Music-based Graph Convolution Neural Network with ECG, Respiration, Pulse Signal as a Diagnostic Tool for Hypertension

Poulomi Pal, Natalia Cotic, Mateusz Soliński, Vanessa Pope, Pier Lambiase, and Elaine Chew*

***Abstract*— Hypertension is one of the prime risk factors of cardiovascular disease. Music has been shown to be beneficial for lowering blood pressure. Here, we investigate if music can help in identifying hypertensive individuals. We acquire simultaneously electrocardiography (ECG), respiration, and pulse signals from 70 participants whilst they listen to music that has been altered digitally to differ only in tempi and loudness. Baseline blood pressure values in the preceding silence was taken as ground truth. After pre-processing, we obtain feature indices E,R,P from the ECG, respiration and pulse signals, respectively. The indices are fused to derive the compound indices ERP, EP, RP, and ER. Classification was performed using GCNN (Graph Convolution Neural Network) to segregate hypertensives from normotensive individuals. The index values formed the nodes and the music attributes (average tempo and loudness) were used to establish the edge connectivity for node based classification. Binary classification was carried out with 0.85 accuracy, 0.87 recall, 0.84 specificity, and 0.86 F1-score. Without edges (music attributes), classification performance was 10% lower on average. We demonstrate for the first time the potential of music based hypertension diagnosis using listeners' ECG, respiration, and pulse signal during music.**

I. INTRODUCTION

Music listening leads to changes in cardiovascular function parameters in individuals. Dousty *et al.* demonstrated the effect of different types of music on electrocardiogram (ECG) signals [1]. Using ECG sensors, Wu *et al.* evaluated changes in heart rate variability in the presence of music [2]. Time delay stability in music signals along with the cardiac signals of musicians and listeners was investigated by Soliński *et al.* [3], showing time dealay stability (TDS) during specific music events. Other research claim that music influences not only emotions but also cardiac rhythms as expressed via physiological signals (photoplethysmography, respiration), blood pressure (BP), and skin conductance [4].

BP is one of the crucial factors which is considered for cardiac well being [5]. Abnormality in the cardiovascular system is apprehended by BP values beyond the normal range of 120/80 mmHg. Clinically, BP beyond 139/89 mmHg indicates hypertension. Hypertension stresses the blood vessels. If untreated, hypertension can lead to heart failure or renal problems. Early diagnosis can allow interventions to be prescribed so as to avoid life threatening outcomes. Hypertension risk has been analysed by Cano *et al.* using ECG signal features and K-nearest neighbour (KNN) classifier with 83% accuracy [6]. Liang et al. was able to classify hypertensives with an F1-score of 84.34% using ECG and PPG signals. Loomba & Arora [7] reviewed literature on music's impact on the vitals–systolic and diastolic BP and heart rate. None have attempted to classify hypertensives using physiological signals from participants listening to music.

With music as an integral part of the investigation, we set out to distinguish hypertensives from normotensive individuals in this study. Analysis of concurrent ECG, respiration, and pulse signals whilst listening to music with transposed loudness and tempi was performed. Graph convolution neural network (GCNN) was implemented for node classification where each node in the graph represented a single individual. The physiological signal features were the node features and the edges were established based on the attributes of the music they heard. Music was central to building the graph connectivity.

II. METHODOLOGY

A. Data acquisition while listing to music

The cohort for this study comprised of 70 (41 women) normotensive and hypertensive individuals (aged 18-80 years, mean $= 47.76 \pm 12.90$, average BMI$= 24.42 \pm 3.6$). Two versions of Chopin's Nocturne in F-sharp minor were played to participants via a reproducing piano: Josef Hofmann's original recording (duration 7:51), which was artificially sped up (3:10) to a maximal perceptually viable tempo. Three sets of physiological signals – ECG via a H10 (Polar Electro Oy, Kempele, Finland) sensor, respiration via a BIOPAC (BIOPAC Systems, Goleta, USA) band, and pulse signal via a CNAP sensor (CN Systems, Graz, Austria) – were simultaneously acquired from this cohort whilst they listened to the music. The total duration of data collection was 16:01 including the initial 5 minutes of silence as baseline. *Gold standard* BP values were recorded during the initial baseline silence, on which we based the hypertensive classification.

B. Signal processing

The ECG was filtered with the Butterworth band pass filter (BPF) with cut-off frequency 0.2-500 Hz (sampling frequency (sF)= 3000Hz) and order 2. The respiration signal was filtered with rolling and moving averages, and window size 200. BPF with cut-off frequency $0.4 - 8$ Hz (sF= 300 Hz) and order 2 filtered the pulse signal. Filtered ECG signals were mean standardised. The product of QT and RR intervals was extracted from the ECG signal as the E feature. The ratio of the area of the inspiration to the expiration portions of the respiratory cycle was set as the R feature. The augmentation index of the pulse signal, the ratio of the amplitude of the first

Poulomi Pal, Natalia Cotic, Mateusz Soliński, Vanessa Pope, Pier Lambiase, and Elaine Chew* are with the School of Biomedical Engineering & Imaging Sciences, Faculty of Life Sciences & Medicine, King's College London, London poulomi.pal@kcl.ac.uk, elaine.chew@kcl.ac.uk

979-8-3503-9205-0/24/$31.00 ©2024 IEEE

wave to that of the second wave in a cardiac cycle, gave the P feature. The combined individual features, $(E, R, andP)$, was used to get the derived features: $ER = E * R, EP = E * P, RP = R * P$, and $ERP = E * R * P$. The cohort – each member having 7 features – was segregated into training:validation:test sets in the proportion 80:10:10.

The identifying of hypertensive individuals was conducted using node classification from GCNN as shown in Fig. 1. GCNN improves accuracy and performance, works efficiently with less data, and increases explainability and adaptibility. Here, each node represents one individual characterised by the 7 features extracted from the signals. The edge connectivity was established by the version of music heard by the individual. Graph properties are utilised to procure the attributes which identify the unknown node (individual) as hypertensive or normotensive.

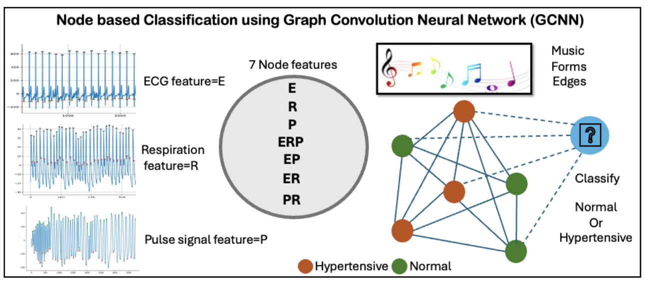

Fig. 1: Schematic of the GCNN classification process

C. Network - GCNN

The input comprised of 70×7 nodes and 2×489 edges mapped to 1×7 actual data. This followed the three layers of graph convolution with 6 hidden channels using the rectified linear unit (RELU) as the non-linearity function. The hyperparameters involved in the network execution are: the Adams optimizer as the training algorithm, learning rate of 0.01, and weight decay rate of 6e$-$5. The training of the network was executed with 56 nodes for 200 epochs. The validation and testing was done within the network by comparing the predicted and actual data. The confusion matrix was used to derive the result matrices. Network computations were done using Python 3.99. GCNN was implemented in Google Colab with Tensor and PyTorch.

III. Results and Discussion

The final performance metrics of the classifier were considered after implementing 5-fold cross-validation and with the leave-one-out method on the dataset. The results were 0.85 accuracy, 0.85 recall, 0.84 specificity, and 0.86 F1-score.

The importance of music in this approach was studied by comparing the results with that derived in the absence of music information in the following study. Without edges, the GCNN becomes a multilayer perceptron (MLP). The outcome of MLP classification was 0.75 accuracy, 0.76 recall, 0.74 specificity, and 0.77 F1-score. This showed that connecting the cohorts based on the music they listened to (segregated by expressive features such as loudness and tempo) was more efficient in distinguishing hypertensives from normotensive individuals. This improvement of the music-based model demonstrates music's pivotal role in enhancing the quality of the results. The GCNN's ability to classify hypertensives increased in the presence of music, i.e. with the edge connectivity.

The decision of considering all seven features as GCNN input was made after inspecting the results of the different input options. Table 1 shows the different results for each input set using independent test sets. Observe that the performance of individual signal features was weaker (0.69 accuracy, 0.68 recall, 0.67 specificity, and 0.68 F1score), combined features performed better but were not outstanding (0.71 accuracy, 0.73 recall, 0.70 specificity, and 0.72 F1 score), whereas all the features combined dominated the classification assessment. Our present results are comparably better than prior studies [6][7].

TABLE I: Comparison of results with different inputs

Input features	Accuracy	Recall	Specificity	F1-score
E/R/P	0.69	0.68	0.67	0.68
E,R,P	0.70	0.68	0.71	0.69
EP/ER/RP	0.69	0.67	0.69	0.68
ER,EP,RP	0.71	0.73	0.70	0.72
All 7 features	0.85	0.87	0.84	0.86

IV. Conclusion

In conclusion, the presence of music information improved GCNN classification of hypertensives vs. normotensive individuals. Three signal (ECG, respiration, and pulse) features formed the nodes. Edge connectivity was established using music information. The node classifier, in the presence of music listening information, identified hypertensives with 0.85 accuracy, 0.87 recall, 0.84 specificity, and 0.86 F1-score. This showed that hypertension-induced changes in physiological parameters were sufficient for diagnosing hypertension, with potential for informing prescriptions of music-based cardiovascular interventions.

ACKNOWLEDGMENT

This result is part of the COSMOS and HEART.FM projects that have received funding from the ERC under the EU's Horizon 2020 research and innovation program (grant nos. 788960 and 957532, respectively).

References

[1] Dousty, M., *et al.* The effects of sedative music, arousal music, and silence on electrocardiography signals. Journal of electrocardiology, 3, 44, 396-e1.2011

[2] Wu, M.H. and Chang, T.C. Evaluation of Effect of Music on Human Nervous System by Heart Rate Variability Analysis Using ECG Sensor. Sensors & Materials, 33. 2021.

[3] Soliński, M., ***et al.***, Time Delay Stability Analysis of Pairwise Interactions Amongst Ensemble-Listener RR Intervals and Expressive Music Features. Computing in Cardiology (CinC), IEEE, 50, 1-4. 2023

[4] Bretherton, B., ***et al.*** The effects of controlled tempo manipulations on cardiovascular autonomic function. Music & Science, 2, p.2059204319858281. 2019.

[5] Ghosh, A., Torres, *et al.* Detection of essential hypertension with physiological signals from wearable devices. IEEE Engineering in Medicine and Biology Society, 8095-8098. 2015

[6] Cano, J.,*et al.*Cuffless Hypertension Risk Assessment and the Significance of Calibration.Computing in Cardiology,IEEE,498,1-4.2022

[7] Liang, Y.,*et al.* Hypertension assessment via ECG and PPG signals:An evaluation using MIMIC database. Diagnostics,3,8,65.2018.

[8] Loomba, R.S., *et al.* Effects of music on systolic blood pressure, diastolic blood pressure, and heart rate: a meta-analysis. Indian heart journal, 3, 64, 309-313. 2012