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NeuroDetect: An AI-Powered EEG Screening and Healthcare Management Platform for Alzheimer's Disease and Depression

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Abstract:

Alzheimer's disease and depression are often diagnosed late because MRI and PET scans are costly, and electroencephalography (EEG), a low-cost alternative, needs specialised expertise to interpret. This paper describes NeuroDetect, a web-based platform that supports preliminary screening for both conditions from resting-state EEG recordings using two Support Vector Machine (SVM) classifiers with a radial basis function (RBF) kernel. Signals are band-pass and notch filtered, scaled, and converted into 25 spectral and time-domain features. The Alzheimer's model, trained on 65 subjects expanded to 520 samples by data augmentation, reached an accuracy of 97.69%. The depression model, trained on 17 depressed and 74 normal subjects from the OpenNeuro ds003478 dataset, first failed to detect any depressed subject (recall 0%); after SMOTE oversampling and restriction to Alpha, Theta and Alpha Asymmetry features it reached an accuracy of 80.65% and a recall of 67% for the depressed class. Around the models, a Flask and SQLite back end provides a live EEG monitor with voice alerts, automated PDF clinical reports, hospital and doctor booking with token generation, and an admin panel for digital e-prescriptions. The live monitor was tested only on simulated streams. The system is meant to assist clinical review and not to replace it.

Keywords — **EEG screening, Alzheimer's disease, depression, support vector machine, SMOTE, class imbalance, Hjorth parameters, Flask.**

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I. INTRODUCTION

Alzheimer's disease is a progressive neurodegenerative disorder, and depression is one of the most common mental health conditions. Both are frequently underdiagnosed. Structural and molecular imaging with MRI and PET can support diagnosis, but the scans are expensive and are not available in many smaller hospitals. Electroencephalography (EEG) records the electrical activity of the brain at low cost and without radiation, and it has been studied as a screening signal for Alzheimer's disease [1], [2] and for depression [3]. The difficulty is interpretation: reading an EEG well requires a trained neurophysiologist, and such specialists are scarce outside large centres.

Machine learning can turn an EEG recording into a screening result, but a trained model on its own does not help a clinic. The recording has to be cleaned, the features have to be computed in a repeatable way, the result has to reach the doctor in a readable form, and the patient has to be able to act on it. Many published studies stop at the classifier [4], [5].

This paper presents NeuroDetect, a full-stack screening and healthcare management platform. Two SVM classifiers screen for Alzheimer's disease and for depression from features extracted with the Fast Fourier Transform (FFT) and power spectral density (PSD). A live monitoring dashboard with voice alerts, automatic PDF reports, hospital and doctor booking with token generation, and an admin panel for digital e-prescriptions

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complete the workflow from recording to follow-up. A particular concern of the work is class imbalance in the depression data, where only 17 of the labelled subjects are depressed. The paper reports how the model failed at first and how oversampling and feature filtering changed that result, and it states the limits of the evidence plainly.

II. THEORETICAL BACKGROUND

EEG activity is conventionally divided into frequency bands: delta (about 0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz) and beta (13–30 Hz). In Alzheimer's disease, EEG studies commonly report a slowing of the rhythm, with more power in the slow delta and theta bands and less in the faster alpha and beta bands [2]. In depression, changes in alpha activity and its asymmetry between the left and right hemispheres have been examined as markers [3]. Band powers are obtained by estimating the power spectral density of each channel from its FFT.

Hjorth parameters describe a signal in the time domain through three quantities: activity (the variance of the signal), mobility (related to its mean frequency) and complexity (how much its shape departs from a pure sine wave) [6]. They are cheap to compute and have been used for EEG-based detection of Alzheimer's disease [1].

A Support Vector Machine finds the boundary that separates two classes with the largest margin, and the RBF kernel lets that boundary be non-linear [7]. SVMs work with small datasets and a modest number of features, which suits clinical EEG collections of a few dozen subjects. When one class is much smaller than the other, a classifier can reach a high accuracy by always predicting the majority class. The Synthetic Minority Over-sampling Technique (SMOTE) counters this by creating new minority-class samples between existing neighbours in feature space [8].

III. SYSTEM ARCHITECTURE

The platform is organised into four layers: the presentation layer, the application layer, the model layer and the data layer (Fig. 1). Keeping them separate makes it possible to replace a model, or later a data source such as a physical headset, without rewriting the rest of the system.

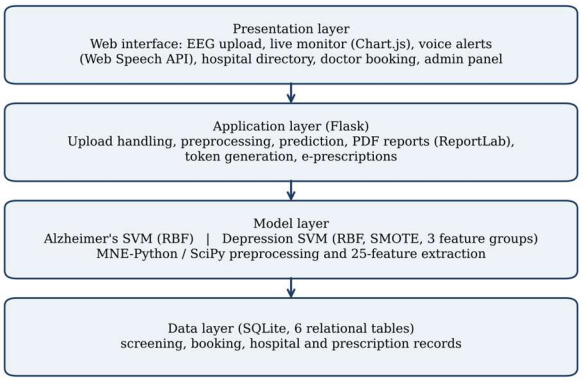


Fig. 1 Layered architecture of NeuroDetect

A. Presentation Layer

The web interface offers EEG file upload, a real-time monitoring dashboard drawn with Chart.js, voice alerts through the browser's Web Speech API, a hospital directory with doctor booking, and the screens of the admin panel.

B. Application Layer

A Flask application receives the recordings, runs the preprocessing and feature extraction, calls the two models, builds the PDF report with ReportLab, issues booking tokens and serves the administrative functions.

C. Model Layer

This layer holds the Alzheimer's SVM and the depression SVM, together with the signal processing code based on MNE-Python [9] and SciPy [10]. Both are described in Section VI.

D. Data Layer

A SQLite database with six relational tables stores the screening results and the records of the healthcare management modules, including hospital directory entries, bookings and e-prescriptions.

IV. LITERATURE REVIEW

The studies in Table I come from work on EEG-based detection of Alzheimer's disease and of depression. Earlier approaches used hand-crafted spectral and time-domain features with classical classifiers [1], [3], while recent work learns features with deep networks [4], [5].

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TABLE I
LITERATURE REVIEW SUMMARY

No	Study	Method	Key focus	Limitations
01	Safi et al. [1], 2022	Hjorth parameters	Early detection of Alzheimer's from EEG	Alzheimer's only
02	Cavanagh et al. [11], 2022	Public dataset (ds003478)	Resting EEG recordings for depression research	Dataset only; classes unequal in size
03	Sharma et al. [3], 2022	Review	Automated depression detection from EEG	Review; no working system
04	Akbar et al. [2], 2023	Overview	EEG in Alzheimer's disease research	Not a screening system
05	NeuroFusionNet [4], 2024	Hybrid feature fusion	Explainable Alzheimer's detection	Alzheimer's only; heavier model
06	Zhou et al. [5], 2024	Shallow 2D self-attention CNN	Depression severity from EEG	Depression only; no care workflow

In the studies we reviewed, the work is aimed at one condition, and the emphasis is on the classifier. We found little that describes how the model sits inside an application that also reports the result, books a consultation and records a prescription, or how a severe class imbalance was handled for a deployable model. The present work addresses that gap for both conditions in a single platform.

V. WORKFLOW OF THE SYSTEM

A user uploads an EEG recording, or starts the live monitor. The recording is filtered and scaled, the 25 features are extracted, and the features are passed to the Alzheimer's model and to the depression model. The result is shown on the dashboard and can be exported as a multi-page PDF report with embedded EEG plots. From the result page the patient can look up a hospital, book a doctor and receive a token. The doctor then uses the admin panel to issue a digital e-prescription. The final clinical decision always stays with the doctor.

VI. PROPOSED METHODOLOGY

Step 1: Collect labelled EEG recordings for Alzheimer's disease and depression

Step 2: Filter the signals (0.5–45 Hz band-pass, 50 Hz notch) and apply smart auto-scaling

Step 3: Extract 25 features using FFT and PSD

Step 4: Expand the Alzheimer's data by augmentation

Step 5: Balance the depression data with SMOTE and keep only Alpha, Theta and Alpha Asymmetry features

Step 6: Train one RBF-kernel SVM for each condition

Step 7: Evaluate both models

Step 8: Deploy the models in the Flask application

Step 9: Produce results, live monitoring alerts and PDF reports

Step 10: Connect the result to hospital booking and e-prescription

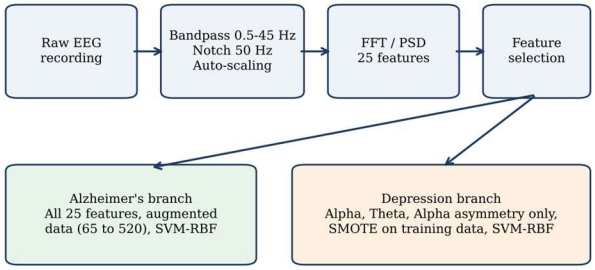


Fig. 2 Signal processing and machine learning pipeline

A. Datasets

The Alzheimer's dataset was obtained from OpenNeuro and contains 65 subjects. It was expanded to 520 samples by data augmentation. The depression data come from OpenNeuro dataset ds003478 [11], a resting-state EEG collection of 122 subjects. The labelled subjects used here comprise 17 depressed and 74 normal subjects, a ratio of about 1 to 4.4.

B. Signal Preprocessing

Raw EEG was processed with MNE-Python [9] and SciPy [10]. A band-pass filter from 0.5 to 45 Hz removes slow drift and high-frequency noise, and a notch filter at 50 Hz removes power-line interference. A smart auto-scaling step normalises the amplitude of the raw signals so that recordings from different sources lie in a comparable range.

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C. Feature Extraction

Twenty-five clinical features were extracted from each recording. The FFT and PSD give the band powers for delta, theta, alpha and beta. The Hjorth parameters [6] describe the signal in the time domain, and alpha asymmetry captures the difference in alpha activity between the two hemispheres.

D. Machine Learning Models

Both classifiers are SVMs with an RBF kernel [7]. The Alzheimer's model is trained on all 25 features of the augmented data.

The first depression model, trained on the imbalanced data, assigned every subject to the normal class, so its recall for the depressed class was 0%. Two changes were made. SMOTE [8] was applied to create synthetic minority samples, and the feature set was reduced to the Alpha, Theta and Alpha Asymmetry features, the groups most closely linked to depression in the literature [3].

E. Evaluation Metrics

Accuracy, precision and recall were used. TP, TN, FP and FN denote true positives, true negatives, false positives and false negatives, with the depressed class as the positive class:

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \quad (1)$$

$$Precision = TP / (TP + FP) \quad (2)$$

$$Recall = TP / (TP + FN) \quad (3)$$

Recall is the main measure for the depression model, because a missed depressed subject is the more costly error in screening.

F. Healthcare Management Modules

The platform adds a real-time monitoring dashboard that plots the EEG stream and speaks an alert through the Web Speech API, a ReportLab generator for PDF clinical reports, a hospital directory with doctor booking and token generation, and a secure admin panel for digital e-prescriptions.

VII. RESULTS AND DISCUSSION

A. Classification Performance

Table II lists the results of the two models. The Alzheimer's model reached an accuracy of 97.69%. The depression model reached an accuracy of 80.65% and a recall of 67% for the depressed class, up from 0% before SMOTE and feature filtering (Fig. 3).

TABLE II
CLASSIFICATION RESULTS

Model	Data	Accuracy	Depressed recall
Alzheimer's SVM	65 subjects, 520 augmented samples	97.69%	Not applicable
Depression SVM, baseline	17 depressed, 74 normal	Not reported	0%
Depression SVM, SMOTE and 3 feature groups	17 depressed, 74 normal	80.65%	67%

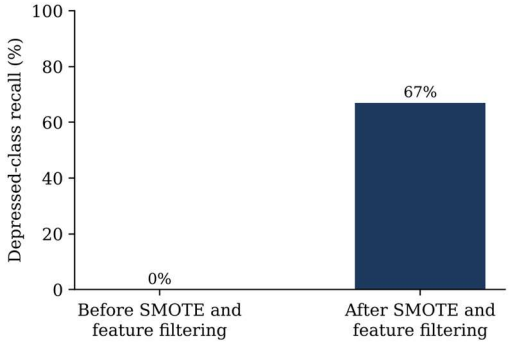


Fig. 3 Recall for the depressed class before and after SMOTE and feature filtering

B. System Tests

The live monitor processed a simulated EEG stream at 500 samples per second and triggered the voice alerts. The PDF module produced multi-page reports with embedded EEG plots. These were functional tests on simulated or stored data, and no physical headset was connected.

C. Discussion

The depression result needs to be read with care. With 74 normal subjects out of 91, a classifier that labels everyone as normal would score about 81% accuracy if the test set kept this class ratio, slightly more than the 80.65% reported. Accuracy therefore says little about this model, and the change in recall from 0% to 67% is the informative result. It shows that SMOTE and a focused feature set let the SVM detect a share of the depressed subjects, in a setting where it detected none before. A recall of 67% still means that about one depressed subject in three is missed, and the test set contains few depressed subjects, so the estimate is uncertain.

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The Alzheimer's accuracy of 97.69% is high, but the dataset is small. Its 520 samples come from only 65 subjects through augmentation, so the accuracy depends on how the data were split. If augmented copies of the same subject appear in both the training and the test data, the score overstates how the model would perform on new patients.

VIII. LIMITATIONS AND FUTURE SCOPE

Several limitations should be stated plainly. The Alzheimer's model was built on 65 subjects, and the 520 training samples were produced by augmentation, so a subject-wise split and an independent test cohort are needed to confirm the 97.69% figure. The depression model was built on 17 depressed subjects. Its recall of 67% comes from a small test set, it rests on synthetic samples, and its accuracy is not above that of a majority-class guess. Both models were developed on one public dataset each, and their behaviour on recordings from other devices, montages or hospitals is unknown. The 50 Hz notch filter assumes a 50 Hz mains supply. The live monitor was tested on simulated streams and not on recordings from a headset. The platform has not been validated in a prospective clinical study or evaluated with clinicians, and an EEG screening result cannot replace clinical assessment, imaging or specialist diagnosis.

Future work will integrate physical EEG headsets through Lab Streaming Layer (LSL), expand the dataset to more than 1,000 subjects, use subject-wise cross-validation and external validation, report precision, F1-score and confusion matrices, and move to deep learning methods such as convolutional neural networks for analysis of the raw signal.

IX. CONCLUSION

This paper described NeuroDetect, a web-based platform that screens EEG recordings for Alzheimer's disease and depression with two SVM models and links the result to monitoring, reporting, hospital booking and e-prescription. The Alzheimer's model reached an accuracy of 97.69% on augmented data, and the depression model raised the recall of the minority class from 0% to 67% through SMOTE and feature filtering, at an accuracy of 80.65%.

The results suggest that low-cost EEG screening combined with a digital care workflow is feasible. The small datasets, the reliance on augmentation and oversampling, and the absence of clinical validation show where further work is needed. In its present form the system is intended to support the judgement of a doctor and not to replace it.

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