International Journal of Electrical and Computer Engineering (IJECE)
Vol. 12, No. 3, June 2022, pp. 3166~3175
ISSN: 2088-8708, DOI: 10.11591/ijece.v12i3.pp3166-3175

Review on hypertension diagnosis using expert system and wearable devices

Muhammad Izzuddin Mohd Sani[1], Nur Atiqah Sia Abdullah[2,3], Marshima Mohd Rosli[2,3]
[1]Department Supervisory Control and Data Acquisition (SCADA), Willowglen (Malaysia) Sdn Bhd, Kuala Lumpur, Malaysia
[2]Center of Studies for Computer Science, Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Shah Alam, Malaysia
[3]Knowledge and Software Engineering Research Group, Research Nexus UiTM (ReNeU) Office of Deputy Vice Chancellor (Research and Innovation), Universiti Teknologi MARA, Shah Alam, Malaysia

Article Info

Article history:

Received Mar 16, 2021
Revised Oct 10, 2021
Accepted Nov 15, 2021

Keywords:

Expert system
Hypertension management
Machine learning
Systematic review
Wearable devices

ABSTRACT

The popularity of smartphones and wearable devices is increasing in the global market. These devices track physical exercise records, heartbeat, medicines, and self-health diagnosis. The wearable devices can also collect personal health parameters include hypertension diagnosis. Hypertension is one of the risk factors for cardiovascular-related diseases among the Malaysian population. Many mobile applications are paired with wearable devices to monitor health conditions, but none of them able to diagnose hypertension. In this study, we reviewed research papers that focused on hypertension using expert systems and wearable devices. We performed a systematic literature review based on hypertension factors, expert systems, and wearable devices. We found 15 specific research papers after the filtering process. The key findings highlighted three main focuses, which are the factors of hypertension, the expert system techniques, and the types of sensors in wearable devices. Blood pressure is the most common factor of hypertension that can be collected by wearable devices. As for the expert system techniques, we determined the three most common techniques are machine learning, neural network, and fuzzy logic. Lastly, the wrist band is the most common sensor for wearable devices in hypertension-related research.

Corresponding Author:

Nur Atiqah Sia Abdullah
Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA
40450 Shah Alam, Selangor, Malaysia
Email: atiqah684@uitm.edu.my

1. INTRODUCTION

The technology of mobile phones becomes trendy and receives high demand since the introduction of smartphones to consumers [1]. The challenges increase when smartphones start to pair with wearable devices like a smart watch and wireless earphones. Moreover, wearable devices have become trending among smartphone users with many other applications [2]–[4]. The popularity of wearable devices is increasing as there are currently used to keep a healthier lifestyle like losing weight and getting a preventive measure for having disease due to inactive physical activities. The rise of the health care cost and aging society in some countries had also contributed to this popularity [5], [6].

As in addition, the fact of active physical activities can lower the risk of suffering for over 20 health conditions [7]. The popularity of wearable devices in Malaysia also seems to follow global trends [8]. The global market of wearable devices will be double by 2021 compared to 2017 statistics [9]. The wearable devices can provide preventive measures, which able to check and monitor the health condition of the users like a heartbeat, blood pressure, walking steps, and distance. Some mobile applications can be paired with these wearable devices to get information regarding hypertension, medicines, self-diagnosis, and physical exercise [6].

Hypertension can be determined based on the level of blood pressure in a person, which reflects the person's cardiovascular system. The higher the blood pressure, the risk for cardiovascular-related diseases also increases [10]. In Malaysia, the survey of hypertension from The National Health and Morbidity Survey 2015, had surveyed adults aged 18 years old and above. This survey involves 19,936 respondents by using a questionnaire and blood pressure measurement. Based on the result, 30.3% of the respondents diagnosed to have hypertension. Based on the statistics, the prevalence shows a significant increment as the age increases. This survey indicates the prevalence of hypertension among Malaysians in general. Based on the surveys, the government initiates clinical practice guidelines to reduce the number of prevalence hypertension [11]–[13].

With the increasing cases of hypertension and its direct impact on heart diseases, there are a lot of mobile applications and studies for health monitoring purposes in the market. These mobile applications are paired with wearable devices in measuring the heartbeat and blood pressure [14]–[17]. These systems are trending among the users of mobile apps in monitoring their health conditions. However, as these applications are only able to read related data on the user's health condition (for monitoring purposes), the current market is still lacking in offering any mobile applications that able to diagnose the hypertension.

Expert systems are normally used in the studies related to health and medical domain such as dengue symptoms [18], autism severity level detection [19], insomnia acupoint [20], dental and mouth disease [21], heart disease [22], and eye disease diagnosis [23]. In this paper, we focused on the common techniques used in expert systems in hypertension diagnosis. The techniques include machine/deep learning [15], [16], neural network [24], and fuzzy logic [25]. However, some studies used hybrid approaches, which are the combination of neural network-fuzzy logic [25], [26], neural network-machine learning [27], and fuzzy logic-decision tree [28].

This paper aims to review research that focuses on hypertension factors, techniques used in the diagnosis of expert systems and wearable devices to find the research gap. We used systematic review as the review method and set the research questions before the searching process. However, the hypertension diagnosis systems are limited to expert systems in this systematic review.

2. RESEARCH METHOD

The review is generated based on the research questions. There are three phases in this systematic review, which are planning, conducting, and reporting [29], [30]. The planning and conduction phases are discussed in this section. The reporting phase is in the results section.

2.1. Planning the review

In the planning phase, we discussed the research objectives, research questions, search strategy, inclusion criteria, exclusion criteria, and quality assessment of the search source [29]. As mentioned earlier, this review aimed to determine the hypertension factors, techniques in expert systems, and commonly used wearable devices in hypertension diagnosis. Then, we constructed three research questions: i) RQ1: what are the factors of hypertension that can be collected and paired with wearable devices?; ii) RQ2: what are the selected techniques used in expert systems to diagnose hypertension? and iii) RQ3: what are the types of sensors in wearable devices for hypertension diagnosis?.

After setting the research questions, we started to implement the search strategy. A good systematic literature review should be based on a predefined search strategy that is fair, unbiased, comprehensive, and accurate. Hence, it will help in creating good research activities [29]. Therefore, this review is conducted as unbiased and fair, and as much as possible with the use of relevant electronic databases. We searched the research papers from databases including ACM, IEEE, Elsevier (Science Direct), Scopus, and Springer. The search is started by defining search terms or keywords. The search terms must be generated from the research objectives as well as the research questions.

The search terms focused on hypertension diagnosis system using an expert system, and hypertension detection using wearable devices. Later, the search terms of both parts were combined to find papers that have an exact topic as this research topic. The terms like "hypertension diagnosis" and "expert system" were used together with a Boolean expression of "AND" are used.

To overcome the low number of results, the term "blood pressure" is also used. There is a need to determine factors associated with hypertension [31], such as blood pressure, diabetes, smoking habits, and age, which contribute to the risk of hypertension [13]. Hence, the terms "blood pressure" or "hypertension" are used together with a "wearable device" in a Boolean expression of "AND".

The next step is determining the review protocol that consists of inclusion and exclusion criteria. It is essential to help the search result to be more specified because we have to review the abstract of the papers based on these criteria. In the inclusion criteria, we set the type of study that must be scientific materials, written in English and must include the defined search terms. The scientific materials include journals, proceeding papers, technical reports, and short papers from 2015 to March 2019. This review excludes the publications that do not contain expert systems, wearable devices, or hypertension diagnosis. Based on the reviewed abstract, if the article does not refer to hypertension diagnosis, an expert system, or a wearable device, it is excluded from this review. If it is on the medication or disease, it is also excluded from this review. All papers must be able to be accessed through online databases to do a comprehensive review.

We also conducted a quality assessment of each paper, which is complementary to the inclusion or exclusion process [29]. The assessment criteria are from the critical appraisal skills programme (CASP) for qualitative assessment [32]. Based on the CASP, we set the following questions for this assessment [30]: i) is there a clear statement of the aims and objectives of the research?; ii) is there an adequate description of the context in which the research was carried out?; iii) is there an adequate description of the proposed contribution, method, or approach?; iv) is the evidence obtained from experimental or observational studies? and v) is the study valuable for research or practice?. After planning, we started to conduct the review according to the RQs, search terms, inclusion and exclusion criteria, and qualitative assessment.

2.2. Conducting the review

To conduct the review, the search was started with finding the papers using the selected keywords. We retrieved 1368 papers. However, some papers were redundant because they appeared in different databases. After filtering the redundant papers, we have 1019 publications. Then, second filtering on the publication year from 2015 to 2019 is carried out. It ended up with 800 papers. The abstracts of these papers are then filtered using “wearable device”, “wearable devices”, “blood pressure”, “hypertension”, “expert system”, “fuzzy”, “rule-based”, and “neural”. By applying the word filtering, it ended with 324 papers.

Then the abstracts of these papers are reviewed thoroughly. Most of these papers focus on the development of a device or sensor in measuring blood pressure. Besides, various electronic blood pressure measurement techniques are tested and evaluated to create a better blood pressure measurement device or sensor. It gives an overview that blood pressure is estimated through wearable devices. After a thorough review of abstracts, we found only 15 papers as shown in Table 1 are exactly related to the review main topics, which are wearable devices, expert system, and hypertension. To simplify the review, we labeled the papers from S01 to S15 in Table 2 to ease the reviewing process. These papers are crossly related to the research questions and based on the guided review processes. The following sections discussed the results based on the research questions to find the factors of hypertension, the selected techniques used in expert systems, and the types of sensors in wearable devices for hypertension diagnosis.

Table 1. Systematic search results

Database	Retrieved	Included (Percentage)	Excluded (Percentage)
ACM	16	1 (6.25%)	15 (93.75%)
IEEE	110	6 (5.45%)	104 (94.55%)
Elsevier	1011	2 (0.20%)	1009 (99.80%)
Scopus	194	6 (3.09%)	188 (96.91%)
Springer	37	0 (0.00%)	37 (100%)
Total	1368	15 (1.10%)	1353 (98.90%)

Table 2. Systematic search results

Paper	Authors	Title of Article
S01	Ahmed *et al.* [33]	Feasibility analysis for estimation of blood pressure and heart rate using a smart eye wear
S02	Lopez *et al.* [15]	Wearable technology model to control and monitor hypertension during pregnancy
S03	Ghosh *et al.* [16]	Detection of essential hypertension with physiological signals from wearable devices
S04	Kańtoch [34]	Human activity recognition for physical rehabilitation using wearable sensors fusion and artificial neural networks
S05	Maria and Laurentiu [35]	Electroconductive materials with high potential for wearable electronic devices integration
S06	Kuwabara *et al.*[14]	Validation of two watch-type wearable blood pressure monitors according to the ANSI/AAMI/ISO81060-2:2013 guidelines: Omron HEM-6410T-ZM and HEM-6410T-ZL
S07	Zhang *et al.* [36]	Hybrid optical unobtrusive blood pressure measurements
S08	Lee *et al.* [37]	Wireless, intraoral hybrid electronics for real-time quantification of sodium intake toward hypertension management
S09	Nohria [25]	Comparative study of adaptive neuro-fuzzy and fuzzy inference system for diagnosis of hypertension
S10	López-Martínez *et al.* [38]	Machine learning classification analysis for a hypertensive population as a function of several risk factors
S11	Melin *et al.* [26]	A hybrid model based on modular neural networks and fuzzy systems for classification of blood pressure and hypertension risk diagnosis
S12	Liang *et al.* [27]	Photoplethysmography and Deep Learning: Enhancing Hypertension Risk Stratification
S13	Ghosh *et al.* [24]	Using accelerometric and gyroscopic data to improve blood pressure prediction from pulse transit time using recurrent neural network
S14	Zhang *et al.* [39]	Predicting blood pressure from physiological index data using the SVR algorithm
S15	Espinilla *et al.* [28]	Fuzzy intelligent system for patients with preeclampsia in wearable devices

3. RESULTS AND DISCUSSION

In this section, we reported the results based on the three research questions, which are highlighted at the beginning of the review. There are factors in hypertension diagnosis, techniques in hypertension diagnosis, and sensors in wearable devices. It follows by a discussion section.

3.1. Factors in hypertension diagnosis

The first research question is related to the factors in hypertension diagnosis and focusing on the possible factors that a wearable device can collect for the hypertension diagnosis as shown in Table 3. S10 showed a significant accuracy on hypertension classification. The classifier uses common factors like blood pressure, body mass index (BMI), heartbeat rate, physical activities, age, diabetes, genetics/family history. Besides, S10 is the only study, which covers extra factors include cholesterol level, cigarette smoking, unhealthy diet, obesity, and gender in determining hypertension [38].

Table 3. Factors of hypertension in diagnosis system

Factor	Papers	Total
Blood Pressure	S01, S02, S03, S06, S07, S09, S10, S11, S12, S13, S14, S15	12
Heart rate/heartbeat	S01, S02, S03, S04, S09, S10, S11, S13	8
Steps/Physical Activities	S02, S04, S09, S10, S13, S14	6
Body Mass Index	S02, S09, S10, S14, S15	5
Age	S09, S10, S11, S14, S15	5
Body Temperature	S03, S04	2
Diabetes	S09, S10	2
Genetics/Family History	S09, S10	2
Skin Response	S03	1
Sodium Intake	S8	1
Cholesterol level	S10	1
Cigarette Smoking	S10	1
Unhealthy Diet	S10	1
Obesity	S10	1
Gender	S10	1
Body Fat Level	S14	1
Race	S15	1

S09 compared adaptive neuro-fuzzy inference system (ANFIS) with the existing fuzzy inference system. It was a controlled comparative work where the systems are compared using the same hypertension factors. The factors are blood pressure, body mass index (BMI), heartbeat rate, physical activities, age, diabetes, and family/genetic history. ANFIS was performed better than the existing fuzzy-based diagnosis system [25]. As a summary of the first research question, we found that blood pressure reading is the most common factor that is collected to determine hypertension. Then, it is followed by heartbeat rate, physical activities, BMI, age, body temperature, diabetes, and genetic/family history. These factors are the most common factors for hypertension diagnosis.

We also observed from the review that wearable devices can auto-measured heartbeat rate, physical activities, body temperature, and skin response through sensors. Some hypertension factors include sodium intake, cholesterol level, and body fat level need to be measured separately using other devices before entering the data into the wearable devices. Other factors such as body mass index (BMI), cigarette smoking, unhealthy diet, obesity, gender, and race need to be entered personally by the user when wearing the devices. Therefore, these factors are not being able to be automatically measured by the wearable devices. The results from this research question highlighted the hypertension factors that can be collected from wearable devices.

3.2. Techniques in hypertension diagnosis

The second research question aimed to find techniques that can diagnose hypertension. We found that the three most common techniques are machine/deep learning, neural network, and fuzzy logic as shown in Table 4. However, S09, S11, S12, and S15 used a hybrid approach. The hybrid approaches are neural network-fuzzy logic (S09 and S11), neural network-machine learning (S12), and fuzzy logic-decision tree (S15). S03, S10, and S14 used the machine or deep learning techniques and S13 uses the neural network as shown in Table 4.

S09 developed ANFIS as a hypertension diagnosis system. ANFIS uses seven inputs and five-layered architecture. The layers are the fuzzification layer, rule layer, normalization layer, defuzzification layer, and summation layer. In the defuzzification layer, a learning algorithm modifies some parameters in the layers automatically. The algorithm evaluated the dataset to determine the fuzzy membership functions. A performance comparison between the ANFIS and a fuzzy expert system shows that the ANFIS has better accuracy, sensitivity, specificity, and precision [25].

Table 4. Techniques in expert systems

Technique	Papers	Total
Machine/deep learning	S03, S10, S12, S14	4
Neural network	S09, S11, S12, S13	4
Fuzzy logic	S09, S11, S15	3
Decision tree	S15	1

S11 uses the combination of neural network-fuzzy logic techniques where it analyses blood pressure, heartbeat rate, and age. It has three separate neural network-fuzzy logic modules for hypertension risk diagnosis. The process starts with a database with systolic blood pressure, diastolic blood pressure, and heart rate, which are also the inputs to the neural network. From the inputs, the neural network learns the behavior of the blood pressure data. This process finds the best possible way to get better diagnosis results in terms of the module architecture parameters. The outputs of the neural network will be the inputs of the fuzzy logic blood pressure classifier, heartbeat classifier, and nocturnal blood pressure classifier. Three fuzzy logic classifiers determine hypertension diagnosis result after confirming with the framingham heart study [26].

S12 has designed a hypertension diagnosis system that uses photo-plethysmography (PPG) and convolutional neural network, GoogLeNet. The PPG signal is transformed using the continuous wavelet transformation method into a scalogram and further processed using GoogLeNet. As the wearable devices have low computational complexity and memory, the expert system is embedded in the cloud platforms to perform data computing. It takes PPG signals only and it is easy to be applied in a clinical environment [27].

S15 has designed a preeclampsia diagnosis system, which uses a medical knowledge inference system with a combination of fuzzy logic and decision tree. A wearable device is paired to estimate blood pressure with other inputs includes age, BMI, and proteinuria. Even though the system is for preeclampsia among pregnant women, it can determine hypertension. Preeclampsia is closely related to hypertension and proteinuria. At the first stage, the decision tree (statistical classifier) is used to gain knowledge from the dataset of the women with a high risk of having preeclampsia. Then, the output of the decision tree is further analyzed using fuzzy logic to improve the interpretability of the decision tree output data. Lastly, a medical knowledge base is generated and used in a mobile application [28].

S03, S10, and S14 developed a system using machine/deep learning [16], [38], [39]. S03 used machine learning to classify and predict hypertension by analyzing physiological signals. The signals are processed by using interpolated inter-beat interval (IIBI) method to produce a smooth signal that helps the classification process. The combination of physiological signals, IIBI, and adaptive boosting learning algorithm has produced the best result with high accuracy in determining hypertension [16].

S10 used a logistic regression classifier to classify hypertension. This expert system can diagnose hypertension with high accuracy [38]. S14 discussed a diagnostic system that used the support vector machine regression (SVR) algorithm. The SVR algorithm is compared with linear regression and the back propagation neural network. As a result, the SVR produces better accuracy [39].

S13 has used long-shot-term-memory (LTSM), which is based on recurrent neural network (RNN) [24]. The architecture of LSTM [40], [41] is used as it can capture long-range dependencies and non-linear dynamics as the deeper architecture of the RNN. This hypertension diagnosis system depends on many inputs that are collected for analyzing blood pressure, heartbeat rate, and physical activities. Although some wearable devices are used in the system include BioRadio, accelerometer, and gyroscopic, however, these devices are connected through wires and not able to be connected with mobile phones [24].

Overall, the expert system design is depending on the types of input data. The expert systems rely on pre-recorded datasets and the live data record (as in S03, S12, and S15). Besides, we found that the expert system for wearable devices depends on live data as wearable devices are capable of auto-measure most of the hypertension factors. The existing datasets are also required for the expert systems to produce a knowledge base. S09, S10, S11, S13, and S14 implemented expert system techniques with wearable devices. S03, S12, and S15 are probably the most related to mobile applications. From the results, there is still lacking in terms of the mobile application that is paired with wearable devices in diagnosing hypertension. However, further research might be needed to evaluate and assess these techniques in terms of performance, efficiency, and other parameters in the expert system.

3.3. Sensors in wearable devices

The third research question is related to the types of sensors used in wearable devices for hypertension diagnosis. We found that there are seven distinctive types of sensors include eyewear, wrist band, waist wear, textile type, camera, finger sensor, and breathable elastomeric membranes as shown in Table 5. The most commonly used sensors are the wrist band. S02, S03, S06, and S15 used a commercial wrist band that utilized PPG signals. Based on the PPG signals, it can estimate the blood pressure and the heartbeat [42]. These wrist bands sometimes equip with an accelerometer to sense the physical motion to record the activities of the user [14]–[16], [28].

The second commonly used sensor is the finger sensor as reported in S04, S07, and S12. In S04, the iHealth pulse oximeter captures PPG signals for its diagnosis system. S07 used the Empatica E3 wearable device to collect data regarding blood pressure and heartbeat. The Empatica E3 is also able to collect the data of skin response [27], [34], [36]. The PPG signals integrate the LED and the photodetector into the system. The LED emits some lights into the skin, while the photodetector receives the absorbed or reflected light as PPG signals for further analysis in blood pressure and heartbeat measurement [33]. The PPG signals are used in eyewear (as stated in S01). The only difference is the location of the sensor, in which the eyewear is located on the user's head. The light is emitted on the skin and the reflected light is used as PPG signals [33].

The other type of sensors such as waist wear, textile type, camera, and breathable elastomeric membrane, are also used. The waist wear is used to detect physical motion with a motion-tracking device, an accelerometer, and a gyroscope [34]. A textile sensor was used to examine the potential of an electroconductive material to be used as a wearable device to find the relationship of the resistivity and conductivity of the material, which is affected by the stretches of the textile [35]. Besides, the camera extracts the PPG signal is called the imaging photo plethysmography (iPPG). A camera was placed on the wrist, and the user needs to scan the user's face by using the camera. From the generated image, some computing is done to estimate blood pressure [36]. Lastly, the breathable elastomeric membrane can also be used to measure sodium intake. This can be done by placing the membrane inside one's mouth. The amount of sodium intake can be used to ease hypertension management [37].

As a summary of the third research question, the wrist band is the most common sensor in wearable devices and is closely followed by the finger sensor. Both sensors also can be paired to improve the accuracy [27]. Both sensors are utilizing the PPG signals to measure blood pressure and heartbeat to diagnose hypertension with an expert system.

Table 5. Sensors in wearable devices

Sensor	Papers	Total
Wrist band/smart watch	S02, S03, S06, S12, S15	5
Finger sensor	S04, S07, S12	3
Eye wear	S01	1
Waist wear	S04	1
Textile type	S05	1
Camera	S07	1

3.4. Discussions

As stated before, this systematic review aims to determine the possible factors for hypertension diagnosis systems, techniques in expert systems, and wearable devices in the hypertension diagnosis system. Three studies, which are S03, S12, and S15, are closely related to these aims. From the review, the blood pressure reading is the most common factor to determine hypertension. The other factors like heartbeat rate, physical activities, BMI, age, body temperature, diabetes, and genetic/family history are also used in hypertension diagnosis.

Machine/deep learning, neural network, and fuzzy logic are the three most common techniques used in expert systems to diagnose hypertension. However, from the literature, most of the systems used a hybrid approach that includes neural network-fuzzy logic, neural network-machine learning, and fuzzy logic-decision tree as the combination. The common type of sensor is the wrist band that is used to measure or estimate blood pressure and heartbeat. From the review, there are several potential sensors for blood pressure and heartbeat estimation, such as eye wear [33], electro conductive textile [35], smart watch [14], camera [36], and fingertip [36]. However, a few authors suggest using expert system techniques for hypertension diagnosis systems with its datasets without any inputs from the wearable device [24], [25], [37]. Figure 1 shows a bubble chart that represents the overall result of this review. It contains the number of studies in terms of hypertension factors, techniques in expert system, and types of wearable devices.

The interesting fact from this review is a mobile application has the potential for a hypertension diagnosis system as stated in a few studies. These studies suggested that the mobile application can be developed and improved to diagnose hypertension. This point of view is supported by the studies conducted for a mobile application that are designed for hypertension and health management [43]–[45]. Besides, the computational process of the diagnosis can be placed in the cloud-based system to ensure data processing performance [46]–[50] and overcome the low computational memory in wearable devices [27].

In terms of the threats to validity, firstly is the bias in primary papers selection. This review cannot assure that all relevant papers are selected throughout the searching and selection process. The search string in the searching process may have included inadequate search terms relating to data quality. To mitigate this threat, we developed a systematic mapping protocol, verified it with another researcher, and consistently followed these protocols. The second threat is an uncertain description of terms. This review found difficulties in classifying the papers using some terminologies because of the vague descriptions. To minimize this threat, we clustered some terminologies to classify the papers consistently.

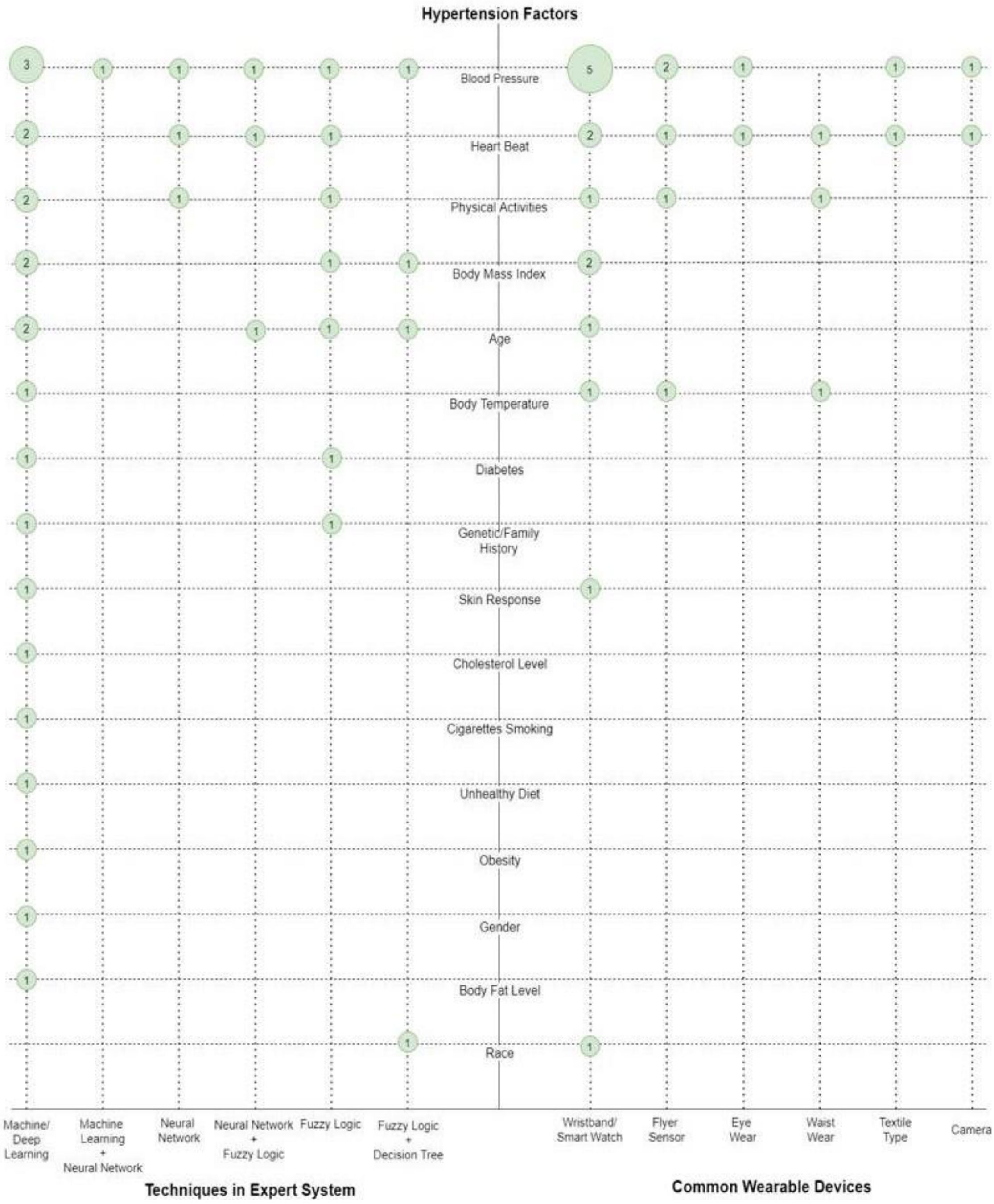

Figure 1. Mapping of review result

4. CONCLUSION

There is a significant increasing popularity of smartphones and wearable devices in tracking physical activities, heartbeat, and self-health management. It motivates this review to find the related areas include hypertension factors, techniques in the diagnosis of expert systems, and wearable devices to identify the research gap. After the systematic review, we found that blood pressure is the most common factor of hypertension to be collected and analyzed. For the expert system techniques, it seems that it needs more exploration to find the best technique for the hypertension diagnosis systems that can be paired with wearable devices. As for the wearable device, the wrist band is the most common type of sensor that utilized PPG signals. These signals show significant accuracy and consistency in diagnosing hypertension. However, to develop a diagnosis system, we have to consider the cost and the feasibility factors during the development of a new product. Then, before the implementation of the new diagnosis system, the hypertension factors, expert system technique, and wearable device sensor have to be determined. Lastly, a mobile application has a great potential to be developed for hypertension diagnosis system and utilize the cloud to do the complex prediction calculation.

ACKNOWLEDGEMENTS

The authors would like to thank the Ministry of Education Malaysia and Universiti Teknologi MARA for their financial support to this project under REI Grant No. 600-IRMI/REI 5/3 (001/2019). We would also like to thank the Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Selangor, Malaysia for all the supports.

REFERENCES

[1] D. M. Mahmud and N. A. S. Abdullah, "Mobile application development feasibility studies: a case study in Universiti Teknologi MARA," in *ICOS 2014 - 2014 IEEE Conference on Open Systems*, Oct. 2014, pp. 30–35, doi: 10.1109/ICOS.2014.7042405.

[2] Z. Mohammed and F. Redzuan, "Parent's acceptance on wearable technology for children's safety," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 17, no. 2, pp. 1066–1073, Feb. 2020, doi: 10.11591/ijeecs.v17.i2.pp1066-1073.

[3] N. Z. E. Zakariya and M. M. Rosli, "Physical activity prediction using fitness data: challenges and issues," *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 1, pp. 419–426, Feb. 2021, doi: 10.11591/eei.v10i1.2474.

[4] N. E. Tabbakha, C. P. Ooi, W. H. Tan, and Y. F. Tan, "A wearable device for machine learning based elderly's activity tracking and indoor location system," *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 2, pp. 927–939, Apr. 2021, doi: 10.11591/eei.v10i2.2737.

[5] N. M. Seshadri, A. S. P, S. K. Vasudevan, and A. J, "Physicians' and users' perceptions towards wearable health devices," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 5, no. 1, pp. 234–242, Jan. 2017, doi: 10.11591/ijeecs.v5.i1.pp234-242.

[6] L. Vesnic-Alujevic, M. Breitegger, and Â. Guimarães Pereira, "'Do-it-yourself' healthcare? Quality of health and healthcare through wearable sensors,'" *Science and Engineering Ethics*, vol. 24, no. 3, pp. 887–904, Mar. 2018, doi: 10.1007/s11948-016-9771-4.

[7] C. Fife-Schaw *et al.*, "Comparing exercise interventions to increase persistence with physical exercise and sporting activity among people with hypertension or high normal blood pressure: study protocol for a randomised controlled trial," *Trials*, vol. 15, no. 1, Dec. 2014, doi: 10.1186/1745-6215-15-336.

[8] J. Müller, "Ownership of wearable tech in Malaysia in 2019," *Statista*. 2019, Accessed: Jun. 06, 2021. [Online]. Available: https://www.statista.com/statistics/1053038/malaysia-ownership-of-wearable-tech/.

[9] P. Lamkin, "Wearable tech market to double by 2021," *Forbes*. 2017, Accessed: Jun. 06, 2021. [Online]. Available: https://www.forbes.com/sites/paullamkin/2017/06/22/wearable-tech-market-to-double-by-2021/#5d35e7e6d8f3.

[10] B. Mahadir Naidu *et al.*, "Factors associated with the severity of hypertension among Malaysian adults," *PLOS ONE*, vol. 14, no. 1, Jan. 2019, doi: 10.1371/journal.pone.0207472.

[11] Ministry of Health, "Non-communicable diseases, risk factors & other health problems," Institute for Public Health, National Institutes of Health, Ministry of Health, Kuala Lumpur, 2015.

[12] "Key findings from the adolescent health and nutrition surveys," *Institute for Public Health, National Health and Morbidity Survey (NHMS)*. Kuala Lumpur, 2018, doi: 10.13140/RG.2.2.27976.78082.

[13] "2018 management of hypertension (5th edition)," *MPS Young Pharmacist Chapter*. 2019, Accessed: Jun. 06, 2021. [Online]. Available: https://mpsypc.com.my/news/2018-management-of-hypertension-5th-edition/.

[14] M. Kuwabara, K. Harada, Y. Hishiki, and K. Kario, "Validation of two watch-type wearable blood pressure monitors according to the ANSI/AAMI/ISO81060-2:2013 guidelines: Omron HEM-6410T-ZM and HEM-6410T-ZL," *The Journal of Clinical Hypertension*, vol. 21, no. 6, pp. 853–858, Jun. 2019, doi: 10.1111/jch.13499.

[15] B. D. B. Lopez, J. A. A. Aguirre, D. A. R. Coronado, and P. A. Gonzalez, "Wearable technology model to control and monitor hypertension during pregnancy," in *2018 13th Iberian Conference on Information Systems and Technologies (CISTI)*, Jun. 2018, pp. 1–6, doi: 10.23919/CISTI.2018.8399200.

[16] A. Ghosh, J. M. M. Torres, M. Danieli, and G. Riccardi, "Detection of essential hypertension with physiological signals from wearable devices," in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Aug. 2015, pp. 8095–8098, doi: 10.1109/EMBC.2015.7320272.

[17] C. R. Srinivasan, G. Charan, and P. C. Sai Babu, "An IoT based SMART patient health monitoring system," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 18, no. 3, pp. 1657–1664, Jun. 2020, doi: 10.11591/ijeecs.v18.i3.pp1657-1664.

[18] F. Ibrahim, M. N. Taib, S. Sulaiman, and W. A. B. W. Abas, "Dengue fever (DF) and dengue haemorrhagic fever (DHF) symptoms analysis from an expert system perspective," in *Proceedings. IEEE International Multi Topic Conference, 2001. IEEE INMIC 2001. Technology for the 21st Century*, 2001, pp. 212–215, doi: 10.1109/INMIC.2001.995339.

[19] N. R. M. Isa, M. Yusoff, N. E. Khalid, N. Tahir, and A. W. binti Nikmat, "Autism severity level detection using fuzzy expert system," in *2014 IEEE International Symposium on Robotics and Manufacturing Automation (ROMA)*, Dec. 2014, pp. 218–223, doi: 10.1109/ROMA.2014.7295891.

[20] E. P. Gunawan and R. Wardoyo, "An expert system using certainty factor for determining insomnia acupoint," *IJCCS (Indonesian*

Journal of Computing and Cybernetics Systems), vol. 12, no. 2, Jul. 2018, doi: 10.22146/ijccs.26328.
[21] S. A. Pasaribu, P. Sihombing, and S. Suherman, “Expert system for diagnosing dental and mouth diseases with a website-based certainty factor (CF) method,” in *2020 3rd International Conference on Mechanical, Electronics, Computer, and Industrial Technology (MECnIT)*, Jun. 2020, pp. 218–221, doi: 10.1109/MECnIT48290.2020.9166635.
[22] S. Sumiati, H. Saragih, T. Abdul Rahman, and A. Triayudi, “Expert system for heart disease based on electrocardiogram data using certainty factor with multiple rule,” *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 10, no. 1, pp. 43–50, Mar. 2021, doi: 10.11591/ijai.v10.i1.pp43-50.
[23] F. Ibrahim, J. B. Ali, A. F. Jaais, and M. N. Taib, “Expert system for early diagnosis of eye diseases infecting the Malaysian population,” in *Proceedings of IEEE Region 10 International Conference on Electrical and Electronic Technology*, 2001, vol. 1, pp. 430–432, doi: 10.1109/TENCON.2001.949629.
[24] S. Ghosh, A. Banerjee, N. Ray, P. W. Wood, P. Boulanger, and R. Padwal, “Using accelerometric and gyroscopic data to improve blood pressure prediction from pulse transit time using recurrent neural network,” in *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Apr. 2018, pp. 935–939, doi: 10.1109/ICASSP.2018.8461959.
[25] R. Nohria, “Comparative study of adaptive neuro-fuzzy and fuzzy inference system for diagnosis of hypertension,” in *2017 International Conference on Computing Methodologies and Communication (ICCMC)*, Jul. 2017, pp. 406–411, doi: 10.1109/ICCMC.2017.8282719.
[26] P. Melin, I. Miramontes, and G. Prado-Arechiga, “A hybrid model based on modular neural networks and fuzzy systems for classification of blood pressure and hypertension risk diagnosis,” *Expert Systems with Applications*, vol. 107, pp. 146–164, Oct. 2018, doi: 10.1016/j.eswa.2018.04.023.
[27] Y. Liang, Z. Chen, R. Ward, and M. Elgendi, “Photoplethysmography and deep learning: enhancing hypertension risk stratification,” *Biosensors*, vol. 8, no. 4, Oct. 2018, doi: 10.3390/bios8040101.
[28] M. Espinilla, J. Medina, Á.-L. García-Fernández, S. Campaña, and J. Londoño, “Fuzzy intelligent system for patients with preeclampsia in wearable devices,” *Mobile Information Systems*, vol. 2017, pp. 1–10, 2017, doi: 10.1155/2017/7838464.
[29] B. Kitchenham, “Procedures for Performing Systematic Reviews,” *Keele University Tech. Report TR/SE-0401*. United Kingdom, 2004.
[30] A. Yague, J. Garbajosa, J. Perez, and J. Diaz, “Analyzing software product innovation assessment by using a systematic literature review,” in *2014 47th Hawaii International Conference on System Sciences*, Jan. 2014, pp. 5049–5058, doi: 10.1109/HICSS.2014.620.
[31] Y. C. Chia, S. Y. W. Gray, S. M. Ching, H. M. Lim, and K. Chinna, “Validation of the framingham general cardiovascular risk score in a multiethnic Asian population: a retrospective cohort study,” *BMJ Open*, vol. 5, no. 5, May 2015, doi: 10.1136/bmjopen-2014-007324.
[32] “CASP qualitative checklist,” *Critical Appraisal Skills Programme*. 2018, Accessed: Jun. 06, 2021. [Online]. Available: https://casp-uk.net/wp-content/uploads/2018/01/CASP-Qualitative-Checklist-2018.pdf.
[33] N. Ahmed, R. Banerjee, A. Ghose, and A. Sinharay, “Feasibility analysis for estimation of blood pressure and heart rate using a smart eye wear,” in *Proceedings of the 2015 workshop on Wearable Systems and Applications*, May 2015, pp. 9–14, doi: 10.1145/2753509.2753511.
[34] E. Kańtoch, “Human activity recognition for physical rehabilitation using wearable sensors fusion and artificial neural networks,” in *Computing in Cardiology*, Sep. 2017, vol. 44, pp. 1–4, doi: 10.22489/CinC.2017.296-332.
[35] A. R. Maria and D. Laurentiu, “Electroconductive materials with high potential for wearable electronic devices integration,” Jun. 2015, doi: 10.1109/ECAI.2015.7301168.
[36] G. Zhang, C. Shan, I. Kirenko, X. Long, and R. Aarts, “Hybrid optical unobtrusive blood pressure measurements,” *Sensors*, vol. 17, no. 7, Jul. 2017, doi: 10.3390/s17071541.
[37] Y. Lee *et al.*, “Wireless, intraoral hybrid electronics for real-time quantification of sodium intake toward hypertension management,” *Proceedings of the National Academy of Sciences*, vol. 115, no. 21, pp. 5377–5382, May 2018, doi: 10.1073/pnas.1719573115.
[38] F. López-Martínez, A. Schwarcz.MD, E. R. Núñez-Valdez, and V. García-Díaz, “Machine learning classification analysis for a hypertensive population as a function of several risk factors,” *Expert Systems with Applications*, vol. 110, pp. 206–215, Nov. 2018, doi: 10.1016/j.eswa.2018.06.006.
[39] B. Zhang, H. Ren, G. Huang, Y. Cheng, and C. Hu, “Predicting blood pressure from physiological index data using the SVR algorithm,” *BMC Bioinformatics*, vol. 20, no. 1, Dec. 2019, doi: 10.1186/s12859-019-2667-y.
[40] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, Nov. 1997, doi: 10.1162/neco.1997.9.8.1735.
[41] G. W. Nie, N. F. Ghazali, N. Shahar, and M. A. As’ari, “Deep stair walking detection using wearable inertial sensor via long short-term memory network,” *Bulletin of Electrical Engineering and Informatics*, vol. 9, no. 1, pp. 238–246, Feb. 2020, doi: 10.11591/eei.v9i1.1685.
[42] N. F. A. Jamal and K. A. Sidek, “Portable health monitoring kit using photolethysmogram signal,” *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 15, no. 2, pp. 638–649, Aug. 2019, doi: 10.11591/ijeecs.v15.i2.pp638-649.
[43] T. Alessa, M. S. Hawley, E. S. Hock, and L. de Witte, “Smartphone apps to support self-management of hypertension: review and content analysis,” *JMIR Mhealth Uhealth*, vol. 7, no. 5, May 2019, doi: 10.2196/13645.
[44] O. AlShorman, M. S. Masadeh, and B. AlShorman, “Mobile health monitoring based studies for diabetes mellitus: a review,” *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 3, pp. 1405–1414, Jun. 2021, doi: 10.11591/eei.v10i3.3019.
[45] H. Rahmi Fajrin, B. Satrio Adi, H. Purwoko, and I. Permata Sari, “Telemedicine-equipped android interface-based heart rate monitoring,” *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 21, no. 3, pp. 1332–1340, Mar. 2021, doi: 10.11591/ijeecs.v21.i3.pp1332-1340.
[46] M. Bakator and D. Radosav, “Expert systems in a cloud computing environment model for fast-paced decision making,” *JITA - Journal of Information Technology and Applications (Banja Luka) - APEIRON*, vol. 13, no. 1, Jun. 2017, doi: 10.7251/JIT1701024B.
[47] A. Bhawiyuga, S. A. Kharisma, B. J. Santoso, D. P. Kartikasari, and A. P. Kirana, “Cloud-based middleware for supporting batch and stream access over smart healthcare wearable device,” *Bulletin of Electrical Engineering and Informatics*, vol. 9, no. 5, pp. 1990–1997, Oct. 2020, doi: 10.11591/eei.v9i5.1978.
[48] F. Abdali-Mohammadi, M. N. Meqdad, and S. Kadry, “Development of an IoT-based and cloud-based disease prediction and diagnosis system for healthcare using machine learning algorithms,” *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 9, no. 4, pp. 766–771, Dec. 2020, doi: 10.11591/ijai.v9.i4.pp766-771.
[49] O. AlShorman, B. AlShorman, M. Al-khassaweneh, and F. Alkahtani, “A review of internet of medical things (IoMT) - based

remote health monitoring through wearable sensors: a case study for diabetic patients," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 20, no. 1, pp. 414–422, Oct. 2020, doi: 10.11591/ijeecs.v20.i1.pp414-422.
[50] J. H. Majeed and Q. Aish, "A remote patient monitoring based on WBAN implementation with internet of thing and cloud server," *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 3, pp. 1640–1647, Jun. 2021, doi: 10.11591/eei.v10i3.1813.

BIOGRAPHIES OF AUTHORS

Muhammad Izzuddin Mohd Sani is a project engineer at Willowglen (Malaysia) Sdn Bhd. He has a master degree in Computer Science from Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA. His experience in the industry is related to mechanical and electrical projects. He works closely in delivering the electrical distribution system, and lightning protection system. Izzuddin is currently involved in preparing Computerised Maintenance Management System. He has working experience as a system engineer and assistant engineer. Therefore, the knowledge in the mechanical and electrical projects is used in carrying out this research. He can be contacted at email: izzuddin@willowglen.com.my.

Nur Atiqah Sia Abdullah is an Associate Professor in the Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA (UiTM), Selangor, Malaysia. She is graduated from the Universiti Putra Malaysia, with Ph.D. in Software Engineering. She involves actively in research and publications in the area of software engineering, software metric, sentiment analysis, data visualization, and social media intelligence. She supervised a number of Ph.D. and master students. She has extensive experience in grant application and software development consultations. She is also the evaluator for university and national grants. Currently, she is holding a post as a Deputy Dean (Research and Industry Linkages) in the faculty. Therefore, she has a lot of experience in international universities and industry linkages. She collaborates with other faculty's members and industry in the software projects and mobile application development. She can be contacted at email: atiqah684@uitm.edu.my.

Marshima Mohd Rosli is a senior lecturer in the Faculty of Computer and Mathematical Sciences at Universiti Teknologi MARA (UiTM), Selangor, Malaysia. She graduated from the Universiti Utara Malaysia, with a Bachelor of Information Technology in 2001 and Master in Real-Time Software Engineering from the Universiti Teknologi Malaysia in 2006. She received her Ph.D. in Computer Science from the University of Auckland, New Zealand, in 2018. Her current research interests include software engineering, particularly empirical software engineering (ESE), software measurement, web technology, machine learning and data quality. She actively engaged with software project development across faculties in Universiti Teknologi MARA. She can be contacted at email: marshima@tmsk.uitm.edu.my.