Journal of Multidisciplinary Engineering Science and Technology (JMEST)
ISSN: 2458-9403
Vol. 10 Issue 1, January - 2023

Development And Evaluation Of Calibration Model Of Embedded Firmware Iot Blood Pressure Data Acquisition Device

Thompson, Emmanuel Enoch[1]
Department of physics
University of uyo, Akwa Ibom state, Nigeria
optimist.thompson@yahoo.com

Ozuomba Simeon[2]
Department Of Electrical/Electronic And Computer Engineering,
University of Uyo, Akwa Ibom State Nigeria
simeonozuomba@uniuyo.edu.ng

Adebayo Olusakun Adniran[3]
Department of physics
University of uyo, Akwa Ibom state, Nigeria

***Abstract*— In this paper, development and evaluation of calibration model of embedded firmware IoT blood pressure data acquisition device is presented. Specifically, in this paper, IoT blood pressure data acquisition hardware device (denoted as IoTBPDAH device) and BP Accoson and Son (Surgical) Ltd 5PQ blood pressure device (denoted as HBP device) are used to explain an approach for developing regression model and applying the model in the firmware program of the IoT blood pressure data acquisition hardware to automatically estimate a more accurate blood pressure value whenever the IoTBPDAH device is used to capture blood pressure data. With the embedded program concept, the calibration of the blood pressure data can be performed in real-time. The flow diagram for the model development and evaluation is presented. A total of 84 blood pressure measurements were made and used in the model development. The dependent samples t-test analysis was conducted on the 84 paired blood pressure data samples and the results gave a mean error of -0.266666667 and standard deviation of 1.34077242, as well as the 95 % confidence interval of -0.287021499 to 0.287021499. The results show also that when the model was applied the mean error of 0.000438988 and standard deviation of 1.302122525 were obtained, as well as the 95 % confidence interval of -0.278747648 to 0.278747648. Essentially, the model greatly reduced the mean error. The model is then recommended for the embedded firmware program to be used for real-time calibration of the blood pressure measurement.**

Keywords*— *Calibration Model, Embedded Firmware, BP Accoson and Son (Surgical) Ltd 5PQ Blood Pressure Device, Internet of Things, Data Acquisition Device, Blood Pressure

1. Introduction

Data acquisition devices enable real-world data to be captured and digitized and possibly further processed, displayed, stored, transmitted or manipulated or utilized in many other ways [1,2,3]. This is possible due to the advances in electronics, communications, and software technologies. The technological advancements in these areas have given rise to embedded systems with applications in wireless sensors, robots, Internet of Thins (IoT), smart systems and many other areas [4,5,6,7]. At the core of every embedded system is a microcontroller or microprocessor which utilizes the embedded firmware in its memory to control the entire components of the embedded system. In this paper embedded firmware IoT blood pressure data acquisition device is considered [8,8,9,10,11]. The device is used to remotely acquire blood pressure measurement data from users or patients and transit such data to a web server equipped with requisite web applications for management of the acquired blood pressure data records.

Particularly, this paper seeks to present an approach for real-time calibration of the IoT blood pressure data acquisition hardware device (denoted as IoTBPDAH device) using BP Accoson and Son (Surgical) Ltd 5PQ blood pressure device (denoted as HBP device) as the reference device [12,13,14]. The approach adopted in this paper is to use field measured paired datasets of blood pressure captured with IoTBPDAH device and with HBP device to derive an analytical model which is then programmed into the microcontroller firmware such that when the IoTBPDAH device is acquired the microcontroller automatically adjusts (that is calibrates) the IoTBPDAH device-measured blood pressure to reflect what the HBP device would have given is the measurement was conducted with the HBP device. The dependent samples t-test approach is used for statistical evaluation of the model [15,16,17,18]. The essence of the study is to provide an approach that can enable real-time calibration of such IoT blood pressure data acquisition hardware device so that it will provide reliable blood pressure reading suitable for use in health care delivery service.

2 Methodology

In this paper, IoT blood pressure data acquisition hardware device (denoted as IoTBPDAH device) and BP Accoson and Son (Surgical) Ltd 5PQ blood pressure device (denoted as HBP device) are used to explain an approach for developing regression model and applying the model in the firmware program of the IoT blood pressure data acquisition hardware to automatically estimate a more accurate blood pressure value whenever the IoTBPDAH device is used to capture blood pressure data. With the embedded program concept, the calibration of the blood pressure data can be performed in real-time. The flow diagram for using field measured pair dataset to develop and evaluate the regression model for calibration of the IoTBPDAH device-measured blood pressure is presented in Figure 1 while the flow diagram for the real-time automatic calibration of the IoTBPDAH device-measured blood pressure is presented in Figure 2.

In the model evaluation (as presented in Figure 1), dependent samples t-test on d(x) at 95% confidence level is used along with Mean Error (ME) and Root Mean Square Error (RMSE). Also, Microsoft Excel trend line tool is used in generating the regression model from the scatter graph of the HBP device-measured blood pressure dataset versus the IoTBPDAH device-measured blood pressure dataset.

Essentially, in this study, the HBP device is the reference blood pressure measuring device used for the calibration of the IoTBPDAH device. The same approach presented here can be used to calibrate the device with respect to other blood pressure measuring devices that may be considered more accurate.

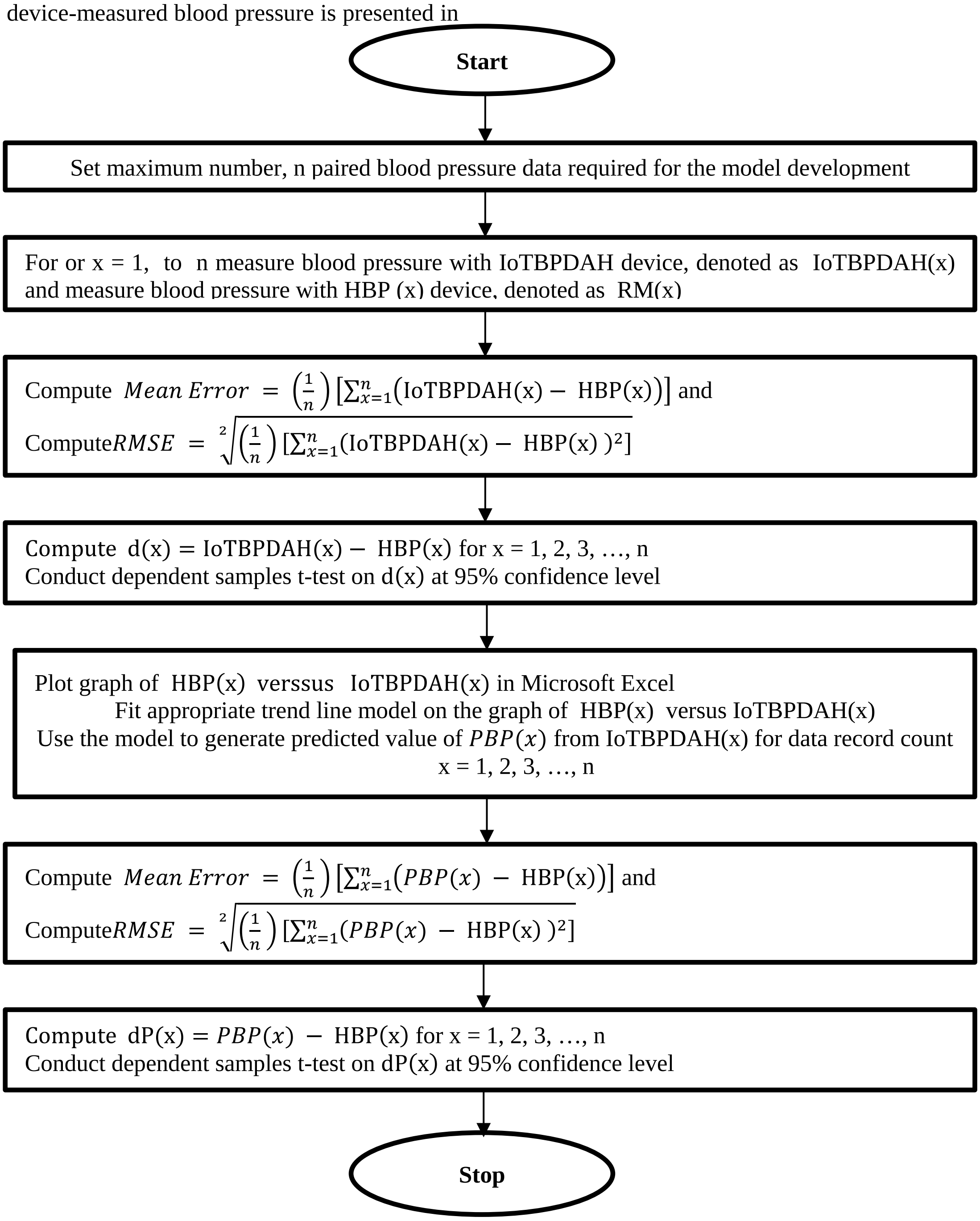

Figure 1 The flow diagram for using field measured pair dataset to develop and evaluate the regression model for calibration of the IoTBPDAH device-measured blood pressure

Importantly, the real-time automatic calibration capability is realized by virtue of embedded program concept, whereby, a low-level firmware program is developed based on the generated regression model and the stored in the program memory of the IoTBPDAH device. The program is invoked each time a blood pressure data is captured by the blood pressure sensor, as shown in Figure 2. In addition, the IoT device (IoTBPDAH device) has requisite transceiver that enables it to transmit the data records to a remoted web server.

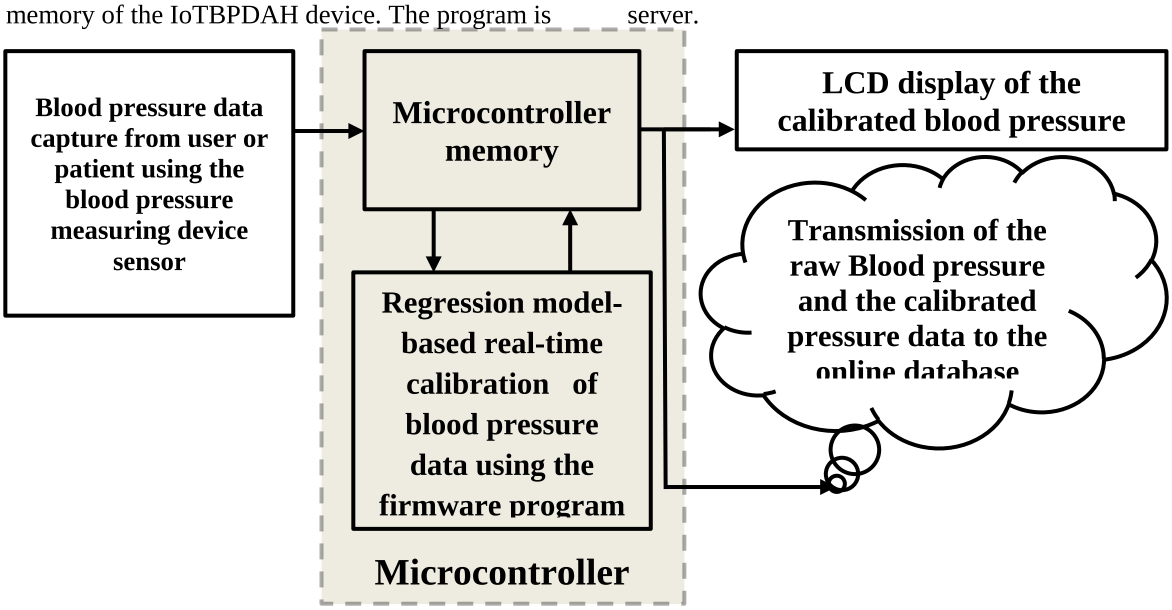

Figure 2 The flow diagram for the real-time automatic calibration of the IoTBPDAH device-measured blood pressure

3. Results and Discussion

A total of 84 blood pressure measurements were made and used in the model development. The 84 blood pressure data item were simultaneously measured using the two blood pressure measuring devices IoTBPDAH(x) and HBP(x), as shown in Table 1 and Figure 2. Dependent samples t-test analysis is conducted on the 84 paired blood pressure data samples and the results are shown in Table 2 and Figure 4. It dependent samples t-test analysis gave a mean error of -0.266666667 and standard deviation of 1.34077242, as well as the 95 % confidence interval of -0.287021499 to 0.287021499.

Table 1 The blood pressure data simultaneously measured using the two blood pressure measuring devices IoTBPDAH(x) and HBP(x)

S/N	IoTBPDAH(x) Blood pressure (mmHg)	HBP(x) Blood pressure (mmHg)	S/N	IoTBPDAH(x) Blood pressure (mmHg)	HBP(x) Blood pressure (mmHg)	S/N	IoTBPDAH(x) Blood pressure (mmHg)	HBP(x) Blood pressure (mmHg)
1	**88.5**	**90**	**29**	**114.1**	**113**	57	124.8	123.8
2	**92**	92.3	**30**	**114.1**	**112.7**	58	124.8	124
3	**92.7**	**93.1**	**31**	**114.5**	**113.1**	59	125	125.4
4	**97.1**	95.2	**32**	**114.7**	**113.2**	60	126.3	125.3
5	**99.2**	98.6	**33**	**116.2**	**120**	61	126.3	125.6
6	**99.5**	98.7	**34**	**116.2**	**120**	62	126.4	127.9
7	**99.7**	99.2	**35**	**117.2**	**118.4**	63	126.4	128
8	**99.8**	99.9	**36**	**118.2**	**117.2**	64	128.2	130
9	**99.9**	98.8	**37**	**118.4**	**120**	65	129.1	130
10	**100.1**	98.9	**38**	**118.9**	**120**	66	129.2	128.5
11	**100.1**	98.8	**39**	**119.4**	**123.1**	67	129.5	128.9
12	**105.1**	106.2	**40**	**120.1**	**121.5**	68	130.8	129.8
13	**105.8**	105.8	**41**	**120.2**	**119.2**	69	130.9	130.1
14	**106**	107.6	**42**	**120.2**	**120**	70	131	130.7
15	**106.2**	107.8	**43**	**120.2**	**119.4**	71	131.4	130.1

16	**106.5**	108	**44**	**120.4**	**120.2**	72	131.6	130.5
17	**108**	106.2	**45**	**120.7**	**120.5**	73	133.1	131.8
18	**108.1**	107.8	**46**	**120.9**	**121**	74	133.7	132.8
19	**108.2**	109.2	**47**	**120.9**	**120.6**	75	133.9	132.8
20	**108.2**	108.2	**48**	**121.2**	**121.1**	76	134.1	132.7
21	**108.2**	110	**49**	**121.5**	**119.9**	77	134.1	133
22	**109.7**	110	**50**	**121.9**	**120.2**	78	135.1	133.2
23	**110.6**	112.1	**51**	**122.2**	**120**	79	138.2	138
24	**110.9**	110	**52**	**123.2**	**121.8**	80	138.6	138.5
25	**111.2**	111.4	**53**	**123.7**	**122.5**	81	138.9	137.7
26	**111.2**	111.1	**54**	**124.4**	**122.2**	82	139.5	138.3
27	**112.1**	110	**55**	**124.7**	**123.7**	83	140.4	140
28	**112.3**	110	**56**	**124.7**	**123.2**	84	140.8	139.6

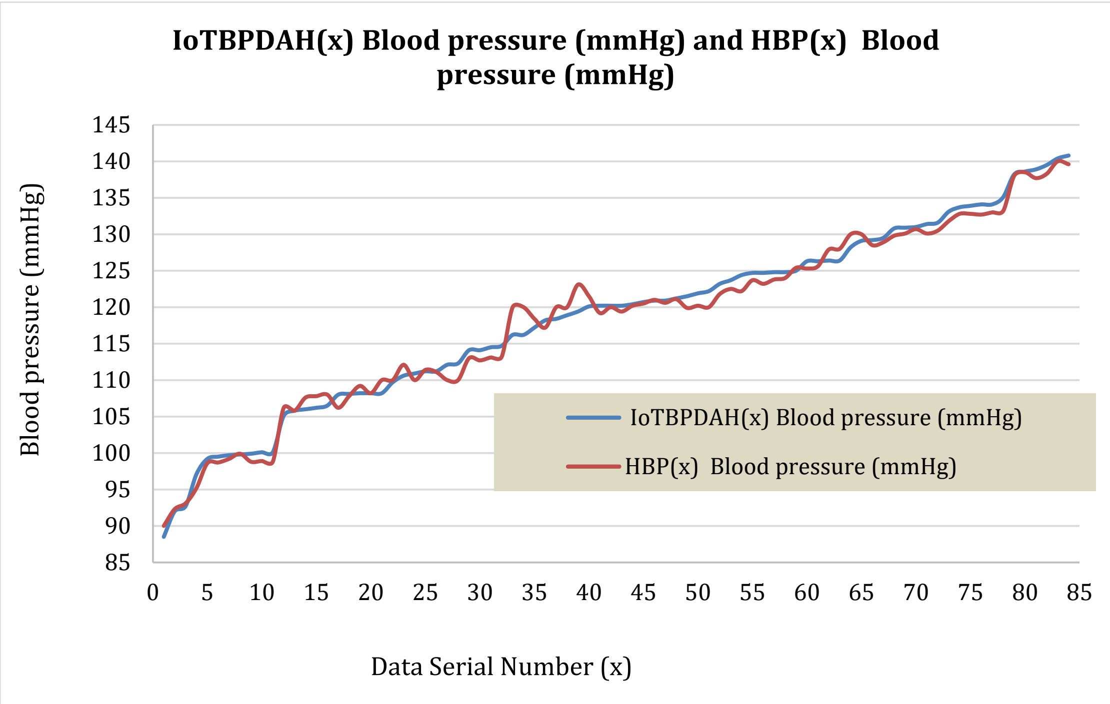

Figure 3 The graph of 84 blood pressure data items captured simultaneously using the two measuring devices

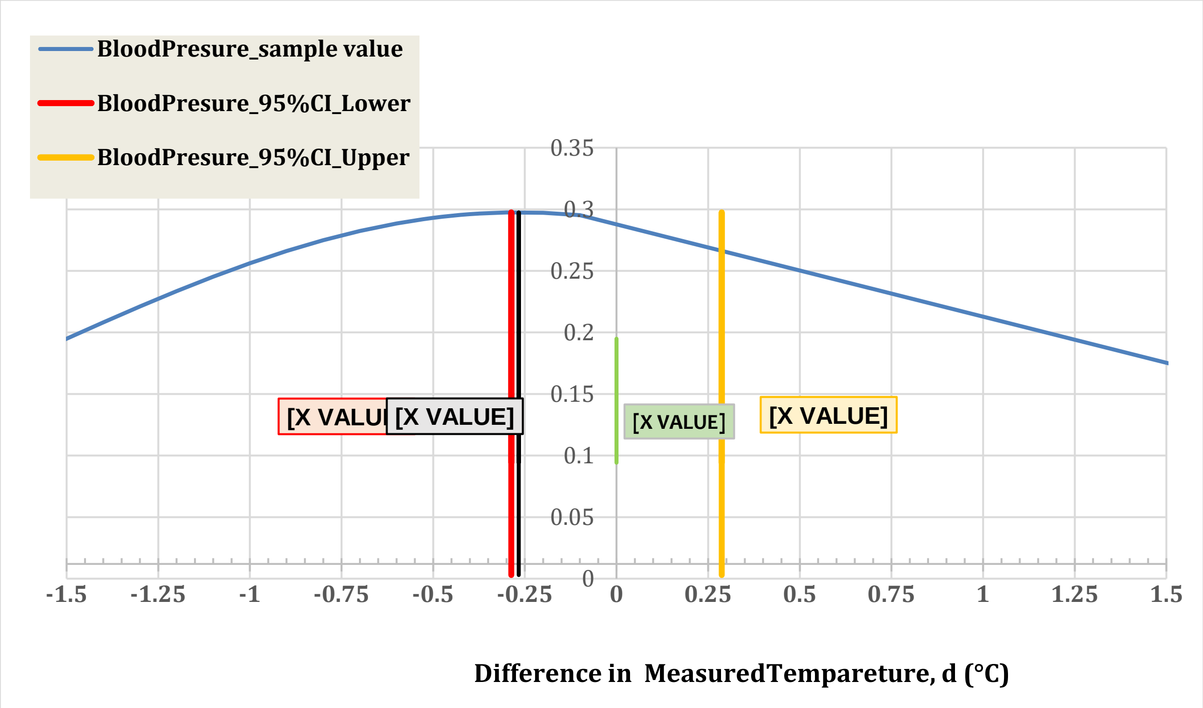

Figure 4 The results of the dependent samples t-test analysis for the 84 paired blood pressure data samples

Table 2 The summary of the results of the dependent samples t-test analysis for the 84 paired blood pressure data samples

Sample Mean	-0.266666667
Sample Standard Deviation	1.34077242
Population Mean	0
95% confidence interval, lower limit	-0.287021499
95% confidence interval, upper limit	0.287021499

A regression model is fitted on the graph of IoTBPDAH(x) Blood pressure (mmHg) versus HBP(x) Blood pressure (mmHg) (show in Figure 5) and Equation 1 where PBP(x) is the predicted value from the given value of IoTBPDAH(x);

$$PBP(x) = -0.000881\,(IoTBPDAH(x))^2 + 1.183518\,(IoTBPDAH(x)) - 9.505629 \quad (1)$$

The actual and the model predicted 84 blood pressure data samples are shown in Table 3. Dependent samples t-test analysis is conducted on the actual and the model predicted 84 blood pressure data samples and the results are shown in Table 4 and Figure 6. It dependent samples t-test analysis gave a mean error of 0.000438988 and standard deviation of 1.302122525, as well as the 95 % confidence interval of -0.278747648 to 0.278747648. The summary of the comparison of the results of the dependent samples t-test analysis for the 84 blood pressure data samples with and without the optimization model is shown in Table 5, Figure 7, Figure 8 and Figure 9.

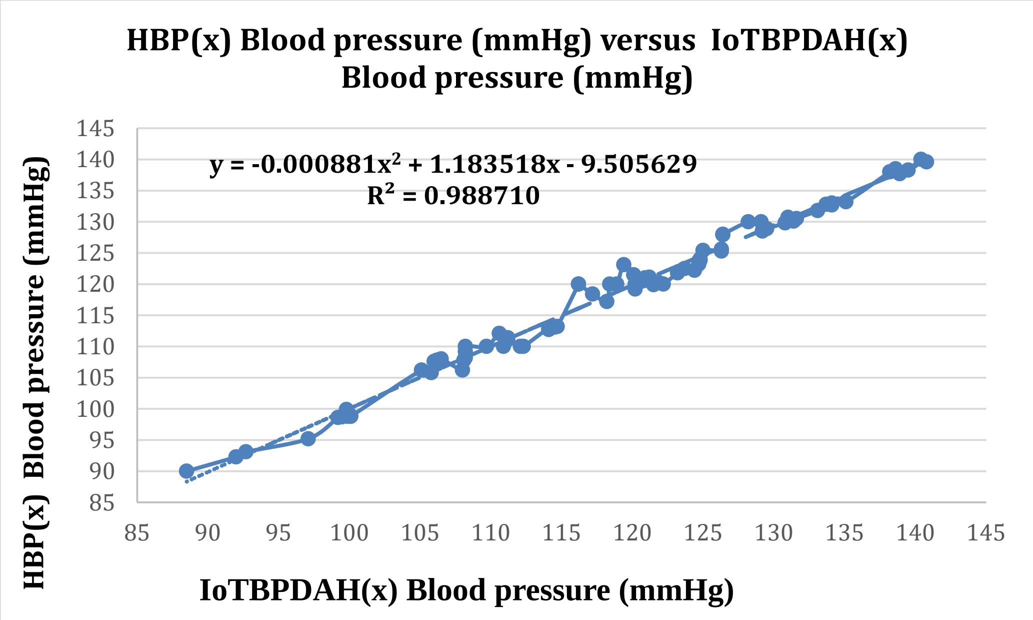

Figure 5 The graph of 84 blood pressure data paired blood pressure data samples showing the regression model for minimizing the measurement error

Table 3 The actual and the model predicted 84 blood pressure data samples

S/N	PBP(x) Blood pressure (mmHg)	HBP(x) Blood pressure (mmHg)	S/N	PBP(x) Blood pressure (mmHg)	HBP(x) Blood pressure (mmHg)	S/N	PBP(x) Blood pressure (mmHg)	HBP(x) Blood pressure (mmHg)
1	88.33556	90	29	114.065	113	57	124.4764	123.8
2	91.92145	92.3	30	114.065	112.7	58	124.4764	124
3	92.63603	93.1	31	114.458	113.1	59	124.669	125.4
4	97.10792	95.2	32	114.654	113.2	60	125.9198	125.3
5	99.23019	98.6	33	116.124	120	61	125.9198	125.6
6	99.53274	98.7	34	116.124	120	62	126.0159	127.9
7	99.73435	99.2	35	117.102	118.4	63	126.0159	128
8	99.83513	99.9	36	118.078	117.2	64	127.7424	130
9	99.93589	98.8	37	118.273	120	65	128.6035	130
10	100.1374	98.9	38	118.76	120	66	128.6991	128.5
11	100.1374	98.8	39	119.247	123.1	67	128.9858	128.9
12	105.1511	106.2	40	119.928	121.5	68	130.2262	129.8
13	105.8496	105.8	41	120.025	119.2	69	130.3215	130.1
14	106.0489	107.6	42	120.025	120	70	130.4168	130.7
15	106.2483	107.8	43	120.025	119.4	71	130.7977	130.1
16	106.5471	108	44	120.219	120.2	72	130.9881	130.5
17	108.0389	106.2	45	120.511	120.5	73	132.4135	131.8
18	108.1383	107.8	46	120.705	121	74	132.9826	132.8
19	108.2376	109.2	47	120.705	120.6	75	133.1721	132.8
20	108.2376	108.2	48	120.996	121.1	76	133.3616	132.7
21	108.2376	110	49	121.287	119.9	77	133.3616	133
22	109.7249	110	50	121.675	120.2	78	134.3079	133.2
23	110.6154	112.1	51	121.965	120	79	137.2303	138
24	110.9119	110	52	122.932	121.8	80	137.6061	138.5

25	111.2083	111.4	53	123.415	122.5	81	137.8878	137.7
26	111.2083	111.1	54	124.091	122.2	82	138.4508	138.3
27	112.0964	110	55	124.38	123.7	83	139.2939	140
28	112.2935	110	56	124.38	123.2	84	139.6682	139.6

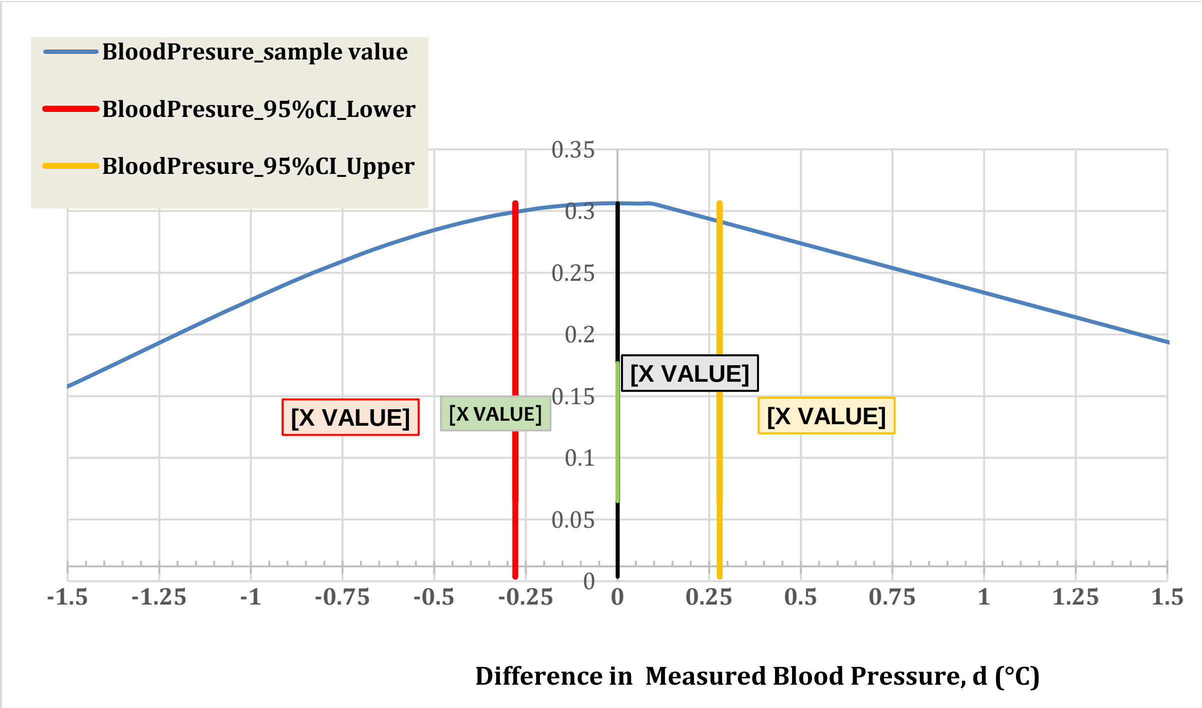

Figure 6 The results of the dependent samples t-test analysis for the actual and the model predicted 84 blood pressure data samples

Table 4 The summary of the results of the dependent samples t-test analysis for the actual and the model predicted 84 blood pressure data samples

Sample Mean (**mmHg**)	0.000438988
Sample Standard Deviation (**mmHg**)	1.302122525
Population Mean (**mmHg**)	0
95% confidence interval, lower limit (**mmHg)**	-0.278747648
95% confidence interval, upper limit (**mmHg)**	0.278747648

Table 5 The summary of the comparison of the results of the dependent samples t-test analysis for the 84 blood pressure data samples with and without the optimization model

	IoTBPDAH device performance without optimization	**IoTBPDAH** device performance with the quadratic Regression optimization model
Absolute value of sample mean error	0.26667	0.000439
RMSE	1.359184	1.294349
Sample Standard Deviation (**mmHg**)	1.34077242	1.302122525

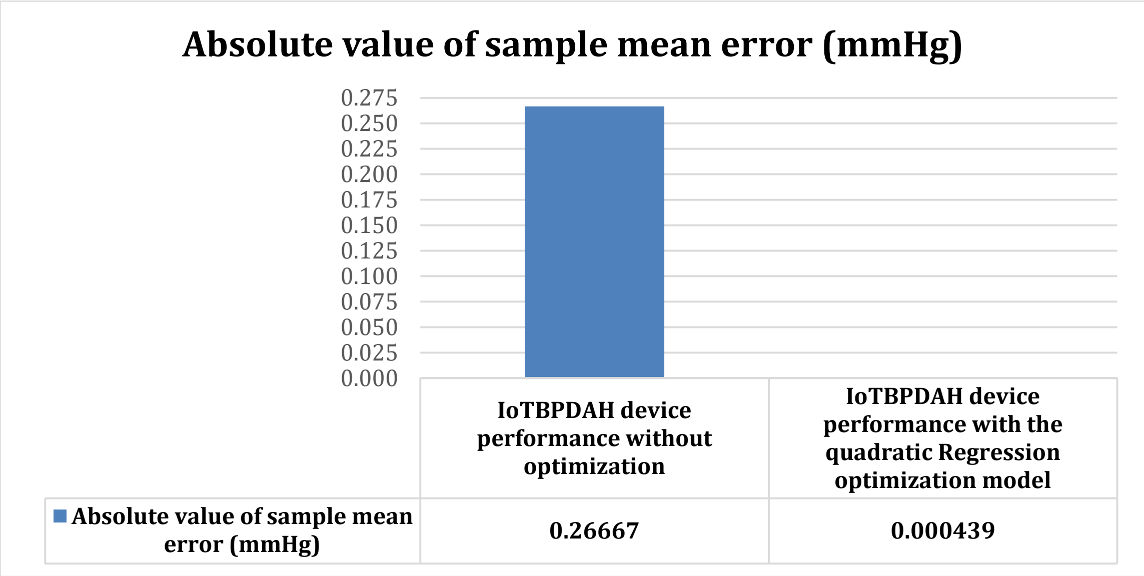

Figure 7 The bar chat of the absolute value of sample mean error (mmHg) for the 84 blood pressure data samples with and without the optimization model

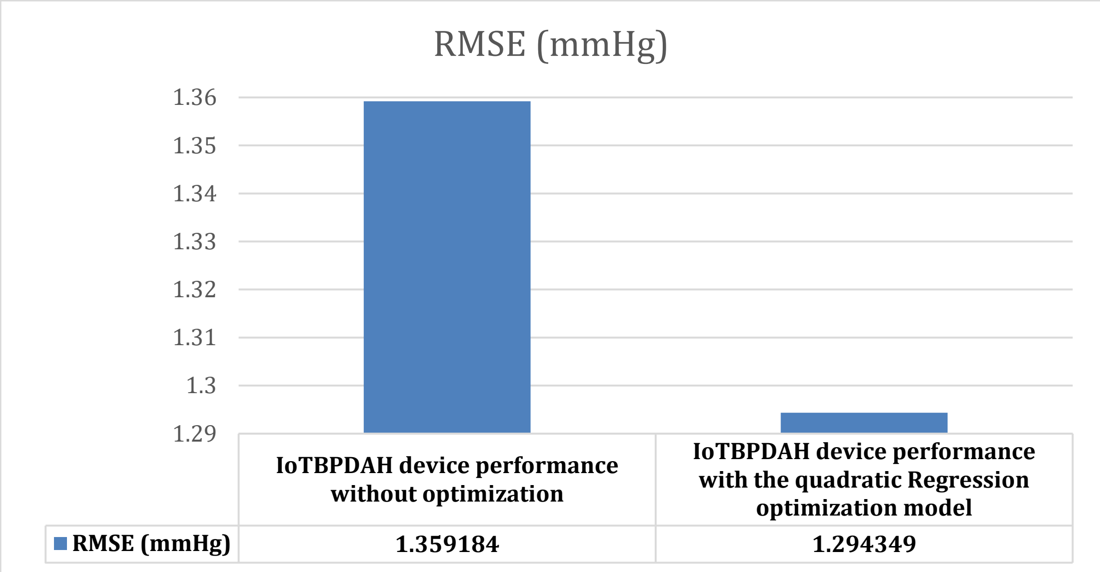

Figure 8 The bar chat of the RMSE for the 84 blood pressure data samples with and without the optimization model

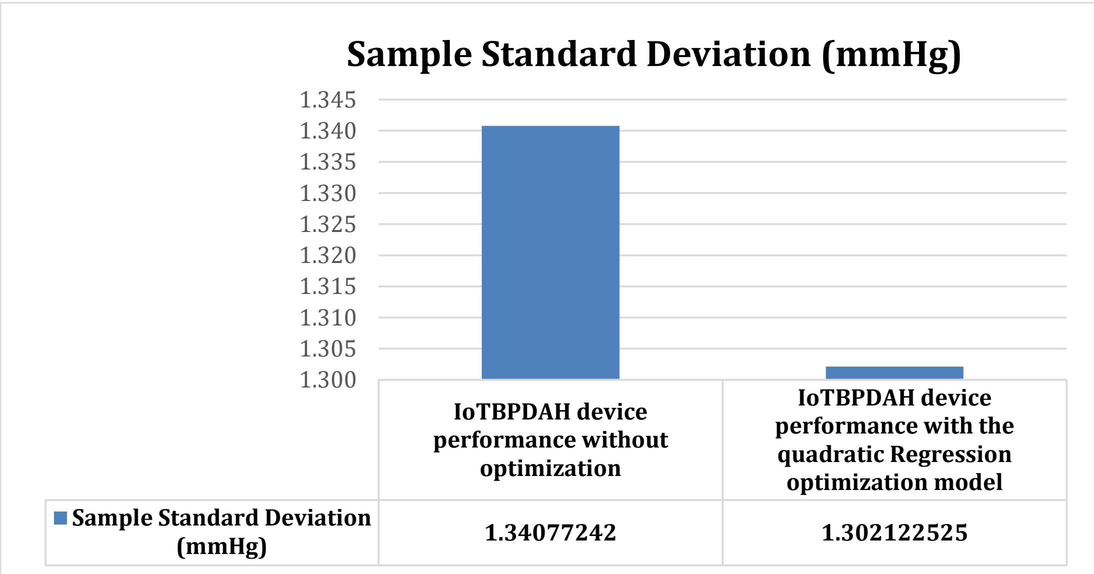

Figure 9 The bar chat of the standard deviation for the 84 blood pressure data samples with and without the optimization model

After the was developed and evaluated, a set of cross validation datasets were collected and used to cross validate the model. The model validation dataset and the summary of the evaluation results are show in Table6 , Figure 10 and Figure 11. The results show that the mean error without the model is -0.174 which reduces to 0.066 when the model is employed. Also, the RMSE without the model is 0.555 which reduces to 0.507 when the model is employed.

Table 6 The model cross validation dataset and the summary of the evaluation results

S/N	HBP(x) Actual Blood pressure (mmHg)	IoTBPDAH(x) Measured Blood pressure (mmHg) {not optimised with model}	PBP(x) Blood pressure (mmHg) {Optimised with model}
1	92.600	92.722	92.658
2	97.550	98.472	98.495
3	103.050	102.493	102.542
4	106.100	105.849	105.898
5	108.100	107.392	107.435
6	109.100	109.575	109.601
7	111.400	111.603	111.606
8	113.600	113.474	113.449
9	116.200	116.366	116.287
10	119.350	119.003	118.861
11	120.850	120.074	119.903
12	120.650	120.608	120.421
13	121.450	121.964	121.736
14	122.500	123.656	123.373
15	124.250	125.15	124.814
16	126.650	126.831	126.430
17	128.900	128.984	128.493
18	130.150	130.607	130.042
19	131.600	132.175	131.535
20	135.600	135.484	134.671
21	134.805	135.637	134.815
Mean Error		-0.1745	0.066
RMSE		0.555	0.507
Sample Standard Deviation		0.539922181	0.515400584

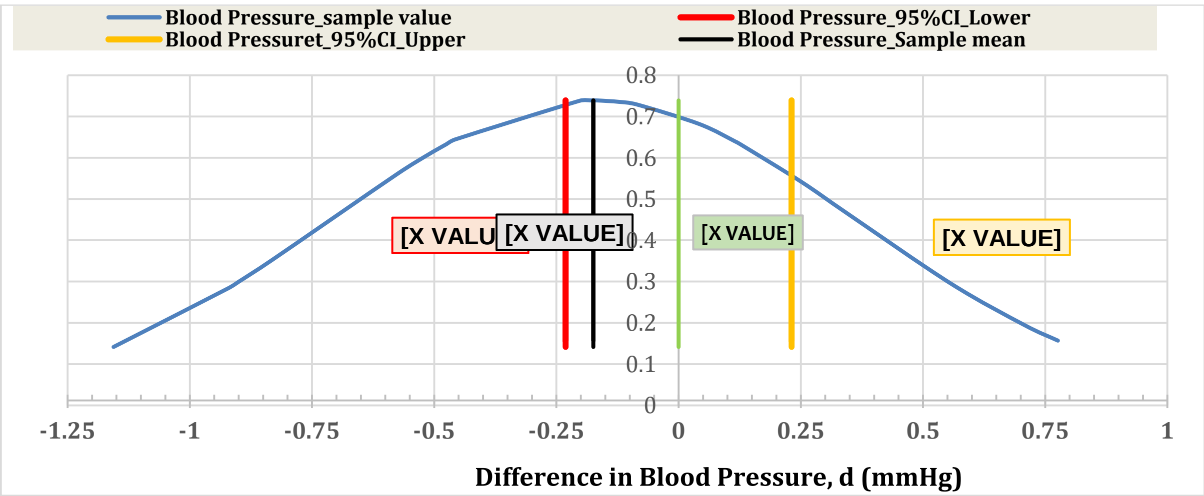

Figure 10 The results of the dependent samples t-test analysis for the actual (un-optimized) 21 cross validation blood pressure data samples

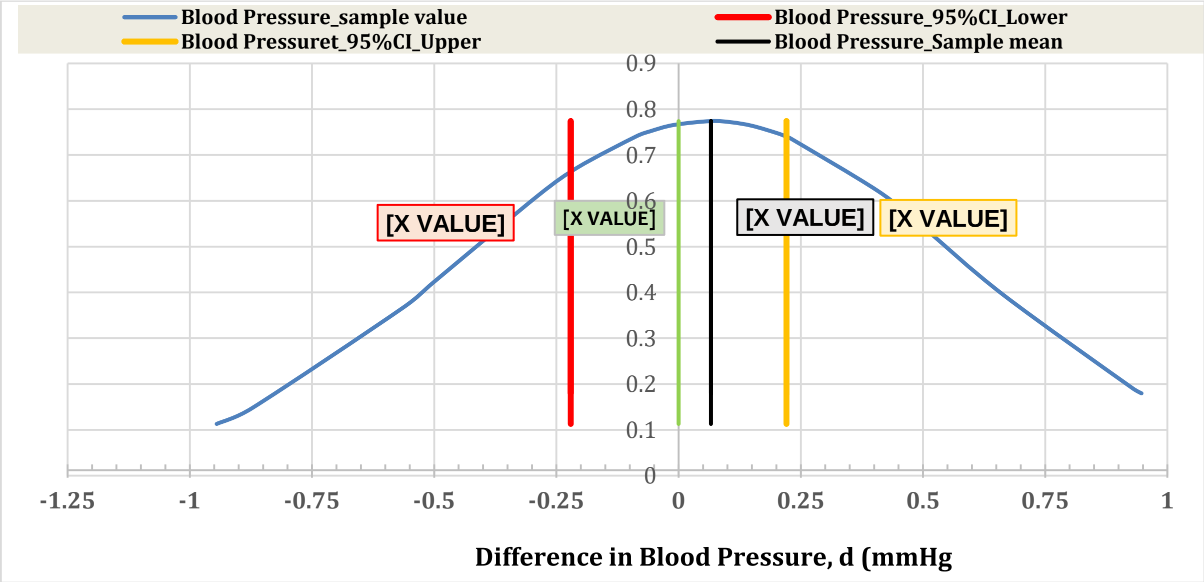

Figure 11 The results of the dependent samples t-test analysis for the model optimized predicted 21 cross validation blood pressure data samples

4. Conclusion

An approach for improving the blood pressure measurement accuracy of a data acquisition hardware device is presented. The device is design to measure blood pressure using a an embedded firmware which can be programed to enhance the measurement accuracy by providing real-time tuning of the raw blood pressure data acquired from the patients. The accuracy of the blood pressure measurement is assessed with reference to the blood pressure captured using BP Accoson and Son blood pressure measurement device.

Notably, paired data collection was conducted with the data acquisition hardware and the BP Accoson and Son blood pressure measurement device. Then. A regression model was developed for improving the measurement accuracy of the data acquisition hardware. The dependent samples t-test was used to assess the accuracy of the data acquisition hardware, first without the use of the regression model and then the regression model was used to minimize the measurement error and the dependent samples t-test was then conducted. The results showed that the regression model afforded significant improvement in the measurement accuracy of the blood pressure data acquisition hardware as it reduced the mean error, the root mean square error and the standard deviation of the measured data records.

References

1. Khozin, S., Blumenthal, G. M., & Pazdur, R. (2017). Real-world data for clinical evidence generation in oncology. *JNCI: Journal of the National Cancer Institute*, *109*(11), djx187.
2. Inkster, B., Sarda, S., & Subramanian, V. (2018). An empathy-driven, conversational artificial intelligence agent (Wysa) for digital mental well-being: real-world data evaluation mixed-methods study. *JMIR mHealth and uHealth*, *6*(11), e12106.
3. Wu, B., Widanage, W. D., Yang, S., & Liu, X. (2020). Battery digital twins: Perspectives on the fusion of models, data and artificial intelligence for smart battery management systems. *Energy and AI*, *1*, 100016.
4. Mahbub, M. (2020). A smart farming concept based on smart embedded electronics, internet of things and wireless sensor network. *Internet of Things*, *9*, 100161.
5. Dey, N., Ella Hassanien, A., Bhatt, C., S Ashour, A., & Chandra Satapathy, S. (2018). *Internet of things and big data analytics toward next-generation intelligence*. by Springer Nature.
6. Romeo, L., Petitti, A., Marani, R., & Milella, A. (2020). Internet of robotic things in smart domains: Applications and challenges. *Sensors*, *20*(12), 3355.
7. Kristiani, E., Yang, C. T., Huang, C. Y., Ko, P. C., & Fathoni, H. (2020). On construction of sensors, edge, and cloud (ISEC) framework for smart system integration and applications. *IEEE Internet of Things Journal*, *8*(1), 309-319.
8. Niesler, C., Surminski, S., & Davi, L. (2021, February). HERA: Hotpatching of Embedded Real-time Applications. In *NDSS*.
9. Konstantinou, C., & Maniatakos, M. (2019). Hardware-layer intelligence collection for smart grid embedded systems. *Journal of Hardware and Systems Security*, *3*, 132-146.
10. Emilio, M. D. P. (2015). *Embedded systems design for high-speed data acquisition and control*. Springer International Publishing.
11. Tan, S. J., Bratus, S., & Goodspeed, T. (2014, December). Interrupt-oriented bugdoor programming: A minimalist approach to bugdooring embedded systems firmware. In *Proceedings of the 30th Annual Computer Security Applications Conference* (pp. 116-125).

12. Esmaili, A., Kachuee, M., & Shabany, M. (2017). Nonlinear cuffless blood pressure estimation of healthy subjects using pulse transit time and arrival time. *IEEE Transactions on Instrumentation and Measurement*, *66*(12), 3299-3308.
13. Chandrasekhar, A., Kim, C. S., Naji, M., Natarajan, K., Hahn, J. O., & Mukkamala, R. (2018). Smartphone-based blood pressure monitoring via the oscillometric finger-pressing method. *Science translational medicine*, *10*(431), eaap8674.
14. Papaioannou, T. G., Karageorgopoulou, T. D., Sergentanis, T. N., Protogerou, A. D., Psaltopoulou, T., Sharman, J. E., ... & Tousoulis, D. (2016). Accuracy of commercial devices and methods for noninvasive estimation of aortic systolic blood pressure a systematic review and meta-analysis of invasive validation studies. *Journal of hypertension*, *34*(7), 1237-1248.
15. Javaid Lone, E., Ali, A., & Khan, I. (2016). Corporate governance and corporate social responsibility disclosure: evidence from Pakistan. *Corporate Governance: The international journal of business in society*, *16*(5), 785-797.
16. Rahmat, A. Y. (2018). The effect of using educational multimedia in dictation on students' listening comprehension at MA Darul Hikmah Pekanbaru. *J-SHMIC: Journal of English for Academic*, *5*(1), 1-19.
17. De Winter, J. C. (2013). Using the Student's t-test with extremely
18. Yang, D., & Dalton, J. E. (2012, April). A unified approach to measuring the effect size between two groups using SAS. In *SAS global forum* (Vol. 335, pp. 1-6).