Music-Based Graph Attention Network using ECG and Respiration Signals to Predict Systolic and Diastolic Blood Pressure

Poulomi Pal[1,2], Pier Lambiase[1,3], Elaine Chew [1,2]

[1] School of Biomedical Engineering & Imaging Sciences, Faculty of Life Sciences & Medicine, King's College London, Lambeth Palace Rd, London SE1 7EU, UK
[2] Department of Engineering, Faculty of Natural, Mathematical & Engineering Sciences, King's College London, Strand, London WC2R 2LS, UK
[3] Barts Heart Centre, St Bartholomew's Hospital, West Smithfield, London EC1A 7BE, UK

Abstract

Music has a considerable influence on human physiology and can modulate listeners' blood pressure (BP), ECG and respiration. Here, we study the predicting of systolic and diastolic BP from physiological signals, and the effect of music on the predictions. ECG, respiration, and BP were acquired simultaneously during music listening following an initial silence baseline. With SBP and DBP as target variables, we perform regression analysis using a graph attention network (GAT). Physiological signals form the nodes in the graph, the music heard establish the edges, and music features constitute the edge attributes. Comparison of loss curves during baseline silence with that during music showed that music listening (with music features as GAT edge attributes) improved both SBP and DBP prediction. The regression values were 0.64 (SBP) and 0.61 (DBP) in the presence of music vs. 0.39 (SBP) and 0.36 (DBP) during silence. The mean absolute error (MAE) was 2.78 (SBP) and 3.58 (DBP) and RMSE was ±3.01 (SBP) and ±3.59 (DBP) while listening to music. On average, SBP and DBP predicted from physiology during music listening, with music features, reduced the MAE by 29.3%, showing that music engagement can enhanced hypertension diagnostic accuracy. The benefit of music-induced physiological changes for predicting SBP and DBP demonstrates music's utility in precision hypertension diagnostics.

1. Introduction

Music impacts human physiology via the autonomic nervous system [1]. Research shows that music affects physiological variables like heart rate, respiration, blood pressure (BP) [2], evidence of its potential for use in precision diagnostics and digital therapeutics [3].

Hypertension is the prime risk for cardiovascular disease (CVD). Early diagnosis of hypertension allows for timely interventions to prevent CVD. A goal is to enable hypertension detection from physiological signals obtainable from wearable sensors. Cano et al. [4] applied machine learning to electrocardiograms (ECGs) and photoplethysmograms (PPGs) to screen individuals for high BP. Our prior work [5] used graph convolution neural network to detect high BP from ECGs and respiration; our study showed that music listening (compared to silence) significantly improved hypertension detection accuracy.

Detection of systolic BP and diastolic BP has also been achieved from wearable sensors, although evaluations disagree about their accuracy [6, 7]. The effect of music on SBP and DBP prediction using physiological signals has not been studied. Here, we investigate SBP and DBP prediction from ECG and respiration signals using the graph attention network (GAT), a deep learning technique, in the presence and absence of music. The advantage of the GAT over the GCNN is the weighting of network edges [8]. Section 2 describes the steps involved, followed by results in Section 3 and discussion and conclusions in Section 4.

2. Methodology

This pilot study utilized data collected in the HeartFM project [9]. The HeartFM study was designed in accordance with the ethical guidelines of the 1975 Declaration of Helsinki. Ethical approval was granted by the Oxford C Research Ethics Committee of the UK Health Research Authorities (IRAS 242471) and the Research Ethics Office at King's College London (minimal risk registration number: MRPP-22/23-34904). A schematic diagram for the current study is shown in Figure 1. This study used data from 50 (38 females) participants collected over a period of eight months. Table 1 shows the demographic details.

Participants listened to Western Classical music rendered on a reproducing grand piano, a Bösendorfer VC280

 ISSN: 2325-887X DOI: 10.22489/CinC.2025.364

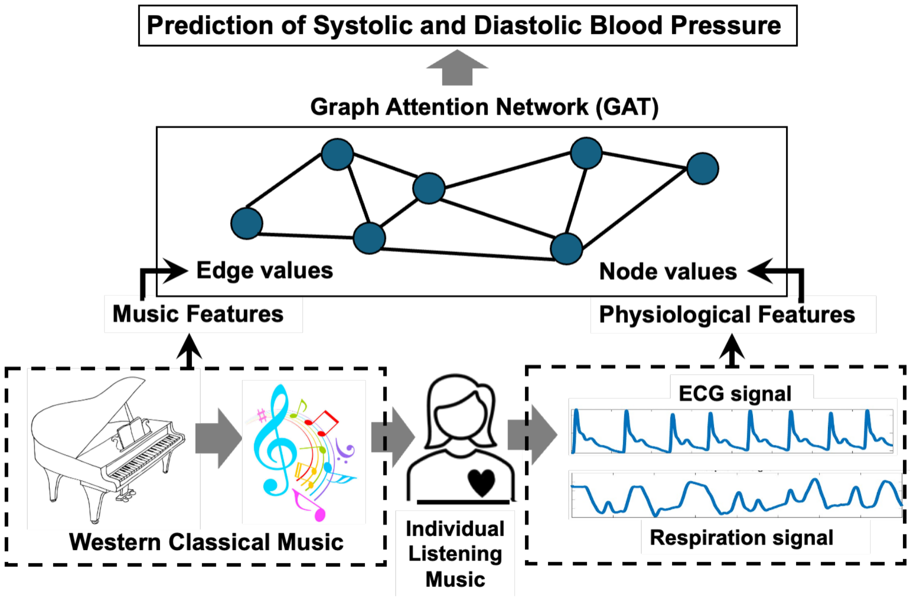

Figure 1. Schematic diagram showing steps involved in deriving BP values from ECG and respiration signals in the presence of music.

Enspire PRO. Participants ranged from 18 to 65 years old; those on beta blockers or having cognitive and/or hearing abnormalities were excluded from the study. Informed consent was obtained from all participants. Whilst participants listened to the music and during an initial 5-minute baseline silence, their BP was measured using a CNAP sensor (CN Systems, Graz, Austria)—the SBP and DBP readings from the CNAP were considered the *gold standard*. Participants' ECG were collected with a Polar H10 heart rate sensor (Polar Electro Oy, Kempele, Finland) and respiratory signals using a BIOPAC respiration belt (BIOPAC Systems, Goleta, USA) via the HeartFM mobile app. Later, physiological signals - ECG and respiratory signals were processed for signal feature extraction.

Table 1. Demographics of the study.

Parameters	Unit	Individuals
Gender	F/M	38/12
Age	years	46 ± 5.7
Height	cm	160 ± 5.7
SBP	mmHg	144 ± 1.41
DBP	mmHg	77.5 ± 12.12

2.1. Signal Pre-Processing

Pre-processing of the ECG signal utilized a 2nd order Butterworth band-pass filter with range 0.2-500 Hz and sampling frequency 1 kHz. The respiratory signals were filtered with a 4th order Butterworth filter and sampling frequency 30 Hz. After pre-processing, features were extracted from the acquired signals. The seven time domain features extracted from the ECG signals were the ST, QT, PR, RR, RT, QS, and RS intervals. The seven frequency domain features extracted from the respiratory signal were the envelope, band power, bandwidth, maximum power, peak power, maximum frequency, and minimum frequency. Music signals were processed to give the four features of loudness, tempo, MFCC, and note density. After extraction, all the features were integrated into the GAT classification network. The physiological signal features formed the node values of the GAT. The edge values were given by the music features.

2.2. Graph Attention Network (GAT)

The GAT comprised of 50 nodes representing individuals, with edges connecting participants who heard the same music track. The 14 values of each node comprised of the ECG and respiration features. Hence, the network was made of 14×50 nodes and 2×81 edges. To evaluate the predictability of the proposed method, the GAT was mapped to 1×7 actual SBP and DBP values. The principle of multi-head attention [10] using the edge features as the weight attributes was used in this GAT. This attention mechanism prioritised those nodes which ultimately help in predicting BP values, thus upgrading the GAT's forecasting ability.

The hyperparameters used in this GAT had 40 hidden layers, the learning rate was 0.001, and the number of

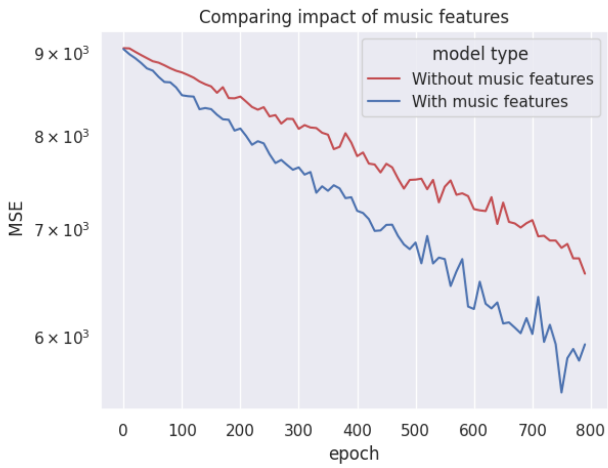

Figure 2. Loss curves for prediction of DBP using ECG and respiration signals with and without music.

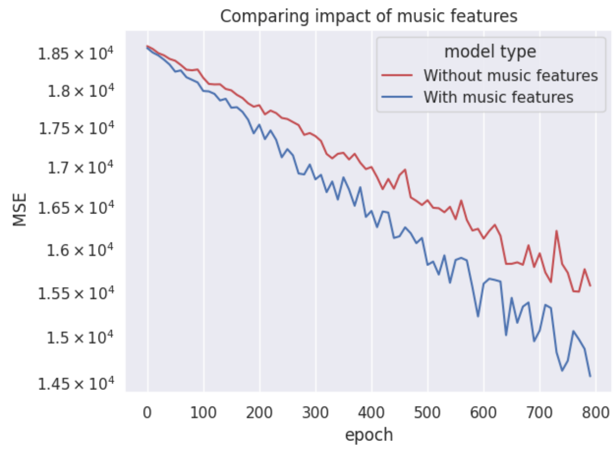

Figure 3. Loss curves for prediction of SBP using ECG and respiration signals with and without music.

epochs was 500. We used the AdamW as an optimizer and the ReLU as the non-linearity function. Two convolution layers were used in the formation of the GAT. Network computations were done via a computer program in Python 3.99 and was implemented in Google Colab with Tensor and PyTorch.

3. Results

The GAT's ability to predict SBP and DBP values based on the physiological signals (ECG and respiration) in the presence of music was assessed with regression values, mean absolute error (MAE), and root mean squared error (RMSE). The regression value was 0.64 (SBP) and 0.61 (DBP), in presence of music, vs. 0.39 (SBP) and 0.36 (DBP) during silence. Table 2 presents the results. For BP predictions during music, the MAE was 2.78 (SBP) and 3.58 (DBP), and RMSE ±3.01 (SBP) and ±3.59 (DBP).

Table 2. Regression values for prediction of BP.

	SBP	DBP
Music	0.64	0.61
No Music	0.39	0.36

Comparative study was also performed using the loss curves of mean squared error (MSE) vs epoch for the GAT predictions with and without music features as shown in Figures 3 for SBP and Figure 2 for DBP. The graphs in Figures 3 (SBP) and 2 (DBP) show lower MSE during music, with the gap increasing with epoch.

4. Discussion and Conclusion

The results provide evidence of the importance of music in discriminating between human physiology under different BP. Using the GAT method, SBP and DBP prediction was possible with ECG and respiration signal features along with music features. Our comparative study shows the benefit of evaluating BP from physiological signals during music listening in contrast to that during the baseline silence.

The results suggest that the impact of music on the cardiovascular system enhances the difference between gradations of blood pressure for both SBP and DBP. Adding music listening information and features to the model reduced the MAE (mean absolute error) by 29.3%, showing that changes to physiology during music engagement enhanced the BP prediction, which in turn improves hypertension diagnostic accuracy.

To our knowledge, this is the first demonstration of music-based assessment of SBP and DBP from physiological signals. Providing accurate and more granular BP predictions through music listening is a step towards precision medicine for hypertension.

Acknowledgments

This result is part of the COSMOS and HEART.FM projects that have received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (Grant agreement No. 788960 and 957532).

Charles A. Picasso developed the heartfm mobile and desktop visualisation applications used for data collection. Vanessa Pope, Courtney Reed, Mateusz Soliński, and Natalia Cotic contributed to data collection and segmentation.

References

[1] Kulinski J, Ofori EK, Visotcky A, Smith A, Sparapani R, Fleg JL. Effects of music on the cardiovascular system. Trends in Cardiovascular Medicine 2022;32(6):390–398.

[2] Bretherton B, Deuchars J, Windsor WL. The effects of controlled tempo manipulations on cardiovascular autonomic function. Music Science 2019;2:2059204319858281.

[3] Chew E, Fyfe L, Picasso C, Lambiase P. Seeing music's effect on the heart. European Heart Journal 2024; 45(41):4359–4363.

[4] Cano J, Fácia L, Hornero F, Langley P, Alcaraz R, Rieta JJ. Cuffless hypertension risk assessment and the significance of calibration. In 2022 Computing in Cardiology (CinC), volume 498. IEEE, 2022; 1–4.

[5] Pal P, Cotic N, Soliński M, Pope V, Lambiase P, Chew E. Music-based graph convolution neural network with ECG, respiration, pulse signal as a diagnostic tool for hypertension. In 13th Conference of the European Study Group on Cardiovascular Oscillations (ESGCO). Zaragoza, Spain, 2024; 1–2.

[6] Almeida TP, Perruchoud D, Alexandre J, Vermare P, Sola J, Shah J, Marques L, Pellaton C. Evaluation of aktiia cuffless blood pressure monitor across 24-h, daytime, and night-time measurements versus ambulatory monitoring: a prospective, single-centre observational study. Journal of Hypertension 2025;43(4):690–697.

[7] Bhatt B, Amir H, Jones S, Jamieson A, Chaturvedi N, Hughes A, Orini M. Validation of a popular consumer-grade cuffless blood pressure device for continuous 24h monitoring. European Heart Journal – Digital Health 2025; 4(6):704–712.

[8] Veličković P, Cucurull G, Casanova A, Romero A, Lio P, Bengio Y. Graph attention networks. arXiv 2017;.

[9] Chew E. Heart.FM: Maximizing the therapeutic potential of music through tailored therapy with physiological feedback in cardiovascular disease, July 2020.

[10] Vaswani A, Shazeer N, Parmar N, Uszkoreit J, Jones L, Gomez AN, Kaiser Ł, Polosukhin I. Attention is all you need. Advances in neural information processing systems 2017;30.

Address for correspondence:

Poulomi Pal

King's College London, Strand, London WC2R 2LS, UK

poulomi.pal@kcl.ac.uk