

SmellSense: Feasibility of Detection of Mild Cognitive Impairment and Alzheimer's Disease using Olfactory Stimulus and Electrophysiology

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ABSTRACT

Alzheimer's is a neurodegenerative disease that affects roughly 8.8 million Indians over the age of 60. Mild cognitive impairment is an early stage of AD and is crucial for early diagnosis and intervention of AD. Unfortunately, early MCI is asymptomatic and is not sensitive to self-reported questionnaires and scans that are widely used for AD diagnosis. In this study, we propose to use olfactory stimuli in an oddball paradigm paired with electroencephalogram (EEG) to classify healthy, MCI and AD subjects. We developed a simple machine learning model that was able to classify the 3 classes with a high accuracy of >94% (33/35 subjects) validated using leave-one-subject-out cross-validation. Additionally, the real-world feasibility of the system was piloted using 5 healthy adult subjects using in-house devices, and interpretable summary reports were generated using Python. Overall, these results support the feasibility of SmellSense as a portable and cost-effective tool for detecting MCI and AD using olfactory stimuli and EEG, though further validation on larger and clinically diagnosed populations is needed before any diagnostic claims can be made.

Keywords: *Alzheimer's disease, mild cognitive impairment, electroencephalogram, oddball paradigm, olfactory stimulus, machine learning, mini-mental state examination.*

1. INTRODUCTION

Alzheimer's disease (AD) is a neurodegenerative disease that is caused by toxic protein buildup, causing neuronal cell death (Kumar et al., 2023). The symptoms of AD are memory loss, asking questions repetitively, poor judgement, less flexibility, increasing confusion, impulsive or obsessive behaviour, delusions, aphasia, disturbed sleep, frequent mood swings, hallucination, and behaving aggressively and restlessly. Mild Cognitive Impairment (MCI) is a clinical stage between normal ageing and dementia, featuring noticeable cognitive changes (often memory-based) that exceed age expectations but do not disrupt daily independence (Albert et al., 2024).

1.1. Statistics

Approximately 8.8 million Indians over age 60 live with dementia, including AD, expected to double to 16.9 million by 2036 (Lee et al., 2023). MCI affects 14-21.3% in urban areas, with subjective cognitive decline at 21.5-25.6%, often tied to low education and vascular risks post-COVID (Frontera et al, 2026). A 2025 study of 2140 participants found 200 dementia cases pre-lockdown and 40 post, with weakened MCI-to-dementia progression possibly from diagnostic disruptions (Kirkin, 2023). Globally, dementia cases, driven by AD, reach 9.8 million new annually, with MCI at 15.5% as a precursor ((Xu et al, 2025). Post-COVID studies show cognitive impairment in 19.1% of severe cases versus 6.8% mild, accelerating risks in low-income regions like India (Araújo et al, 2024). Projections indicate India's cases could surge 197% by 2050 (Vasileios Papaliagkas et al, 2023).

1.2. Current practice in diagnosing AD

Currently, these diseases are being diagnosed using Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI) scans along with the Mini Mental State Examination (MMSE). However, their drawbacks are that they are not sensitive to early changes, they are only for late stages of cognitive impairment. And they are inaccessible to rural populations, they are expensive, and they are not practical for large-scale screening.

1.3. Literature review

Researchers have addressed these drawbacks using electroencephalogram (EEG) and other biomarkers to precisely early diagnose MCI and early AD. A study conducted in 2024 demonstrates that EEG biomarkers combined with simple cognitive tasks can accurately classify MCI, dementia, and healthy individuals using a machine learning model. Finger tapping and continuous performance tests were especially effective.. achieving close to 90% accuracy (Wan et al, 2024). Another study shows that EEG measures of gamma synchronisation and theta–gamma coupling during an olfactory task can distinguish healthy ageing, MCI, and AD. All these network-level EEG markers offer a promising, non-invasive method for early MCI detection and intervention (Tripanpitak et al, 2026). Another research group from Greece published a paper that reviews cerebrospinal fluid (CSF) biomarkers for early Alzheimer's diagnosis, highlighting total tau, phospho-tau, and A β 42 as the most accurate indicators. It also discusses emerging CSF biomarkers that may improve early detection and prediction of AD in MCI patients. (Vasileios Papaliagkas et al, 2023).

1.4. Proposed solution

Olfactory stimulus recognition invokes involuntary memory of the smell.. In the Alzheimer's and MCI populations as impaired memory is an early symptom - olfactory stimulus recognition is affected. When presented with a deviant stimulus, EEG signatures such as P300 and N200 may show differences in the disordered population. Based on previous research and the above rationale, we propose to use EEG-based biomarkers, machine learning algorithms, and olfactory stimuli to test the feasibility of detecting MCI and AD.

2. METHODOLOGY

The SmellSense project employs a structured methodology combining publicly available EEG datasets with planned prospective data collection, rigorous signal processing, and statistical modelling to validate olfactory-EEG biomarkers for early Alzheimer's detection. This section details the objectives datasets preprocessing, feature extraction, and analyses..

2.1 Objectives

The primary objective is to develop and validate a non-invasive, portable EEG system using dual-nostril nasal spray-delivered olfactory stimuli to differentiate healthy controls (HC), mild cognitive impairment (MCI), and Alzheimer's disease (AD) groups (Sedghizadeh, 2022). My specific aims include (1) identifying sensitive event-related potentials (ERPs) like P300 and N200, plus spectral band powers (delta, theta, alpha, beta), in frontal and central electrodes (Fp1, Cz, Fpz, Pz) during an olfactory oddball paradigm. (2) conducting univariate statistical tests to quantify group differences in neural responses to standard (frequent e.g., lemon) versus deviant (rare, e.g., rose) odours. (3) training a multilayer perceptron (MLP) classifier and assessing the cross-validated subject-level accuracy in multi-class classification and (4) generating interpretable reports for pilot subjects. These steps establish olfactory EEG as a low-cost biomarker for MCI and enable early screening before cognitive symptoms emerge.

2.2. Dataset Description

2.2.1. Publicly available open dataset

The dataset used in this study was obtained from Mendeley Dataset, published in 2022, comprising EEG recordings collected during an olfactory stimulation task in elderly participants with mild cognitive impairment and Alzheimer's disease.. as curated by Sedghizadeh. As reported by the authors, although data were initially collected from 44 individuals, participants with poor EEG signal quality, histories of stroke or traumatic brain injury or documented olfactory dysfunction were excluded and resulting in a final sample of 35 subjects with a mean age of 70.97 ± 8.58 years and 57.14% female representation, including 15 healthy controls, 7 individuals with amnesic MCI, and 13 Alzheimer's disease patients. The EEG recordings were acquired during an olfactory oddball paradigm consisting of 120 trials, in which lemon odour was presented as the standard stimulus with a probability of 0.75 and rose odour as the deviant stimulus with a probability of 0.25, each involving two seconds of odour exposure followed up by eight seconds of rest. Signals were sampled at 200 Hz from frontal and parietal electrodes (Fp1, Fz, Cz, and Pz) using an A1 reference and segmented into stimulus-locked epochs, In addition to electrophysiological data, the dataset includes demographic information and detailed Mini-Mental State Examination (MMSE) subscores, enabling cognitive performance to be incorporated as a covariate in the analysis.

2.2.2. Collected Dataset

Pilot participants were recruited from the experimenter's society and informed consent was obtained from them using google form. Data was collected using our custom 8-channel EEG headset of Infinda Technologies Pvt Ltd and bioamplifier of Menteve Pvt Ltd paired with a dual-nostril nasal spray to deliver olfactory stimuli. Recordings were acquired during an olfactory oddball paradigm consisting of 20 trials, in which lemon was presented as the standard stimulus with a probability of 0.75 and rose as the deviant with a probability of 0.25, each involving approximately two minutes of odour exposure. The timing of each spray was recorded using Lab Streaming Layer (LSL), which synced odour markers with the EEG recording for accurate epoch segmentation.

Participants were included if they were 18 or older, with no history of neurological or psychiatric conditions, no olfactory dysfunction, and able to give informed consent. Exclusion criteria included history of stroke, epilepsy, or traumatic brain injury, use of psychoactive medications, nasal congestion on the day of recording, or allergy to lemon or rose fragrances.

In total, a pilot of 5 participants have been recruited (P001–P005), aged between 18 and 74 years, all scoring between 27 and 30 on the MMSE with no prior Alzheimer's diagnosis.

2.3. EEG Signal Feature Processing

The EEG data preprocessing for the pilot dataset and the feature extraction for the entire dataset are identical for the Mendeley dataset and the collected pilot dataset. The pipeline is elaborated in the following subsection.

2.3.1. Data Cleaning

The data was bandpass filtered between 0.1 and 40 Hz, and Z-score normalisation was performed to reduce the conductivity variations and ensure a reliable extraction of the features happens. For each given channel and trial, the computation of the mean and standard deviation points across all time periods happened, and each of the data points was standardized by subtracting the mean and dividing it by standard deviation. This helped us to make sure that the differences in amplitudes of the signals across all subjects and the electrodes were normalised, so we could make fair and reliable comparisons across all the trials. After this, baseline correction was performed to account for the differences in resting stages of the participants. For each epoch, the average EEG amplitude before the stimulus is calculated for every electrode, and then it is subtracted from the whole epoch. This helped align all the trials to one constant baseline and hence isolated the responses to stimulus.

2.3.2. Feature Extraction

Using fourier transform, the time domain signals were converted into frequency domain signals. For each of the electrodes and trials, the power spectral density was computed for the post-stimulus presentation. Then the bandpower values were calculated by averaging the spectra values within the frequency ranges of delta (1-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), and beta (12 to 30 Hz). The ERP components were computed by finding the mean of the EEG amplitudes during the post-stimulus time period. The N200 component was calculated as the average between 150 and 250 ms, the P300 component was calculated between 250 and 350 ms after the stimulus and similarly for P500 and P700.

2.4. Statistical Analyses

Three univariate statistical analyses were conducted to evaluate group-wise and stimulus-related differences in EEG features. All analyses were performed strictly on extracted ERP and band power features. The data was tested for normality using Anderson Darling test and t-test or Wilcoxon rank-sum test was used accordingly to test for significance. The reported p-values are uncorrected for multiple comparisons.

1. ***Between-Group Comparison (HC vs. MCI vs. AD):***

ERP components and band power features were compared across healthy controls, MCI, and Alzheimer's groups for both standard and deviant stimuli. This analysis aimed to identify EEG features sensitive to disease progression.

2. ***Within-Group Stimulus Comparison (Standard vs. Deviant):***

For each group independently, EEG responses to standard (lemon) and deviant (rose) stimuli were compared to determine whether olfactory deviation elicited measurable neural changes.

3. ***Difference-of-Differences Analysis Across Groups:***

The change from standard to deviant stimulus responses was computed for each subject and compared across groups to understand if between-stimuli differences are sensitive to disease progression.

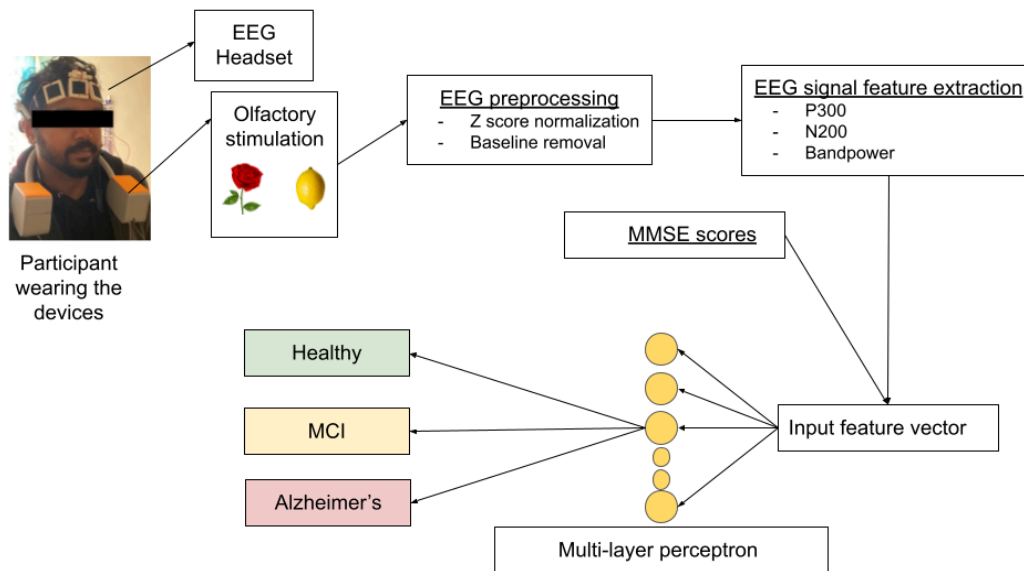


Figure 1: This figure is a flowchart highlighting the entire methodology of this study. The participant is wearing the EEG headset and the dual-nostril nasal spray. The EEG features are extracted and fed to the classifier (MLP) along with the MMSE scores for disease label prediction.

2.5. Model Development

Model development in SmellSense was based entirely on EEG, cognitive, and demographic data obtained from the Mendeley Data Repository. EEG features were extracted from olfactory oddball experiments involving healthy controls (HC), mild cognitive impairment (MCI), and Alzheimer's disease (AD) participants. For each subject - event-related potential features (P700, P500, P300, and N200) were computed from four electrodes (Fp1, Fpz, Cz, and Pz). Deviant olfactory responses were quantified by subtracting subject-wise averages of standard (lemon) trials from deviant (rose) trials.

These EEG features were combined with question-wise Mini-Mental State Examination (MMSE) scores and demographic variables- (age and gender) available in the dataset. All input features were normalised using the mean and standard deviation value before model training within the fold. To address class imbalance across the HC, MCI, and AD groups, Synthetic Minority Oversampling Technique (SMOTE) was applied only to the training data. To prevent data leakage, all preprocessing steps were performed strictly within each training fold of the cross-validation. EEG feature normalization was calculated per-trial using only that trial's own timepoints, so no cross-subject information was used at this stage. MMSE and demographic feature normalization, previously computed across the full sample, was moved inside the cross-validation loop so that normalization parameters were calculated using only the training subjects and then applied to the held-out test subject. SMOTE was applied only after the fold split was made, and only to the training set, so synthetic samples were never generated using information from the

test subject. Majority voting for subject-level prediction was performed only on the trial-level predictions of the held-out subject, after the model had already been trained without any exposure to that subject's data. The classification task involved learning patterns that distinguish HC, MCI, and AD populations using a multi-layer perceptron.. Predictions were first generated at the trial level and then aggregated using majority voting to obtain final subject-level predictions ensuring that classification reflected consistent subject-specific neural responses rather than isolated trials.

2.6. Model architecture

The input to the model consisted of concatenated differences between deviant and standard stimuli in EEG ERP features (P700, P500, P300, N200) from four electrodes, along with MMSE question-wise scores and encoded demographic features. Each input sample corresponded to a single deviant olfactory trial.

The output labels represented three classes: healthy control (HC), mild cognitive impairment (MCI), and Alzheimer's disease (AD). A multi-layer perceptron (MLP) classifier with one hidden layer containing four nodes with ReLU activation function was used to perform the classification.

2.7 Model evaluation

The SmellSense model was evaluated using subject-level performance metrics including accuracy, sensitivity, and specificity to assess its ability to correctly classify healthy controls (HC), mild cognitive impairment (MCI), and Alzheimer's disease (AD).. Sensitivity was used to measure how effectively the model identified true cases within each class- particularly MCI as the early stage while specificity evaluated how well the model avoided misclassification between groups. To ensure robust evaluation a subject-level validation approach was implemented similar to leave-one-subject-out cross-validation where data from each subject was kept completely separate between training and testing. This ensured that the model was always tested on unseen individuals and also prevented data leakage and made the results more reliable. In addition to accuracy and sensitivity, precision and F1-score were calculated for each class to provide a more balanced view of model performance given the unequal group sizes. Predictions were first generated at the trial level and then aggregated using majority voting to produce final subject-level classifications. This made sure that the evaluation reflected consistent neural patterns across each subject rather than individual trials hence making the results more clinically meaningful and reliable for early detection.

3. RESULTS

3.1. Overview

The results are presented in three parts.. First, univariate analyses were performed on EEG features extracted from the Mendeley dataset to identify group-level differences across healthy controls (HC), mild cognitive impairment (MCI), and Alzheimer's disease (AD). Following this, an MLP classification model was developed and evaluated using Leave-One-Subject-Out Cross-Validation (LOSOCV) to ensure the results generalised across unseen subjects. Finally, a pilot study was carried out on 5 participants using the in-house olfactory spray device and EEG setup, with automated reports generated for each subject.

3.2. Demographics of Datasets

3.2.1 Mendeley Dataset

The Mendeley dataset comprised 35 participants after exclusions, with a mean age of 70.97 ± 8.58 years and 57.14% female representation. The sample was divided into three groups: 15 healthy controls, 7 individuals with amnesic MCI, and 13 Alzheimer's disease patients.

3.2.2. Collected Dataset

The in-house collected dataset comprised 5 participants (P001–P005), aged between 18 and 74 years, all right-handed. MMSE total scores ranged from 27 to 30, and none of the participants carried a prior diagnosis of Alzheimer's disease. While the sample size is small at this stage, it served as a useful pilot to validate the data collection pipeline, including the nasal spray delivery system and LSL-based stimulus synchronisation with the EEG recording.

3.3. Univariate Analyses

3 univariate analyses were conducted on EEG features extracted from the Mendeley dataset to examine both group-level differences and stimulus-related neural changes across the HC MCI and AD populations.

i) Between-Group Comparison (HC vs. MCI vs. AD)

ERP components and band power features were compared across the three groups for both standard and deviant stimuli. Significant differences were found in delta band activity at Fp1 (p-value = 0.0083) and theta band activity at Pz (p-value = 0.0072) during deviant olfactory stimulation. This shows that lower frequency oscillations, particularly in frontal regions, are sensitive to disease progression and could possibly reflect the underlying disruption in neural synchrony commonly associated with AD and MCI.

ii) Within-Group Stimulus Comparison (Standard vs. Deviant)

Within each group -EEG responses to the lemon and rose stimuli were compared to assess whether the deviant odour elicited a measurable neural change. The MCI group showed a significant difference in P300 amplitude at the Cz electrode (p -value = 0.0168), indicating that MCI participants retained sensitivity to stimulus novelty, albeit in a pattern distinguishable from healthy controls. This finding suggests that the oddball paradigm is capturing meaningful neural variation even at the early MCI stage.

iii) Difference-of-Differences Analysis

The change from standard to deviant stimulus responses was computed per subject and then compared across groups. P300 at Cz (p -value = 0.0064, 0.0197) and N200 at Fpz (p -value = 0.0459, 0.0443) and Cz (p -value = 0.0352, 0.0128) showed distinct patterns in MCI participants compared to both HC and AD groups. This is an important finding, as it suggests that MCI occupies a neurophysiologically distinct space between healthy aging and full Alzheimer's pathology, and these ERP components could serve as sensitive early markers for detecting that transition.

Overall, across all three analyses, P300 at Cz and N200 at Fpz consistently emerged as the most diagnostically informative EEG features, with the MCI group showing response patterns that were clearly separable from both ends of the disease spectrum.

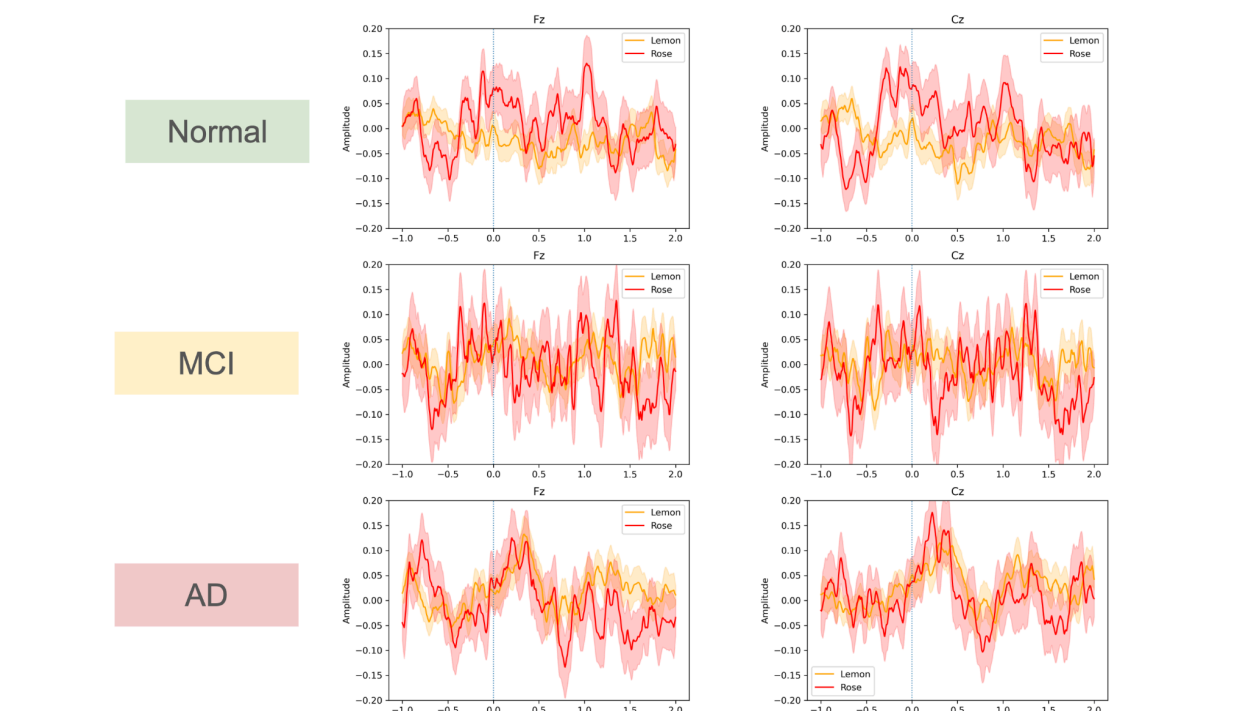


Figure 2: Displays waveforms across groups at Fz and Cz. Each group's reaction to Lemon and Rose stimuli is shown. Groups are split into HC, MCI, and AD. Dashed lines indicate stimulus onset. Shading

shows standard error. The MCI groups diverged the most (waveforms diverged the most between conditions) and had the most variable waveforms (noted divergence and variability were observed at Cz and noted P300 in the within-group analysis), and showed the largest difference (noted divergence and variability were observed at Cz and cited P300 in the within-group analysis). The AD group had less differentiated responses, while the HC had stable waveforms with less variability. The MCI group illustrates the neurophysiological positioning between the HC and AD. The AD group had the smallest P300 response, and the HC group had stable waveforms with less variability.

3.4. Model Performance

Evaluating the classification performance using a Leave-One-Subject-Out Cross-Validation (LOSOCV) method meant that the model was trained on the majority of the samples, and tested on completely novel subjects at every fold. Model accuracy with the addition of features is shown with a Waterfall Plot in Figure 3. The baseline model was created using only demographic features, which produced an accuracy of 51%, a value that is statistically insignificant for a three-way classification problem. Adding the MMSE scores to the model along with the demographic data provided a tremendous increase in the accuracy to 91%, which showed the value in the MMSE scores of the cognitive screening. The model performance was improved again to 94% with the EEG derived features. This value showed that the added sensory-evoked neural signals provided diagnostic value that was not captured with demographic features and the MMSE scores. The confusion matrix and additional model parameters are available in Table 1.

Looking at the details of the data that was collected in the pilot study, all 5 participants (P001 - P005) were classified as healthy control subjects. This was as expected since the participants MMSE scores were between 27 and 30 and they had all not been previously diagnosed with AD. While the small number of subjects decreases the validity of the results, the findings do confirm the full pipeline from the delivering of the olfactory stimuli, the extraction of the features from the EEG, and the classification.

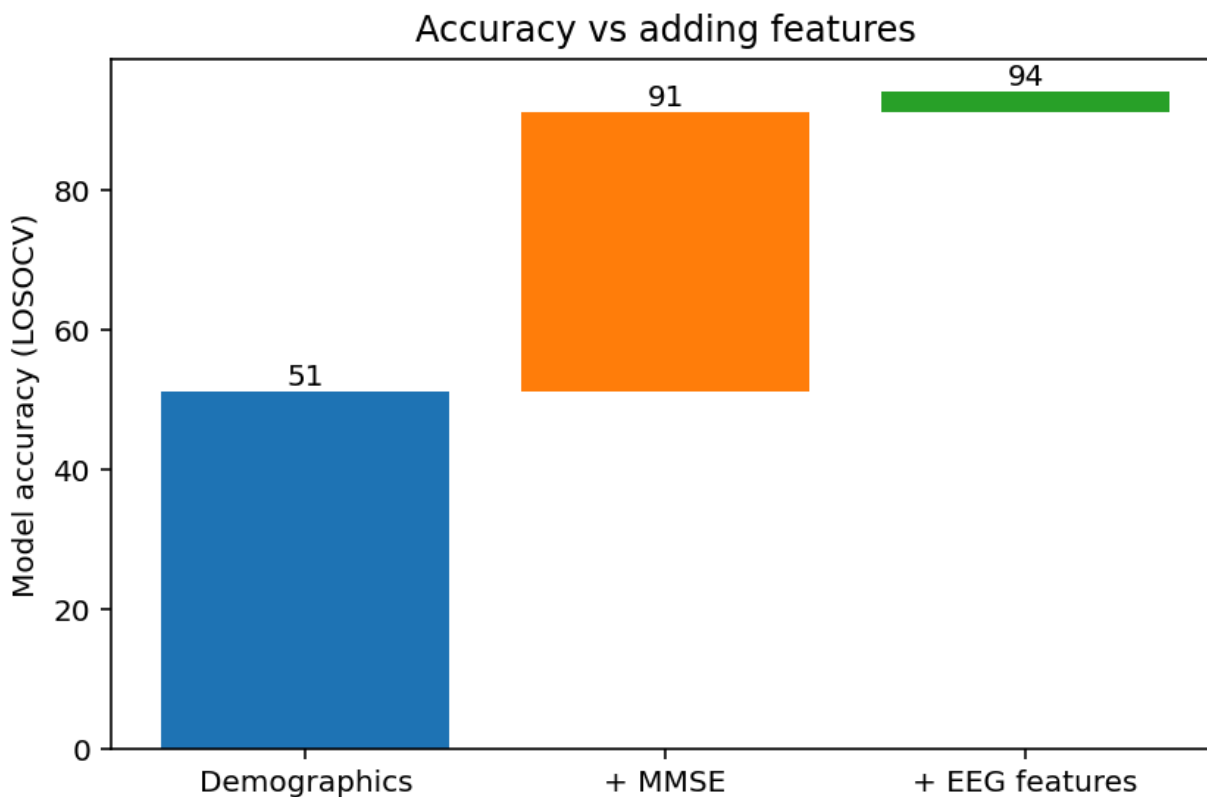


Figure 3: Increase in model accuracy as a function of adding features. The features are added based on their increasing level of availability and difficulty in procuring the data.

A)

Metric	Value
Accuracy	94.29%
Sensitivity (HC, MCI, AD)	93.33%, 100%, 92.31%
Precision(HC, MCI, AD)	100%, 77.8%, 100%
F1 score(HC, MCI, AD)	96.6%, 87.5%, 96%

B)

	<i>PREDICTED</i>
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A C T U A L		HC	MCI	AD
	HC	14	1	0
	MCI	0	7	0
	AD	0	1	12

Table 1: A) Metrics for final 3-class model predictions using all features. B) Confusion matrix for LOSOCV.

3.5. Report generation

To improve the usability of SmellSense, a graphical user interface (GUI) was developed using the Python tkinter library that automatically generates subject-specific diagnostic reports. The system integrates EEG-derived ERP features, MMSE scores, demographic information, and classification outputs from the trained MLP model into a single report format. The generated report provides a summary of the participant's EEG responses, extracted biomarkers, and predicted diagnostic categories.

Oral consent was obtained from the pilot subjects and the MMSE questionnaire was administered by the experimenter. The participants wore the nasal spray device along with the EEG as shown in figure 4B and the data was simultaneously collected and saved as a .xdf file.

Figure 4C shows the generated report from the data collected. The ERP plots, MMSE score, and model confidence are highlighted in the generated report as seen. The top section of the generated report has the cumulative MMSE score, age, and gender of the participant. Below that, in the middle left side of the report, the 4 ERP plots of the participant comparing rose and lemon stimuli are present. On the right of which, the extracted ERP features for the 4 channels (Fp1, Fz, Cz, Pz) are tested for statistical significance between standard and deviant stimuli. On the bottom of the report, the model confidence is shown as a bar graph, and the predicted label is highlighted to the right of the graph.

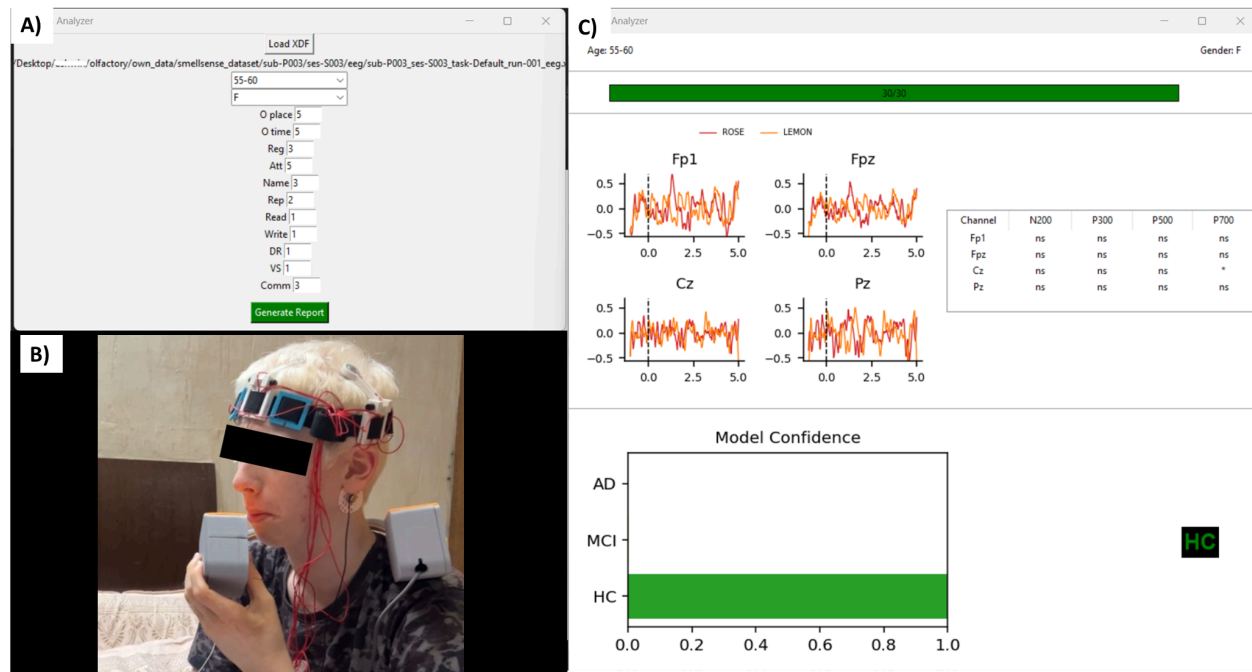


Figure 4: A) GUI for entering the details required for prediction and report generation. B) Hardware setup for SmellSense. C) A sample report for the pilot subject.

4. DISCUSSION

4.1. Summary of Findings

In this study, we investigated whether EEG responses to olfactory stimuli could be used as biomarkers for the early detection of Alzheimer's disease. Using the Mendeley olfactory EEG dataset, ERP features were extracted (P700, P500, P300 and N200) and spectral band power features (delta, theta, alpha, and beta) from key electrodes. Three univariate statistical analyses were performed to compare healthy controls (HC), mild cognitive impairment (MCI), and Alzheimer's disease (AD) participants. Significant differences were observed in delta activity at Fp1 and theta activity at Pz during deviant olfactory stimulation. Within-group analyses showed that the MCI group exhibited significant changes in P300 at Cz, while difference-of-differences analyses revealed that P300 at Cz and N200 at Fpz and Cz distinguished MCI participants from both HC and AD groups. These findings were then incorporated into a machine learning framework. The MLP classifier achieved a subject-level accuracy of >94% when EEG features were combined with MMSE scores and demographic information. Additionally, the pilot SmellSense prototype successfully classified all five collected participants as healthy controls, demonstrating the feasibility of the complete data acquisition and reporting pipeline. These results represent a proof of feasibility rather than clinical validation, and the classification accuracy reported here

should not be interpreted as diagnostic performance until tested on larger, independent, and clinically diagnosed cohorts.

4.2. Scientific Interpretation of Results

An interesting observation was that the MCI group's responses to odd olfactory stimuli were stronger and more distinct than those of the other groups. This may reflect the fact that MCI sits at the boundary between normal aging and the early stages of AD, a period when the brain networks that support smell, memory, and attention begin to show the first signs of degeneration. This may explain why the P300 and N200 may be more discernable and distinguished in MCI than in healthy participants. In Alzheimer's disease, the degeneration of the brain's networks may lead to the loss of the brain's olfactory networks, which may result in a more generalized and graded response to olfactory stimuli. Considering that the brain's olfactory circuits are among the earliest brain networks to begin to degenerate in Alzheimer's disease, we suggest that odour stimuli may be an early detection of Alzheimer's disease.

4.3. Limitations

Several limitations should be considered when interpreting these results. The Mendeley dataset contained only 35 participants, particularly a small MCI group of seven subjects, which limits statistical power. The collected pilot dataset consisted of only five participants, preventing meaningful validation on real-world populations. The study relied primarily on ERP and band-power features from four EEG electrodes, which may not capture all disease-related neural activity. The model was trained and evaluated using a single dataset, so its performance on independent external datasets remains unknown. The collected pilot participants were healthy individuals only, meaning the prototype has not yet been tested on clinically diagnosed MCI or Alzheimer's patients.

Additionally, the class imbalance in the Mendeley dataset, particularly the small MCI group of only seven subjects, raises the possibility of overfitting despite the use of SMOTE and subject-level cross-validation. The reliance on only four EEG electrodes (Fp1, Fz, Cz, Pz) also limits the spatial resolution of the neural signals captured. Olfactory perception varies considerably between individuals due to factors such as age, smoking history, and prior nasal conditions, which were not fully controlled for in this study. Since the model was trained and validated on a single dataset, external validation on independent cohorts collected at different sites and with different equipment will be necessary to confirm that these findings generalize beyond the Mendeley dataset.

4.4. Future Directions

Future work will be focused on expanding participant recruitment particularly including clinically diagnosed MCI and Alzheimer's patients to validate the SmellSense prototype under real-world

conditions. Additional EEG channels can be incorporated to capture more comprehensive neural activity and potentially improve classification performance. The olfactory stimulation system can also be refined by introducing a wider range of odours and optimising stimulus timing. Larger multicentre datasets would allow more robust model training and external validation. Finally, future versions of SmellSense could integrate real-time signals, processing and cloud-based analysis to create a portable screening tool suitable for routine use in clinics, community health centres, and resource-limited settings.

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