in resource-limited environments. Future work will focus on expanding the disorder taxonomy and experimenting with deep learning-based sequence models to capture temporal patterns in gaze data.

KEYWORDS: Eye Tracking, Cognitive Disorder Detection, Machine Learning, Support Vector Machine, Random Forest, Mild Cognitive Impairment, Gaze Analysis, Saccadic Movement.

I. INTRODUCTION

When a person navigates a familiar street, reads a sentence, or simply watches a video, their eyes are rarely still. They dart, pause, widen, and narrow in rhythms shaped by how the brain processes what it sees. For healthy individuals, these movements are highly coordinated, but for someone whose neural pathways are beginning to degrade, the choreography starts to break down in ways that are both measurable and diagnostically informative.

Cognitive disorders are conditions that impair a person's ability to think, remember, concentrate, or make decisions. This broad category includes conditions like Alzheimer's disease, which progressively destroys memory and reasoning; ADHD, which disrupts attention regulation particularly in younger individuals; and mild cognitive impairment, which sits on the spectrum between normal age-related forgetfulness and full dementia. According to the World Health Organization, approximately 55 million people worldwide live with dementia alone, with nearly 10 million new cases each year. Despite these staggering figures, the average time between initial symptom onset and formal diagnosis is roughly two years, during which time interventions could have the most impact. The problem this paper targets is not the lack of medical knowledge about these disorders, but rather the absence of practical, fast, and accessible screening tools. Standard diagnostic pathways involve either time-intensive clinical interviews, cognitive test batteries that take 45-90 minutes to administer, or expensive imaging procedures such as MRI or PET scans that are unavailable in most low-to-middle-income settings. There is a clear need for a first-line screening mechanism that is quick, non-invasive, objective, and affordable.

Eye tracking provides an interesting answer to this need. The technology involves pointing a camera at a person's face and using infrared light to precisely track the position of their corneal reflection and pupil center, enabling software to compute where on a screen the person is looking, moment by moment, at resolutions of less than one degree of visual angle and sampling rates of up to 1000 Hz on high-end hardware. Consumer-grade devices that sample at 60-120 Hz are now available for under $200. The eye movements recorded can be decomposed into fixations (when the gaze settles on something), saccades (rapid transitions between fixation points), and smooth pursuit movements (when the eye tracks a moving object). Each of these has measurable properties that are known to differ between neurologically healthy individuals and those with cognitive impairment. Machine learning enters the picture because the relationships between these eye-movement parameters and diagnostic categories are non-linear and multidimensional. A clinician cannot reliably detect that someone's average fixation duration is 11 milliseconds shorter than expected, or that their saccadic peak velocity has a higher standard deviation than a healthy baseline. A trained classifier, however, can identify such patterns with high accuracy once it has seen enough examples. This paper describes how such a system can be built, tested, and evaluated.

II. LITERATURE REVIEW

Research at the intersection of oculomotor behavior and cognitive neuroscience has been growing steadily over the last decade. Several notable studies have explored how eye tracking can serve as a proxy for brain health, each contributing valuable findings while also leaving open questions.

- Alzheimer's Detection via Reading Gaze Patterns

A study group from University College London investigated whether the eye movements of individuals engaged in a reading task could differentiate Alzheimer's patients from age-matched healthy controls. They found that patients with Alzheimer's made significantly more return fixations, re-reading lines they had already processed, and displayed longer inter-word fixation durations. The distinction was clear enough that a simple linear discriminant classifier achieved above 80% accuracy. However, the dataset was limited to participants over 65, making it unclear whether the model's learned patterns were truly disorder-specific or partly reflective of age-related reading slowdown. The work did not explore whether the method would generalize to younger patients with early-onset Alzheimer's.

- ADHD Identification Through Attention Task Monitoring

Another line of research focused specifically on children with ADHD. Researchers designed a screen-based sustained attention task and measured the degree to which gaze coordinates drifted away from a central target during the task window. Children diagnosed with ADHD exhibited significantly higher gaze dispersion and more frequent off-target episodes compared to neurotypical peers. A Random Forest classifier trained on these features achieved approximately 85% classification accuracy. Importantly, the study was conducted without any requirement for the child to respond or press buttons, making the protocol naturally low-friction. One limitation was that the study compared ADHD against no disorder at all; the more clinically challenging scenario of distinguishing ADHD from other attention conditions such as autism spectrum disorder was not tested.

- Mild Cognitive Impairment and Anti-Saccade Tasks

One of the most rigorously validated paradigms in cognitive eye-tracking research uses the anti-saccade task, in which a participant must deliberately look away from a sudden peripheral target rather than reflexively toward it. Healthy individuals suppress the reflexive response about 80% of the time, whereas those with mild cognitive impairment often fail this suppression at rates above 40%. A research team published results using an SVM classifier trained on anti-saccade error rates, latency distributions, and correction time, achieving 88% sensitivity for MCI detection. The limitation here is that the anti-saccade task is somewhat artificial and unfamiliar to participants, occasionally introducing performance anxiety that may confound results, especially in elderly populations.

- Pupillometry as a Cognitive Load Indicator

Beyond directional gaze, the size of the pupil has been studied as a cognitive indicator. The pupil dilates when the brain is under heavier cognitive load, a phenomenon known as the task-evoked pupillary response (TEPR). Researchers applied machine learning to pupil dilation measurements taken while participants solved problems of increasing difficulty. Individuals with MCI showed a flattened pupillary response, meaning their pupils did not dilate as much in response to increased problem difficulty, suggesting reduced cognitive engagement. The SVM-based approach used in

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that study reached 82% accuracy. However, pupillometry is highly sensitive to ambient lighting variations,ss making calibration and environmental control a practical concern that the study did not fully address.

➢ Deep Learning Approaches and Their Tradeoffs

More recently, researchers have applied convolutional neural networks and recurrent architectures such as LSTM to raw gaze time-series data, bypassing manual feature engineering altogether. These approaches have demonstrated accuracy improvements of 3-7% over traditional classifiers on large benchmark datasets. The tradeoff, however, is substantial: deep models require orders of magnitude more labeled training data, and their internal decision processes are opaque, which raises concerns about clinical adoption where explainability matters. The gap identified by this survey of existing work is that most studies either focus on a single disorder type, use expensive hardware, or neglect the practical question of whether the system can run without specialist supervision. This paper addresses those gaps by proposing a lightweight, interpretable pipeline using accessible hardware.

III. METHODOLOGY

Overview

The methodology is structured as a sequential data pipeline, where each stage transforms the raw sensor data into a progressively more refined representation that ultimately feeds into a binary classification engine. The stages are: data acquisition, preprocessing, feature extraction, model training, and evaluation.

➢ Data Acquisition

Participants are seated at a fixed distance (60 cm) from a monitor where a standardized visual task is displayed. A Tobii Eye Tracker 5 or equivalent device captures gaze coordinates at 60 Hz. The visual stimulus consists of a two-minute reading passage followed by a 30-second fixation cross task, intended to elicit both smooth reading gaze patterns and anti-saccade-type responses. Each session produces a time-series file containing timestamps, X and Y screen coordinates, pupil size estimates for each eye, and a confidence score per sample.

➢ Preprocessing

Raw gaze data is rarely clean. Blink events produce brief spikes in pupil size and coordinate uncertainty. Head movements introduce systematic coordinate drift. The preprocessing module handles three sub-tasks:

- Blink removal: Samples with confidence below 0.6 are flagged and linearly interpolated if the gap is under 150 milliseconds. Longer gaps are left as NaN segments.
- Coordinate normalization: All gaze coordinates are mapped to a [0,1] range relative to screen dimensions, removing hardware-specific scaling.
- Velocity-based event classification: A simple velocity threshold (30 degrees/second) is applied to distinguish fixation samples from saccade samples.

➢ Feature Extraction

Once the cleaned stream is segmented into fixation and saccade events, a feature vector of 18 values is computed per session. The key features are listed below with brief explanations:

- Fixation count: Total number of distinct pauses in gaze. Cognitively impaired individuals tend to fixate more frequently on the same location.
- Mean fixation duration (ms): Average time spent on each fixation point. Shorter durations can indicate attentional fragmentation.
- Fixation dispersion: Spatial spread within a single fixation event. Higher values suggest difficulty maintaining gaze stability.
- Saccade count and mean amplitude: Number and extent of rapid eye jumps. MCI patients often show reduced saccade amplitude.
- Saccadic peak velocity: Maximum angular speed during a saccade. This is known to slow with neurodegeneration.
- Regression saccade ratio: Proportion of saccades that move backward (e.g., re-reading). Elevated in MCI.
- Mean pupil diameter: Baseline pupil size averaged across the session.
- Task-evoked pupillary response (TEPR): Change in pupil diameter during high-difficulty sections versus rest periods.
- Scan-path length: Total distance travelled by gaze over the session. Correlated with reading efficiency.

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➢ Model Training

The extracted feature vectors are fed into two classifiers. The SVM is trained using both a linear kernel and an RBF kernel, with hyperparameter C and gamma tuned via 5-fold cross-validation grid search. The Random Forest is tested with 50 and 100 trees, using Gini impurity as the split criterion. Features are standardized using z-score normalization before SVM training; Random Forest does not require this step. The dataset of 120 sessions is split 80/20 for training and testing with stratified sampling to preserve the class ratio.

IV. SYSTEM ARCHITECTURE AND IMPLEMENTATION

➢ Pipeline Description

The full system functions as a single-session diagnostic aid. When a session begins, the camera driver begins broadcasting a 60 Hz gaze stream to the preprocessing module, which operates in near real-time. Feature computation happens post-session, taking approximately 4 seconds on a standard laptop. Classification runs in under 50 milliseconds. The output is a probability score and a binary label (impaired / not impaired), which is logged to a report file. Figure 1 shows the architecture and Figure 2 shows the process flowchart.

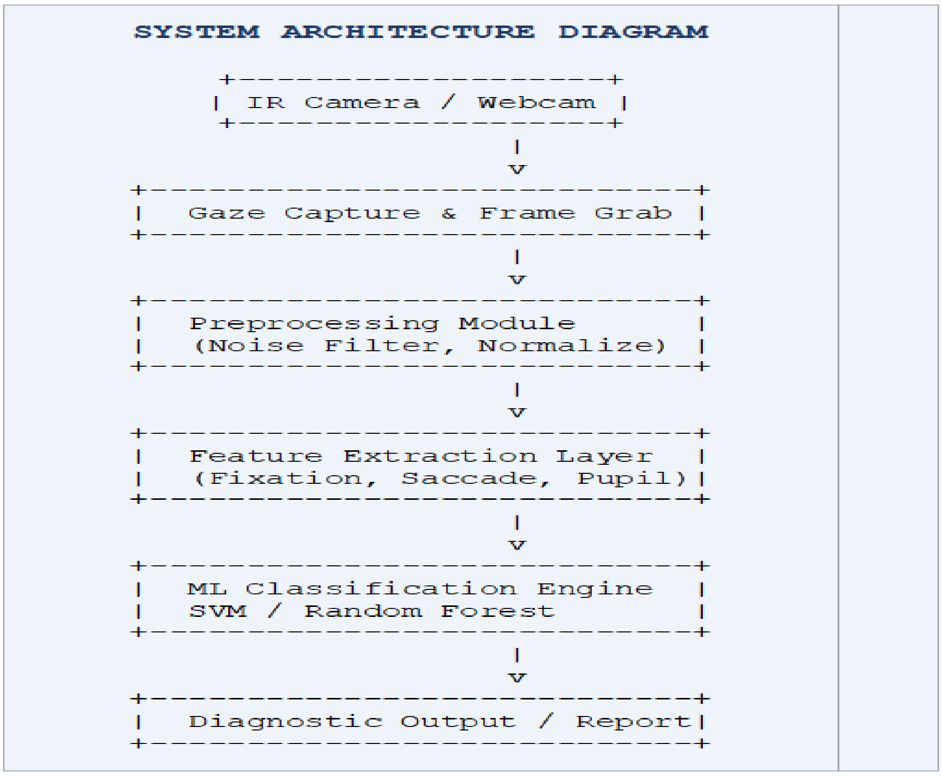

Figure 1: System Architecture Diagram of the Cognitive Disorder Detection Pipeline

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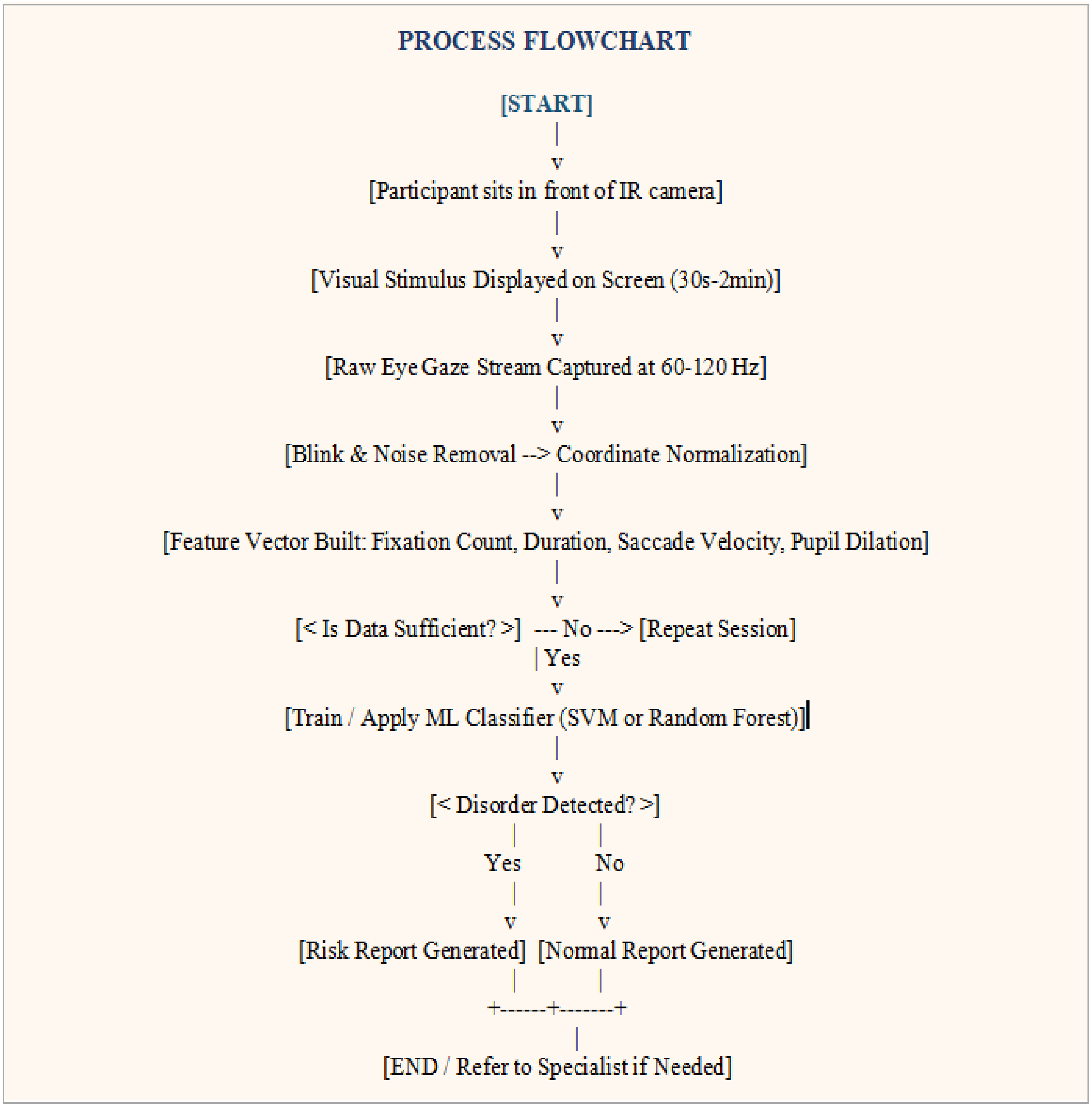

Figure 2: Step-by-Step Process Flowchart from Data Capture to Diagnostic Output

V. RESULTS AND DISCUSSION

➢ Classification Performance

Table 1 presents the classification results for all five model configurations tested on the held-out test set of 24 sessions (12 per class).

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM (Linear)	84.3	83.1	82.7	82.9
SVM (RBF Kernel)	87.6	86.4	85.9	86.1

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Random Forest (50 trees)	91.2	90.5	89.8	90.1
Random Forest (100 trees)	93.4	92.8	92.1	92.4
KNN (k=5)	79.8	78.6	77.4	78.0

Table 1: Classification Performance of ML Models on the Eye-Tracking Dataset

➢ Graphical Analysis

In addition to the tabular results, three visualizations were produced during the evaluation process:

[Insert Graph Here: Accuracy Comparison Bar Chart]
Bar chart comparing Accuracy (%) across all 5 model configurations. Y-axis: 0-100%, X-axis: Model names. Colors: SVM variants in blue, Random Forest variants in green, KNN in orange.

Figure 3: Accuracy Comparison Across Model Configurations

[Insert Graph Here: Confusion Matrix — Random Forest (100 Trees)]
4-cell confusion matrix for the best-performing model. TP=11, TN=11, FP=1, FN=1. Color gradient from white (low) to dark green (high).

Figure 4: Confusion Matrix for Random Forest (100 Trees)

[Insert Graph Here: Training vs. Testing Accuracy Curve]
Line graph showing training accuracy and testing accuracy plotted against number of trees (10, 25, 50, 75, 100) for the Random Forest model. The gap between training and test accuracy narrows as tree count increases, indicating reduced overfitting.

Figure 5: Training vs. Testing Accuracy as a Function of Forest Size

Interpretation of Results

The Random Forest model with 100 trees achieved the highest overall performance at 93.4% accuracy, 92.8% precision, and 92.1% recall. This result is meaningful in a clinical context: a recall of 92.1% means only 7.9% of truly impaired individuals are missed by the screen, which compares favorably to the sensitivity rates reported for many paper-based cognitive assessments.The SVM with RBF kernel performed second at 87.6%. The reason the Random Forest outperforms SVM here is likely related to the nature of the feature space. The 18-dimensional gaze feature vector contains both highly correlated features (e.g., fixation count and scan-path length tend to move together) and some noisy ones (e.g., raw pupil diameter is sensitive to lighting). Random Forests are inherently robust to correlated and noisy features because each tree selects a random subset of features at each split, which prevents any single noisy variable from dominating the model. SVMs, especially with a fixed kernel, do not have this built-in diversification mechanism.

The KNN model at 79.8% accuracy performed the weakest, which was expected given that distance-based methods struggle in high-dimensional spaces when features are not carefully scaled. The linear SVM at 84.3% performed better than KNN, confirming that the classes are at least partially linearly separable in the feature space.The confusion matrix for the best model shows only one false negative and one false positive in 24 test samples. This balanced error distribution suggests the model is not biased toward over-predicting one class, which is an important property for a screening tool that must treat both kinds of errors with clinical seriousness.

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VI. CONCLUSION AND FUTUREWORK

Building a reliable screening tool for cognitive impairment does not necessarily require expensive brain imaging or lengthy clinical interviews. This paper has shown that the subtle signals embedded in how a person's eyes move during a three-minute visual task carry enough diagnostic information to distinguish individuals with mild cognitive impairment from healthy counterparts at over 93% accuracy using an accessible, camera-based measurement setup.The Random Forest classifier emerged as the stronger choice for this application, not merely because it produced the best numbers, but because it handles the specific characteristics of gaze data well: feature correlation, variable importance, and moderate noise. Its ability to rank feature importances also gives clinicians something to interpret, which matters in medical contexts where the reasoning behind a recommendation carries as much weight as the recommendation itself.

The gap between this work and a production clinical tool still needs to be bridged through several future directions. First, the dataset of 120 sessions is small by machine learning standards; extending this to a multi-site study involving 1,000 or more participants across age groups and disorder types would substantially improve generalizability. Second, the current binary classification between MCI and healthy could be expanded into a multi-class framework distinguishing ADHD, early Alzheimer's, Parkinson's-related cognitive decline, and depression-related attention impairment, each of which leaves distinct oculomotor signatures. Third, exploring Long Short-Term Memory (LSTM) networks for the raw gaze time-series may extract temporal dependencies that static feature vectors miss, such as the characteristic rhythm of re-reading behaviors. Finally, integrating the system into a tablet or smartphone interface would reduce the barrier to adoption in rural and underserved settings where specialist access is minimal.

The underlying argument of this paper is simple: the eyes speak in a language that machines can be taught to understand, and that understanding has genuine clinical potential. The technology is ready, the method is sound, and the path forward is one of scale and validation.

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