# Machine Learning-Based Classification of Syncope and Presyncope Using Heart Rate Variability

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## Abstract

*Syncope is also known as fainting, while presyncope is a sensation of fainting that does not result in loss of consciousness. The standard diagnostic test for these conditions is the Head-Up Tilt Test (HUTT), which is uncomfortable, somewhat invasive and requires special equipment. This work investigated a possible alternative test using heart rate variability (HRV) analysis.*

*Wavelet analysis was applied to the heart rate time series consisting of inter-beat intervals, and summarised using the mean, variance, skewness and kurtosis. Significant differences were found between syncope and presyncope groups. These significant results persisted over a range of wavelet scales.*

*A further analysis using machine learning classification provided a significant discrimination between syncope and pre-syncope with an accuracy of 80%.*

*The results have implications for understanding these conditions and the possible links between disease and the autonomic system. In addition, such analysis may provide an alternative diagnostic tool, avoiding the expensive and invasive HUTT and enhancing patient comfort.*

## 1. Introduction

Syncope is a sudden loss of consciousness, caused by a lowering of blood pressure in the brain [1]. Syncope occurs over a short time scale but may be caused by several factors. These include high risk underlying conditions, such as cardiovascular disease including arrhythmias or structural heart disease (cardiac syncope). However, syncope can also be caused by more benign conditions such as dehydration, intense emotions, anaemia, hypersensitivity to various stimuli (reflex or neurally mediated syncope), and postural change, such as standing up (orthostatic syncope).

Presyncope is the sensation that one is going to faint and does not lead to a loss of consciousness. Presyncope may last for several minutes, but causes are usually mostly benign. It may be the case that Presyncope is much less likely that syncope to be associated with arrhythmia, at least in children [2]. However, presyncope should not be dismissed, because serious outcomes have been reported [3]. As symptoms of these two conditions may be similar, it can be difficult to distinguish these related conditions. However, the diagnosis of true syncope is important to achieve in order to address any serious underlying conditions.

A number of clinical challenges exist for the diagnosis of syncope. There is a degree of symptom overlap, as syncope and presyncope share similar symptoms, such as dizziness, light-headedness, and transient loss of vision. Clinicians often rely on patient history and physical examination, which may not always provide definitive differentiation. In addition, the lack of objective markers complicates the diagnostic process.

The gold standard of diagnosis for these conditions is the Head-Up Tilt Test (HUTT), but this can be an uncomfortable experience for the person being diagnosed. As syncope may be associated with arrhythmias to a greater extent than presyncope, it follows that an analysis of the electrocardiogram may provide a diagnostic tool. However, the full 12-lead ECG can be somewhat invasive, whereas the heart rate variability (HRV), comprising only the time elapsed between each beat, is very accessible.

## 2. Heart Rate Variability (HRV)

HRV refers to the variation in time intervals between successive heartbeats. When expressed as the inter-beat interval, occurring over the time of a recording, it forms an inter-beat time series. It reflects the autonomic nervous system's influence on heart rate regulation. While HRV can be more accurately obtained using a full electrocardiogram (ECG), the inter-beat series is easier to

obtain and may be recorded from wearable devices using pulse readings. These methods are less invasive than full ECGs and provide valuable insights into autonomic nervous system activity [4].

Arrhythmia can be associated with syncope, and other studies suggest that HRV patterns may accompany episodes of syncope [5]. This leads us to suggest that analysing HRV features could provide valuable insights for the detection of syncope, and may even lead to diagnostic tests that avoid some of the disadvantages of the HUTT. Indeed, this is the aim of other reported research efforts. For example, an attempt to distinguish participants with neurally mediated syncope from healthy subjects reported an accuracy of almost 90% using HRV frequency measures and a neural network [6]. As there may be complex links between HRV and syncope, it makes sense to look to machine learning techniques to provide the basis for methods of detection, or discrimination between different categories of participants following interbeat analysis such as wavelet analysis.

## 3. Wavelet Analysis

Wavelet Analysis refers to using a wavelet transform, where a wavelike function is applied to a time series signal. The wavelet function is translated along the signal to obtain a series of coefficients at a variety of different scales. Each scale corresponds to a frequency component of the signal. However, unlike periodic sinusoids as used in Fourier analysis, wavelets are oscillations that decay quickly. Therefore, the wavelet transform can produce a decomposition of a signal in both time and frequency. The theory behind the Wavelet Transform is based on the work by Morlet and Grossman [7]. Wavelet analysis finds applications in various fields, including signal analysis, image processing, and numerical analysis. It allows us to study localized variations of power within a time series, making it useful for understanding complex data patterns. The discrete wavelet transform (DWT) is a convolution of the wavelet function with the discrete time series of the HRV recording $x$ of length $n$ samples. At each time step $\tau$ the wavelet coefficient $y(p,\tau)$ is defined by:

$$y(p,\tau)=\sum_{i=1}^{p} w(i)\,x(\tau+i)$$

where $w(i)$ is the wavelet function comprising $p$ discrete samples, where $p$ determines the scale. There are a number of well-known options for the wavelet function including the Morlet and the Haar wavelet [8].

## 4. Methodology

This study uses 24-hour Holter data collected from 147 patients of the Wangaratta Cardiology and Respiratory Centre in Wangaratta, Australia. The patients were classified into syncope and presyncope groups based on clinical data and review by a physician. All data were de-identified, and an ethics approval for the study was obtained from the Charles Sturt University Human Ethics Committee under approval number H18161. All patients provided informed consent to take part in the study and for data disclosure in accordance with the principles of the 2001 Helsinki Declaration. The study included 75 patients, 28 with syncope and 47 with pre-syncope: the remaining patients with palpitations only were excluded. All patients had a normal sinus rhythm. Heart Rate Variability (HRV) data were extracted from the Holter ECG recordings, yielding RR interval series. For each patient, 50,000 RR intervals were extracted from the middle of the recording, corresponding to approximately 10 hours. Common time domain features were calculated for each series: standard deviation of RR intervals, root mean square of RR intervals (rmssd) and the median RR interval. These measures were supplemented by features extracted using wavelet analysis based on Haar and Morlet wavelets, chosen as two well-known but different wavelet functions. Real and imaginary parts of each wavelet were used, as recommended by other authors e,g. [9] and as illustrated in Figure 1. The scale was implemented as the number of samples used to form the wavelet function. At the smallest scale, the wavelet function was calculated as 25 points, and applied to 25 samples from the RR interval series. At the largest scale, the wavelet function was calculated as 1000 points, and applied to 1000 samples from the RR interval series.

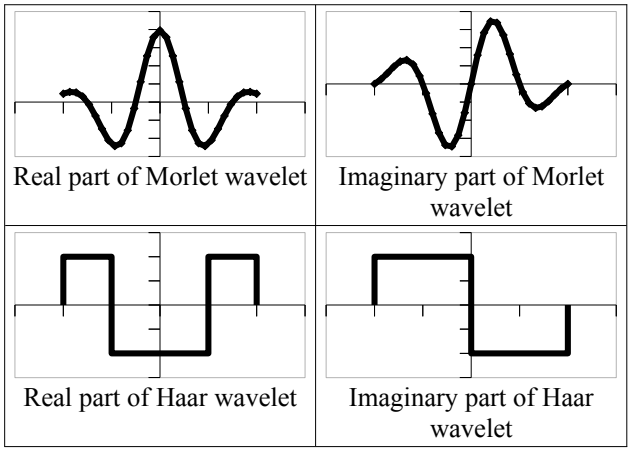


Figure 1. Wavelet functions used in this work.

The wavelet coefficients were calculated for a variety of scales. For each recording, summary statistics of the

wavelet coefficients were calculated as mean, variance, skewness and kurtosis. The Kruskal Wallis test was applied to all features and resulted in a p-value indicating possible discrimination between Syncope and Presyncope. As the wavelet features were calculated across a wide range of scales, it is desirable to reduce this to a smaller range to identify a range of scales that may be used in future work and to make the calculation required for a diagnostic test more efficient. This range was chosen from each summary statistic by observing graphs of p-value against scale, and choosing a single range from each graph, where the p-value was consistently low across a wide range of scales. This smaller set of features was further reduced using Principal Components Analysis (PCA), performed using the open source Python library *sklearn*. All features were first transformed using the *Yeo-Johnson* transform in order to reduce any skewness, and to normalise ranges, before applying PCA [10]. These transformed features were then classified using *XGBClassifier* from the open-source Python library *xgboost*, which uses gradient boosting to combine a variety of machine learning models to create an ensemble model in a tree structure [11]. The classifier used the multi-class log loss metric to measure the performance of the model in terms of the negative log-likelihood of the predicted class probabilities compared to the true class labels. Ten-fold cross validation was used.

## 5. Results

The four summary statistics (mean, variance, skewness and kurtosis) were examined in terms of the p-value from the Kruskal Wallis test. For both Morlet and Haar wavelets, the statistic that stood out for achieving low p-values was the skewness. Graphs of the p-value versus the wavelet scale are presented in figures 2 and 3 for skewness (6 other graphs showing p-value for mean, variance and kurtosis are omitted to save space). In both of these figures, the real part of the wavelet transform is indicated by a solid line, while a dashed line indicates the imaginary part. The scale of the wavelet increases left to right, and the dotted line represents a p-value of 0.05.

In both figures the p-value obtained from the Kruskal Wallis test falls below the value of 0.05 for a considerable range of wavelet scale, suggesting that this significant result is fairly robust. In figure 2, the real part of skewness derived from the Morlet wavelet provides a significant result at the p = 0.05 value for scales between approximately 250 to 450. In figure 3 the real part of skewness derived from the Haar wavelet produced significant values for a shorter range of scales from approximately 150 to 220. However, figure 3 also shows that the imaginary part produced a significant result for a much larger range from 220 to 1000 approximately. These large ranges and smooth curves in these regions suggest a robust effect that is maintained across a range of scales.

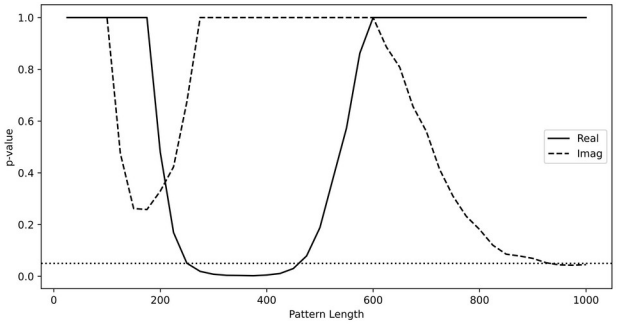


Figure 2. Graph of p-values from Kruskal Wallis test applied to the skewness of the Morlet wavelet, plotted against scale.

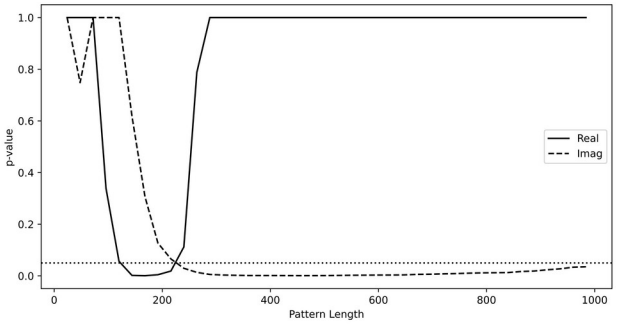


Figure 3. Graph of p-values from Kruskal Wallis test applied to the skewness of the Haar wavelet, plotted against scale.

By observing these graphs, we selected continuous ranges for each wavelet type, statistic and part (real or imaginary) as shown in Table 1. The table has columns for wavelet type, statistic and part, followed by two columns for the minimum and maximum of the range selected. Some rows are blank indicating that no range was selected. For example, the range selected for skewness of the imaginary part of the Morlet wavelet is from 835 to the maximum value included in this analysis, This range is included near the bottom of Table 1 and can be observed in Figure 2.

The results of the PCA are shown in Figure 4. The vertical axis shows accuracy from the machine learning analysis. The horizontal axis shows the number of features selected by PCA. Most of the graph shows an accuracy of 70% on cross validation. Towards the right-hand side of the graphs, where the number of features used by PCA is higher, the graphs accuracy improves to approximately 80%. This suggests that less reduction using PCA, and therefore more features retained, provides higher accuracy in machine learning. The highest accuracy found was 80.5% correct in classifying

Syncope or Presyncope from features derived from Heart Rate Variability.

Table 1. Selection of ranges for each feature type.

| Wavelet | Statistic | Part | Range |
|---|---|---|---|
| Haar | mean | Real | None |
| Haar | mean | Imaginary | None |
| Haar | variance | Real | None |
| Haar | variance | Imaginary | None |
| Haar | skewness | Real | 110 to 230 |
| Haar | skewness | Imaginary | 200 to 1000 |
| Haar | kurtosis | Real | None |
| Haar | kurtosis | Imaginary | None |
| Morlet | mean | Real | None |
| Morlet | mean | Imaginary | 650 to 820 |
| Morlet | variance | Real | None |
| Morlet | variance | Imaginary | None |
| Morlet | skewness | Real | 230 to 480 |
| Morlet | skewness | Imaginary | 835 to 1000 |
| Morlet | kurtosis | Real | None |
| Morlet | kurtosis | Imaginary | None |

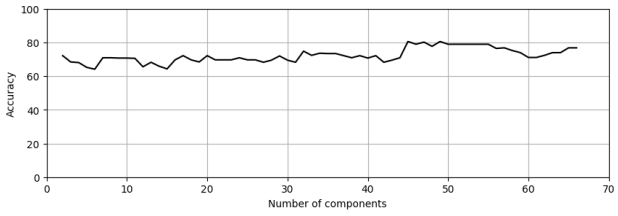


Figure 4. Graph of classifier accuracy against number of components selected by PCA.

## 5. Conclusion

Syncope, commonly known as fainting, is a sudden and transient loss of consciousness due to inadequate cerebral blood flow. It affects millions of individuals worldwide and can have serious consequences, including falls, injuries, and accidents. Distinguishing between syncope and presyncope (near-fainting) is crucial for accurate diagnosis and appropriate management.

Traditional methods, such as electrocardiography (ECG) and tilt table testing (HUTT), have limitations in distinguishing between the two conditions. In this study we used HRV data acquired from participants who were assigned to these diagnosis groups by using clinical symptoms augmented by HUTT. We extracted novel features from HRV, in particular, summary statistics of the wavelets transform. Features obtained showed robust and consistent low p-values extending over a range of wavelet types and scales. A further analysis using machine learning was able to differentiate syncope from presyncope. By leveraging appropriate advanced algorithms, we aim to create a robust and interpretable model capable of accurate classification.

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