

EEG-Based Acrophobia Detection for Pilot Candidate Screening

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ABSTRACT Acrophobia, or an excessive fear of heights, may compromise situational awareness, decision-making, and operational performance, making its early identification particularly relevant in pilot candidate screening. This study develops an electroencephalography (EEG)-based framework for distinguishing individuals with and without acrophobic tendencies using a Decision Tree classifier implemented independently in MATLAB and Python. EEG signals were acquired from 16 participants and preprocessed using WinEEG to obtain discriminative brainwave features for binary classification. The two implementations were evaluated under the same experimental conditions using classification accuracy as the primary performance metric. In this dataset the Python Decision Tree reached 98.68% accuracy and the MATLAB Classification Learner reached 94.73%. Because the two tools used different train/test partitions of the same 16-participant dataset and the labels were derived from amplitude thresholds rather than a validated acrophobia scale, this 3.95-percentage-point gap should be read as an implementation- and split-dependent difference on a small sample, not as evidence that one language classifies acrophobia better. The results further demonstrate the feasibility of combining EEG-derived features with an interpretable machine-learning classifier for objective assessment of acrophobic responses. Although validation with a larger and more diverse cohort is required, the proposed framework provides a promising basis for developing data-driven neurophysiological screening tools to complement conventional psychological assessment in pilot candidate selection.

KEY WORDS : Acrophobia; Electroencephalography (EEG); Decision Tree; Machine Learning; Brainwave Features; Fear of Heights

1. INTRODUCTION

Pilot selection is a safety-critical process in which candidates must demonstrate not only technical competence but also adequate psychological and physiological readiness. The substantial cost and time required to train pilots make reliable candidate assessment essential, as unsuccessful candidates can result in considerable resource loss and training attrition. Previous research has demonstrated that machine-learning models can support pilot candidate selection by identifying factors associated with training success, highlighting the potential of data-driven approaches for complementing conventional selection procedures [1]. However, psychological factors that may directly influence performance under flight-related stress remain insufficiently explored.

One relevant factor is acrophobia, commonly characterized as an excessive and persistent fear of heights. Exposure to height-related situations may induce anxiety, avoidance, and physiological responses that can interfere with concentration and behavioral control [2], [3]. In aviation, where pilots routinely operate at considerable altitude and must maintain effective decision-making under demanding conditions, identifying pronounced fear responses during candidate assessment is therefore potentially valuable. Importantly, acrophobia should not be regarded solely as a self-reported psychological characteristic; its associated neurophysiological responses may provide complementary objective information for assessment.

It is important to distinguish clinically defined acrophobia - a persistent, excessive fear of heights that meets diagnostic criteria - from an acrophobic tendency and from an acute fear or stress response elicited during a single simulator exposure. The present study labels participants from EEG amplitude patterns recorded

during one aircraft-simulator session and does not use a diagnostic interview or a standardized height-fear questionnaire; the classification target is therefore best described as a pronounced height-related fear response under the experimental conditions, not a diagnosis of acrophobia.

Recent advances in neurotechnology have enabled the investigation of fear-related states through non-invasive brain signals. Electroencephalography (EEG) provides high temporal-resolution measurements of electrical brain activity and has been extensively investigated for feature extraction, brain-computer interfaces (BCIs), and machine-learning-based physiological state classification [4]–[7]. EEG-based feature extraction has also demonstrated the feasibility of identifying event-related neural responses in real time [4]. Furthermore, EEG has been successfully applied to characterize neural oscillations associated with psychological and cognitive states, including alterations in theta, alpha, and beta activity [8], [9]. These findings support the use of EEG as a potential objective modality for investigating fear-related neurophysiological responses.

Machine learning further enables EEG signals to be transformed into discriminative patterns for automated classification. Previous studies have employed artificial neural networks, k-nearest neighbors, support vector machines, decision trees, and other learning algorithms for EEG-based classification across neurological, psychological, and affective applications [10]–[13]. Decision Tree models are particularly attractive for practical screening systems because of their relatively simple structure, computational efficiency, and interpretability. Their applicability to biomedical signal classification has also been demonstrated in ECG-based arrhythmia analysis and other physiological signal-processing studies [14], [15]. More broadly, machine-learning-based processing of biomedical signals has demonstrated the potential to transform complex physiological measurements into clinically or operationally meaningful decision-support information [16], [17].

Despite these developments, objective EEG-based assessment of acrophobia remains comparatively underexplored, particularly in the context of aviation-oriented screening. Existing studies have demonstrated that EEG can distinguish different levels of acrophobia or fear of heights. For example, EEG-based functional brain-network features have been used to classify acrophobia severity, with deep-learning approaches achieving high classification performance [18]. More recent work has investigated multiple machine-learning and deep-learning classifiers for real-time acrophobia assessment using EEG signals [19]. Multimodal approaches combining EEG and ECG have also been proposed to improve the classification of fear-of-heights

states in virtual-reality environments [20]. In parallel, fNIRS-based studies have demonstrated that fear responses elicited by virtual height exposure can be detected from cortical hemodynamic activity [21]. These studies establish the feasibility of neurophysiological fear assessment but also reveal an important methodological gap: the development of a simple, interpretable, and reproducible EEG-based classification framework specifically oriented toward acrophobia screening remains limited.

This gap motivates the present study. Rather than relying exclusively on subjective questionnaires or observable behavioral responses, this work investigates whether EEG-derived features can provide an objective basis for distinguishing individuals according to their acrophobic response during an aircraft-simulator-based assessment. A Decision Tree classifier is implemented and evaluated in two computational environments, MATLAB and Python, enabling a direct comparison of their classification performance under the same experimental conditions. The study therefore contributes in three ways: (1) development of an EEG-based framework for acrophobia classification, (2) evaluation of an interpretable Decision Tree approach for neurophysiological screening, and (3) comparison of MATLAB- and Python-based implementations to identify a practical computational framework for future deployment.

–[20]; a MATLAB-versus-Python comparison is not by itself a sufficient contribution. State explicitly what is new here - for example the aviation-screening framing, the specific feature set, the simulator protocol, or an interpretability analysis of the learned tree - relative to that prior work.]

The ultimate objective is not to replace established psychological or aviation medical assessments, but to investigate whether EEG-based classification can serve as a complementary objective measure for identifying pronounced acrophobic responses among pilot candidates. Such a framework could provide an additional evidence-based parameter for pilot screening and motivate future studies involving larger populations, standardized acrophobia scales, cross-subject validation, and multimodal physiological measurements.

2. METHOD

In an aviation academy-Banyuwangi, 16 subjects, including 8 prospective pilots and 8 controls, were involved in a study using the Mitsar 202 EEG tool. The device, consisting of flat metal discs placed in various lobes of the head, was used to simulate flight flow. The study employed WinEEG software to process the results, obtaining values in frontal, temporal, occipital, central,

and parietal in the form of Alpha, Beta, Gamma, Delta, and Theta. Only three waves were processed, Beta1, Beta2, and Gamma, as Beta1 and Beta2 were used for active and conscious subjects and Gamma for focus subjects. The WinEEG software filters waves from 0.5 Hz to 50 Hz to eliminate noise from artifacts in each lobe. The results of WinEEG processing are displayed through a histogram, brain mapping, and a table of amplitude and frequency of waves in each lobe.

The results of processing on WinEEG itself are processed with excel to find the sum value of 4 frequencies, namely Alpha, Beta1, Beta2, and Gamma and will later be used for classification using the Decision Tree method using the learner classifier on Matlab. The use of the Decision Tree method in Matlab as a classification itself is due to its easy use because the parameters can be determined and adjusted to the needs of the researcher so that when compared to other methods, the use of the Decision Tree method is easier. In addition, the results of accuracy using Decision Tree have a high value compared to other methods. For the Decision Tree model universally can be seen in Fig 2.

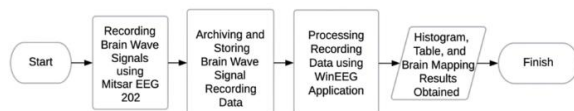


Figure 1. Working Diagram of data recording and processing

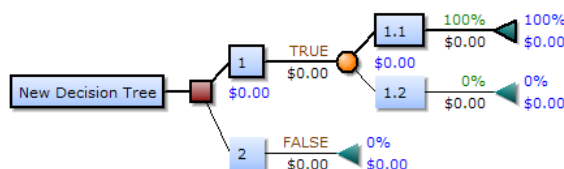


Figure 2. Decision Tree classification model universally

To assess the consistency of the proposed classification approach, a Decision Tree model was independently implemented in Python and compared with the corresponding Decision Tree model developed using the MATLAB Classification Learner. Both implementations were evaluated using the same EEG-derived features and classification task under comparable experimental conditions. The results showed highly consistent classification performance between the two implementations, with only a small difference in accuracy. This close agreement indicates that the proposed Decision Tree approach is robust to the choice of computational environment and can be reliably implemented using either Python or MATLAB. The Python implementation, however, achieved slightly higher accuracy, suggesting a marginal performance advantage while retaining the interpretability and computational efficiency characteristic of Decision Tree classifiers.

3. RESULTS AND DISCUSSION

Data acquisition shows the results of recorded signals. The resulting signal shows the results of recording 19 channels against the trial time. From the recording results, there is noise in the signal so it needs to be filtered. The signal is filtered using a Band Pass Filter (BPF) with a cut off of 0.5 Hz – 50 Hz. Signals that fall outside these frequency limits will be considered noise. The comparison of recording results on the signal before and after the filter is shown in Fig 3.

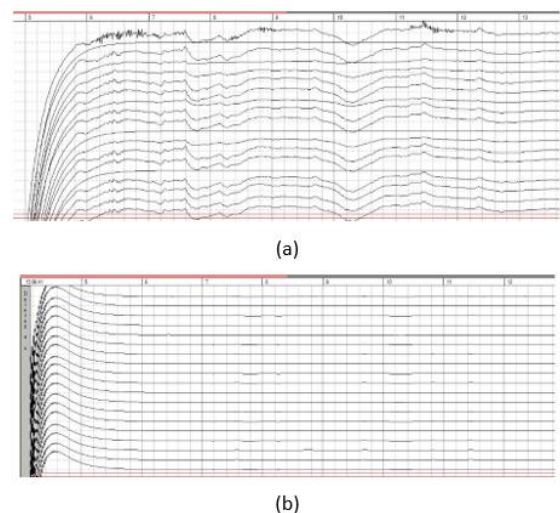


Figure 3. The comparison of recording results on the signal before and after the filter

The results of data processing using WinEEG we get several data models, namely Histogram data model, table data model and also brain mapping data model. In data processing with WinEEG itself, we use frequency cutoff to reduce noise and also artifacts in the data waves obtained by using cutoff between 0.5 Hz – 50 Hz. In the results of the histogram data itself, each subject has a significant difference where in some subjects the amplitude given has a fairly high value while in some other subjects the amplitude given has a low value as can be seen in Fig 4.

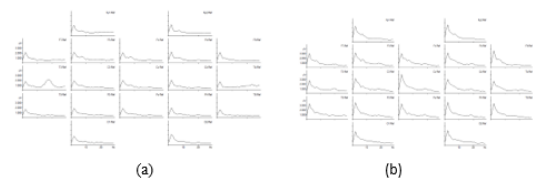


Fig. 4. (a) Histogram Results with low amplitude, (b) Histogram Results with high amplitude

The results of the Brain Mapping model itself each subject has a significant difference where each subject in the results of this model has different data where the results of this Brain Mapping model are the results in the table displayed on each node and categorized in each

wave where the greater the amplitude value in the results given, the color in the Brain Mapping model will be brighter as in Fig 5.

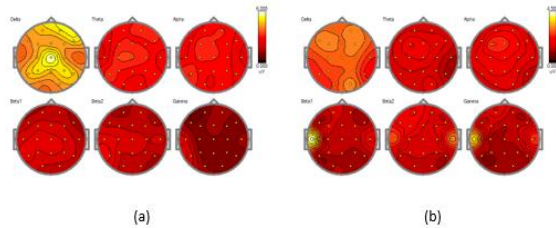


Figure 4. Example 2 results of brain mapping model

After the EEG signal is finished in the filter, data extraction is then carried out. This stage is done to take

data from brain wave signals, namely: beta 1, beta 2, and gamma. These three brain wave signals have a wide variety of characteristics based on this experiment. Beta waves 1 and 2 have the characteristics of thinking and focusing while gamma waves have the characteristics of full consciousness. Therefore, these three brain wave signals are very supportive in experiments under flight simulation conditions. So, based on the three brain waves, amplitude is obtained as a feature. This process uses the EEG Spectra method with an epoch length of 2 seconds. The three brainwave signals from each data are summed to facilitate the determination of the classification classes shown in Table 1.

Table 1. Table Type Styles

Channels	Beta1	Beta2	Gamma	SUM
	A(uV)	A(uV)	A(uV)	
fp1-ref	3.04	3.48	3.04	9.56
Fp2-Ref	1.06	1.21	1.01	3.28
F7-Ref	1.05	1.17	0.97	3.19
F3-Ref	0.92	1.05	0.80	2.77
Fz-Ref	1.31	1.41	1.01	3.73
F4-Ref	0.90	0.99	0.76	2.65
F8-Ref	1.74	1.83	1.33	4.90
T3-Ref	1.07	1.24	1.15	3.46
C3-Ref	1.17	1.22	0.96	3.35
cz-ref	1.25	1.27	0.94	3.46
C4-Ref	1.04	1.03	0.81	2.88
T4-Ref	2.34	3.34	2.80	8.48
T5-Ref	1.18	1.39	1.24	3.81
P3-Ref	1.56	1.61	1.34	4.51
Pz-Ref	1.47	1.40	1.05	3.92
P4-Ref	1.60	1.49	1.14	4.23
T6-Ref	1.30	1.38	1.22	3.90
O1-Ref	2.36	3.11	3.15	8.62
O2-Ref	1.30	1.49	1.32	4.11

Table 1 describes the results of data extraction on 19 channels from the first subject. Eksperiments were carried out on 16 subjects as interviewees, so that the data obtained were 304 data. This makes it easy to produce good accuracy from determining the classification class on each data. The extraction results from EEG signals can be classified by the Decission Tree method. The classification is divided into 5 classes, namely: not acrofobic, low acrofobic, moderate acrofobic, active acrofobic, and strongly acrofobic. The classification criteria depend on the cumulative value, which is the sum

of the average amplitude and latency values of individual data. In classification, the maximum and minimum values of the data are first determined to obtain the span value of Equation 1. From the span value can be obtained the interval value in equation 2 to determine the range of values of each class.

$$\text{Span} = \text{maximum value} - \text{minimum value} \quad (1)$$

$$\text{Interval} = \text{span} / (\text{number of category}) \quad (2)$$

Table 2 illustrates the ranges for each classification category. The lower bound of the first class results from the minimum value and the upper bound of the sum of

minimum values and intervals. For the lower limit of the second class is used the upper limit of the first class, and for the upper limit of the second class is done the same as in determining the upper limit of the first class. The procedure for determining the upper and lower limits of other classes is carried out to determine the upper and lower limits of other classes.

Table 2. Classification Category

Class	Interval
Strongly Acrofobic	11,664 - 14,58
Active Acrofobic	8,478 - 11,664
Moderate Acrofobic	5,832 - 8,478
Low Acrofobic	2,916 - 5,832
Not Acrofobic	0 - 2,916

Table 3. Results of Classification with matlab

Types of Decission Tree	Result				
	Training (seconds)	Time	Mis data	Prediction (obs/sec)	Accuracy
Fine Tree	2.2628		6	8900	95.00%
Medium Tree	0.21555		6	5400	95.00%
Coarse Tree	0.25071		7	16000	94.20%
Average					94.73%

```
# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
```

Accuracy: 0.9868421052631579

Figure 5. Classification Accuracy Rate Results with Python Algorithm

In addition to the ratio of training data models and prediction models that reached 50:50, the cause of the results of the classification accuracy rate reached 98.68% and 94.73% was in the distribution of the data itself where the distribution of data evenly in certain areas caused the results of the accuracy level of the classification to be high. As can be seen in the scatter plot diagram in Fig 6. where the distribution of data on the level of impulsivity of 13 army subjects has a distribution of data around the classification group so that when the data model is trained and later classified, the results will be accurate and almost similar when the data model is trained. The results of the accuracy rate itself can only reach 94.73% because there are 7 prediction errors in the Classification Learner so that accuracy decreases. The error occurred in all criteria so that the decrease caused was quite significant. For example, in the strongly acrofobic criterion there are no cases so that when the data model in the training algorithm does not learn the case and causes When there are cases such as strongly acrofobic, the prediction results experience errors. The Confussion Matrix can be seen in Fig 7.

In this study, the classification of impulsivity was carried out using the Decision Tree method using Classification Learner on Matlab and also with an algorithm using python language. The results of the classification of 16 subjects using algorithms using Python language itself have a very high level of accuracy where the accuracy rate reaches 98.68% where if we compare using Clasification Learner on Matlab, the accuracy obtained reaches 94.73% using the Decision Tree method. The results of the high level of accuracy obtained due to the use of many training models and also the ratio between the training model and the prediction model itself up to 40: 60 in Clasification Learner or in Python algorithms cause the accuracy rate of classification to reach 98.68% and 94.73%.

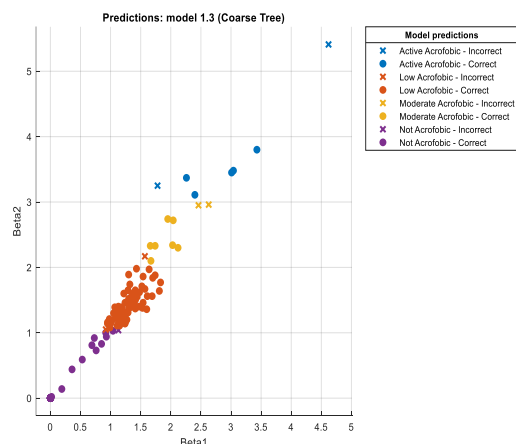


Figure 6. Scatter Plot diagram of a prediction model

	Model 1.3 (Coarse Tree)				
True Class	Active Acrofibic	Low Acrofibic	Moderate Acrofibic	Not Acrofibic	Strongly Acrofibic
	5		2		
		89		1	
	1	1	7		
		1		33	
	1				
	Active Acrofibic	Low Acrofibic	Moderate Acrofibic	Not Acrofibic	Strongly Acrofibic

Figure 7. Confussion Matrix results of Clasification Learner on Matlab

In addition to the confusion matrix in Clasification Learner, in the python algorithm there is also a confusion matrix used to display the prediction results of the algorithm where this confusion matrix has differences because the division of data used for training and testing is different from Clasification Learner so that the results are different and can be seen in Fig 8. The result of the accuracy rate itself can reach 98.68% because there are only 2 prediction errors so that the resulting uration valueis quite high. The error occurs in the strongly impulsive criterion.

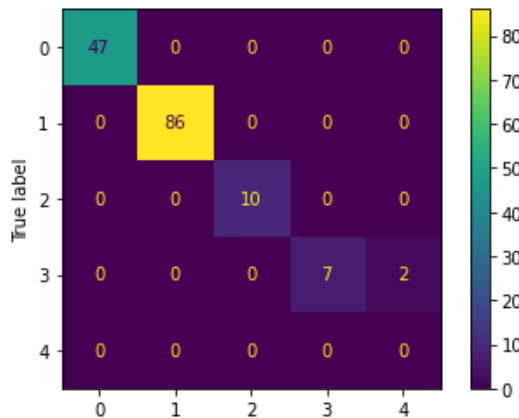


Figure 8. Confussion Matrix Algorithm results using python

4. LIMITATIONS

This study has several limitations. First, only 16 participants were recorded at a single site, so the reported accuracies are vulnerable to overfitting and cannot yet support use in real pilot selection. Second, class labels were derived from cumulative EEG amplitude thresholds rather than from a validated acrophobia scale or clinical assessment, so it is not established that the model detects clinically defined acrophobia rather than an acute fear or

stress response during the simulator task. Third, subject-independent validation was not reported, and the MATLAB and Python models used different train/test partitions, so their accuracies are not directly comparable and may be optimistic. Fourth, only a Decision Tree was evaluated, without baseline classifiers. Fifth, the manuscript contains internal inconsistencies (binary versus five-class labelling, differing sample counts, residual "impulsivity" terminology) that should be resolved. The framework should therefore be regarded as a preliminary feasibility study.

5. CONCLUSION

In this study, acrophobic responses were classified in a cohort of 16 participants, comprising eight prospective pilot candidates and eight control participants. The proposed Python-based Decision Tree classifier achieved an accuracy of 98.68%, compared with 94.73% obtained using the MATLAB Classification Learner implementation. The two implementations differed by 3.95 percentage points, but because they used different data partitions on a 16-participant sample this difference should not be attributed to the programming language itself. These results demonstrate the feasibility of using EEG-derived features combined with an interpretable Decision Tree classifier to distinguish acrophobic and non-acrophobic responses. The findings are consistent with previous studies demonstrating the potential of EEG-based machine learning for objective assessment of fear of heights and acrophobia. However, given the relatively small sample size, the reported performance should be interpreted as preliminary evidence rather than definitive clinical or operational validation. Further studies involving larger and more diverse cohorts, independent subject-level validation, and standardized psychological assessments are required to establish the generalizability and practical utility of the proposed framework for pilot candidate screening..

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