P.Vinoth Kumar,2021, 9:3
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

An IoT Based Solution for Smart Maternal and Fetal Health Monitoring with One Dimensional CNN

Associate Prof. P. Vinoth Kumar, M.Balaji, M. Gopalakrishnan, A. Stephy, S. Subadharshini
Department of Electronics and Communication Engineering,
Nandha College of Technology,
Perundurai - 638052, Tamil Nadu, India.

Abstract-The fast-modernizing medical field can be developed and utilized with the help of IoT. Our project work approaches to simplify the patients monitoring by our integrated system of IoT sensors, an emergency diagnostic subsystem a smart health analytic system approaches to secure the patients by automatic monitoring and recording of clinical parameters, and treat them if necessary. The maternal and fetal parameters such as blood pressure, temperature, oxygen level, heart rate are monitored and recorded for those who are hospitalized under high risk condition. The sensors assembled to sense specified parameters record them and the sensed information are recorded and saved in cloud environment. The specialized emergency subsystem developed is used to analyze the data with the threshold levels. The features of the parameters recorded are extracted using CNN. Using deep leaning the features are classified and studied for further consultations with the specialists. A quick and instant remedies can be sought out in case of emergencies.

Keywords:-Artificial intelligence, CNN, think speak algorithm, emergency subsystem, feature extraction, patient monitoring.

I. INTRODUCTION

Every today's processes can be sophisticated on IoT approach which includes medical systems which is getting more demand along with need of best solution for communication quality, data security and storage/retrieval efficiency, data analysis and artificial intelligence systems for better health care. Here, we adopted IoT for healthcare monitoring of pregnant women and their fetus who are hospitalized at high-risk condition.

Basically, the health parameters of a pregnant women are in quite elevated state comparing to normal body. During labor time or hospitalized condition, the parameters may have the chances of getting raised to an intolerance level. This results in complex situation for both mother and fetus. So, an intensive care and observation should be given for them by continuously monitoring their health parameters and instant treatments should be provided. In earlier practices, the health condition is monitored at certain time and at the time of emergency call after any elevation on clinical parameters which caused delayed analysis of health problems that leads to drastic issues to pregnancy. So, our proposed work of integrated solution attempt to have constant monitor and medical aid system protects the pregnancies efficiently and effectively. The deep learning technology we use here is convolutional neural network (CNN) for analyzing visual imagery.

The process is done by one dimensional CNN which consists of several layers such as convolutional layer, pooling layer, dropout layer, fully connected layer, activation functions. It helps in processing the date at one dimension and aids in image detection and classification. The artificial intelligence detects the parameter variation and alerts the system. The think speak algorithm we use here helps to save and access data in cloud. The effective sensors support

International Journal of Science, Engineering and Technology

An Open Access Journal

the sensing of assigned parameters. The data privacy, security, and best accuracy in the proposed work will make it a best choice in medical field.

II. PROPOSED FRAMEWORK

The proposed system has a work flow of four steps which includes

- Sensors and devices layer
- Emergency monitoring subsystem
- Automatic feature extraction subsystem using CNN
- Prediction subsystem using think speak algorithm

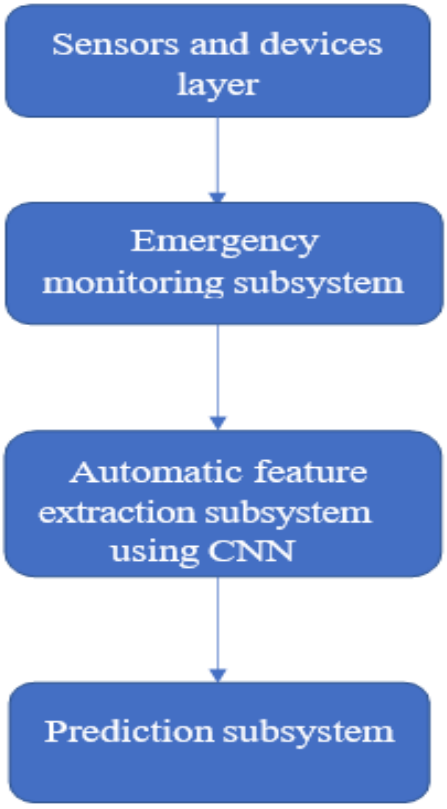


Fig 1. The flow diagram for the proposed integrated solution for healthcare monitoring.

The clinical indicators of mother and fetus are sensed by the sensors and devices layer. The sensors and other devices are embedded in Arduino uno board which provides well-formed support for the storing and saving of data. The sensed data are then transferred to the cloud. The cloud is used to save and access the data when necessary. The Wi-Fi module we install transfers the data to cloud. The internet gateway established acts as a connectivity between the wi-fi module and the cloud. The cloud data are stored in the mobile application.

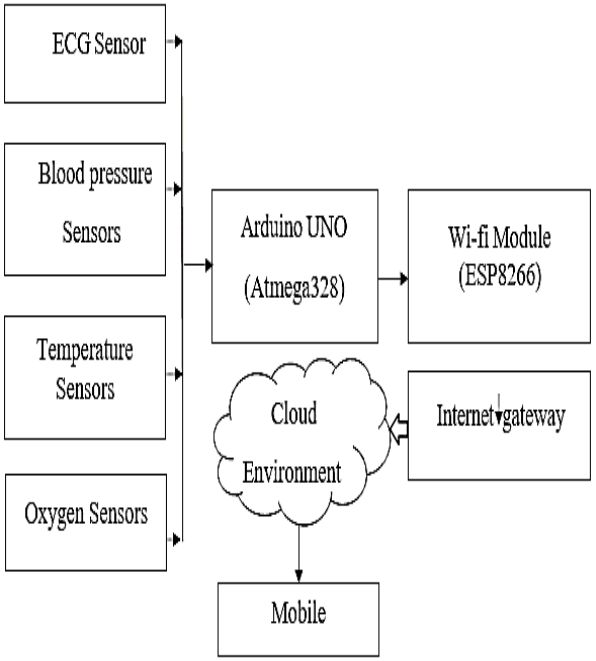


Fig 2. Block diagram for the integrated system with IoT, CNN classifier, with help of an artificial intelligence for healthcare monitoring.

1. Sensors and Devices Layer:
The sensors we used are assigned for sensing certain parameter such as heart rate of both mother and fetus, temperature, oxygen level and blood pressure of mother. Different types of sensors are used for each type of indications.

2. ECG Sensor:
The ECG sensor is used to monitor the fetal and mother ECG value. We can measure only Fetal Heart Rate (FHR) before the birth. So, measuring fetal heartrate is an important parameter and which is combined with the mother heartrate. The threshold level is fixed for fetal and mother for getting the classified results.

3. Temperature Sensor:
The mother's body temperature is measured by using temperature sensor for emergency monitoring. Change in temperature for a pregnant-women may affect the fetus. So, we considered temperature is one of the parameters to be monitored for constant maintenance.

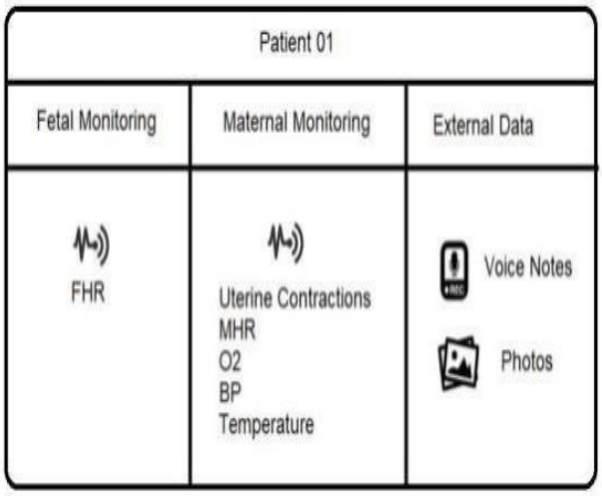
4. Oxygen Sensor:
The pregnant women inhale higher level of oxygen and measuring the oxygen level is one of the key factors in an ambulance. The gas sensor is used here to measure the oxygen level.

International Journal of Science, Engineering and Technology

An Open Access Journal

5. Blood Pressure Sensor:
To measure the pressure level of mother it is used. The blood pressure is measured to know the condition of the mother to analyze both systolic and diastolic pressures to alert when deviating from threshold values.

Table 1. Representation of multiple bio-signals and external non-structured output.



6. Emergency Monitoring Subsystem:
This layer collects data and process them for analysis of health status. The proposed layers developed with an automatic diagnostic system of clinical signals based on a set of fixed thresholds that are already assigned. For the maternal vital signs monitoring, after considering all the measures, a group of 6 features are selected. The calculation was performed every second, considering the last 5 seconds, with a window of 80% of superposition with the previous calculation with the aim to smoothly monitor changes in maternal health conditions.

The 6 statistical measures are: arithmetic mean; standard deviation; median, third quartile; maximum value and minimum value. All the fetal and maternal selected features were considered as inputs for the CNN prediction subsystem, presented in the following section.

A total of 6 classes were considered. The results showed that a one-dimensional CNN with 6 convolutional layers and considering 10 seconds windows achieved the best performance, for the maternal, fetal and both conditions. The assigning of each threshold values and the corresponding diagnostic classifications are done based on the international guidelines of the Federation of Gynecologists and Obstetrics (FIGO) for the fetal and maternal parameters.

7. Automatic Feature Extraction Subsystem using CNN:
The third layer is used to extract the features of sensed parameters that are compared with the threshold level initially set obtained from the above subsystem. For the analysis of these vital data, its feature extraction is very important. The FHR interpretation requires a long-term analysis and FHR changes, such as baseline adjustments and long decelerations need several minutes to be confirmed. So, the measures are calculated for the first time after 10 minutes of signal acquisition and updated every 5 minutes, always considering the entire examination.

8. Prediction Subsystem:
The last prediction system layer is used to evaluate the results for further consultations and treatments for the concerned patient. The prediction is computed by the use of one dimensional convolutional neural network. It analyses the obtained data and classifies it according to the classes of bio-signals. The set of alternative pooling and convolutional layers provides a clear-defined output. To simulate the results Think speak algorithm is effectively used.

The final results classified are given to the specialists for the analysis and required treatments are provided to the concerned patients, if there is any emergency call. In our proposed work, we attempt to simplify the complex structure. The work is proposed with low-cost hardware and accurate measurement of parameters are done with effective layers of CNN. The hardware system assembled for our proposed work involves the usage of following components:

8.1 Sensors
- ECG sensor
- Temperature sensor
- Oxygen sensor
- Blood pressure sensor
- Arduino UNO Microcontroller Board
- ESP8266 Wi-Fi module
- Internet Gateway
- Cloud Environment

Sensors are an integral part of modern living. A sensor is a device that measures physical input from

its environment and converts it into data that can be interpreted by either a human or a machine. It generates an electrical signal or optical output signal corresponding to the variations in the level of inputs. The Arduino microcontroller board contains an Atmega328 microcontroller.

It consists of 14 digital pins and 6 analog pins for input/output operations. It can be powered by the USB cable or by an external 9-volt battery, though it accepts voltages between 7 and 20 volts. It measures the sensor readings and categorizes the ECG, Blood pressure, Oxygen and temperature. These measured values further uploaded in the cloud. To upload the sensor data in a cloud environment we required a wired/wireless communication module.

The ESP8266 Wi-Fi Module is a self-contained SOC with integrated TCP/IP protocol stack that can give any microcontroller access to your Wi-Fi network. An internet gateway as an optional virtual router that connects the edge of the VCN with the internet. To use the gateway, the hosts on both ends of the connection must have public IP addresses for routing.

Connections that originate in your VCN and are destined for a public IP address (either inside or outside the VCN) go through the internet gateway. Here, it gives connectivity support to the internet and acts as an intercommunication module to connect Wi-fi and Cloud environment. All the collected sensor data will be gathered in Cloud Environment.

In this work, we using Thing Speak Open-source cloud for collecting and analyzing the sensor information. The ECG, blood pressure, oxygen, temperature sensor values are received and viewed through graphically. Every sensor value will be uploaded with every 20 seconds.

III. EXPERIMENTAL RESULTS AND DISCUSSIONS

In this section, the results of emergency subsystem are presented which are then to be worked for the feature extraction by using CNN. The final results are derived for the analysis of the level of clinical parameters for proceeding with the required treatments.The fetal and maternal heart rate interpretation requires a long-term analysis and FHR changes, such as baseline adjustments and long decelerations need several minutes to be confirmed.

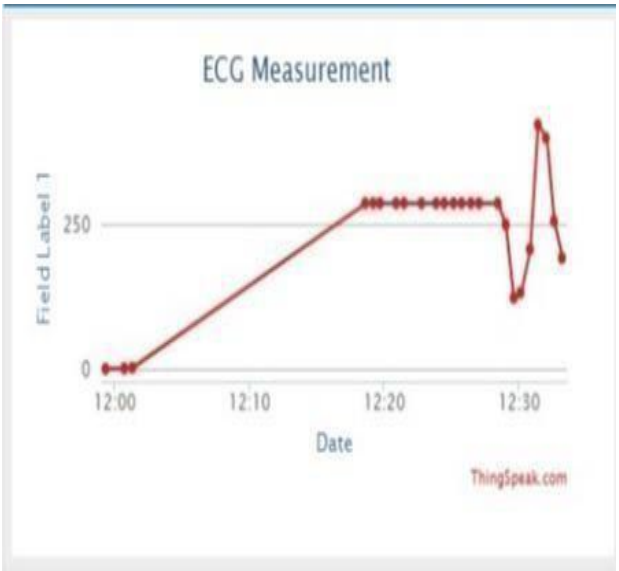


Figure 3: The graph indicating output of combined ECG analysis.

Because of that, the measures are calculated for the first time after 10 minutes of signal acquisition and updated every 5 minutes, always considering the entire examination.

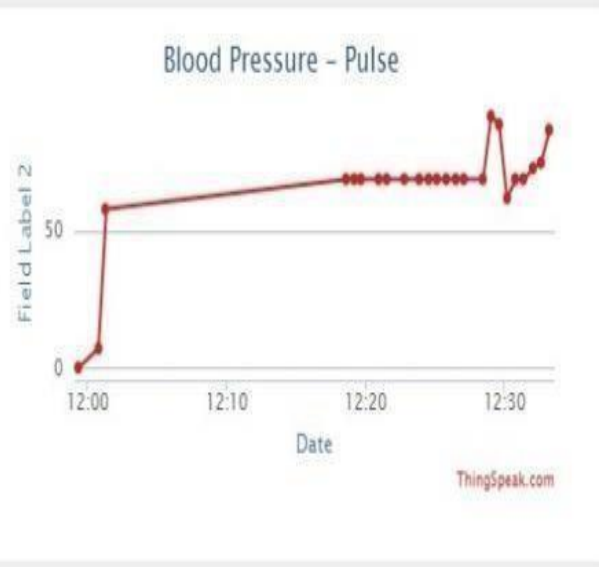


Figure 4: The graph showing the blood pressure level of mother.

The above graph shows the output of measuring the blood pressure of the hospitalized mother. The blood pressure rate is basically set for normal level of 120/80 mm Hg. If the level measured exceeds the normal rate, then the necessary measures are taken for reducing it by the specialist.

International Journal of Science, Engineering and Technology

An Open Access Journal

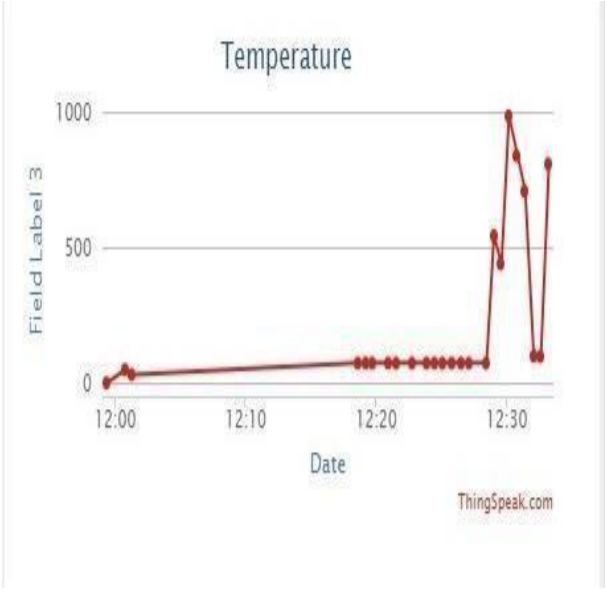


Figure 5: The graph indicating temperature level of the mother.

Through the above graph the body temperature of the mother is analyzed. It shows that for every 10 seconds the temperature level is noted. If the normal level increases for above 100F, necessary steps are taken.

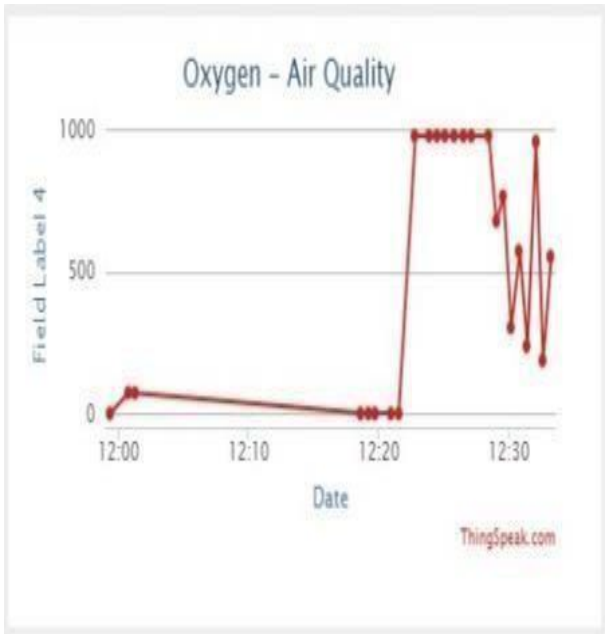


Figure 6: The graph indicating the oxygen level of mother.

The air quality inhaled by the mother is monitored here. The graph shows the high and low-level intake of the oxygen by the mother. According to the analysis, required measures are done to provide adequate oxygen to both mother and baby.

IV. CONCLUSION AND FUTURE WORKS

An integrated solution of artificial intelligence, IoT and CNN are proposed for the high- risk maternal and fetal monitoring along with health subsystems. Our work involves less staffing, reduced cost monitoring affordable for all class of patients. The demand of best accuracy, data privacy, communicational capability and handling of data traffic can all be met.

The integrated approach results in effective and efficient analysis of health status of mother and fetus. A quick and instant remedies can be sought out in case of emergencies and hence, the risk during labor is reduced and lives are saved. Future works can be done by using advanced level of CNN and more integrating of circuit. The attempts should be made for monitoring and extracting other important clinical parameters also. The data privacy, data accessing from cloud and accuracy can also be worked on. Moreover, other AI approaches should be considered for the classification module to compare performance.

REFERENCES

[1] Aloi, G.; Caliciuri, G.; Fortino, G.; Gravina, R.; Pace, P.; Russo, W.; Savaglio, C. "Enabling IoT interoperability through opportunistic smartphone-based mobile gateways" Journal of Network and Computer Applications, 2017, v 81, pp 74-84, doi 10.1016/j.jnca.2016.10.013

[2] Albahri et.al.O.S. "Fault-Tolerant mHealth Framework in the Context of IoT-Based Real-Time Wearable Health Data Sensors," in IEEE Access, vol. 7, pp. 50052-50080, 2019, doi: 10.1109/ACCESS.2019.2910411.

[3] Chen M. and Y. Hao, "Label-less Learning for Emotion Cognition," in IEEE Transactions on Neural Networks and Learning Systems, vol. 31, no. 7, pp. 2430- 2440, July 2020, doi: 10.1109/TNNLS.2019.2929071.

[4] Chen M, J. Zhou, G. Tao, J. Yang and L. Hu, "Wearable Affective Robot," in IEEE Access, vol. 6, pp. 64766-64776, 2018, doi: 10.1109/ACCESS.2018.2877919.

[5] Chhowa T, M. A. Rahman, A. K. Paul and R. Ahmmed, "A Narrative Analysis on Deep Learning in IoT based Medical Big Data Analysis with Future Perspectives," 2019 International Conference on Electrical, Computer and

Communication Engineering (ECCE), Cox's Bazar, Bangladesh 2019, pp. 1-6, doi: 10.1109/ECACE.2019.8679200.

[6] Dourado C M J M, S. P. P. Da Silva, R. V. M. Da Nóbrega, P. P. R. Filho, K. Muhammad and V. H. C. De Albuquerque, "An Open IoHT based Deep Learning Framework for Online Medical Image Recognition," in IEEE Journal on Selected Areas in Communications, doi: 10.1109/JSAC.2020.3020598.

[7] Ding W, M. Abdel-Basset, K. A. Eldrandaly, L. Abdel-Fatah and V. H. C. de Albuquerque, "Smart Supervision of Cardiomyopathy Based on Fuzzy Harris Hawks Optimizer and Wearable Sensing Data Optimization: A New Model," in IEEE Transactions on Cybernetics, doi: 10.1109/TCYB.2020.3000440.

[8] Diogo Ayres-de-Campos; Catherine Y. Spong; Edwin Chandra Haran. "FIGO consensus guidelines on intrapartum fetal monitoring: Cardiotocography", in FIGO Intrapartum Fetal Monitoring Expert Consensus Panel, 2015, DOI 10.1016/j.ijgo.2015.06.020.

[9] Fortino, Pace, Pasquale; Aloi, Gianluca; Gravina, Raffaele; Caliciuri, Giuseppe; Giancarlo; Liotta, Antonio. "An Edge-Based Architecture to Support Efficient Applications for Healthcare Industry 4.0". IEEE Transactions on Industrial Informatics, 2019, v 15 pp.481-489, doi 10.1109/TII.2018.2843169.

[10] Guimaraes et al. R R, "Intelligent Network Security Monitoring Based on Optimum- Path Forest Clustering," in IEEE Network, vol. 33, no. 2, pp. 126-131, March/April 2019, doi: 10.1109/MNET.2018.1800151.

[11] Hassan M, M. R. Hassan, S. Huda and V. H. C. de Albuquerque, "A Robust Deep Learning Enabled Trust-boundary Protection for Adversarial Industrial IoT Environment," in IEEE Internet of Things Journal, doi: 10.1109/JIOT.2020.3019225.

[12] Kotenko M, I. Saenko, A. Kushnerevich and A. Branitskiy, "Attack Detection in IoT Critical Infrastructures: A Machine Learning and Big Data Processing Approach," 2019 27th Euromicro International Conference on Parallel, Distributed and Network-Based Processing (PDP), Pavia, Italy,2019, pp. 340-347, doi: 10.1109/EMPDP.2019.8671571.

[13] Kotronis, C., Minou, G., Dimitrakopoulos, G., Nikolaidou, M., Anagnostopoulos, D., Amira, A., Bensaali, F., Baali, H., and Djelouat, H. (2017). Managing criticalities of e- health IoT systems. In 17th International Conference on Ubiquitous Wireless Broadband (ICUWB), pages 1–5. IEEE. Lin R, Z. Ye, H. Wang and B. Wu, "Chronic Diseases and Health Monitoring Big Data: A Survey," in IEEE Reviews in Biomedical Engineering, vol.11, pp275-288, 2018, doi:10.1109/RBME.2018.28294.

[14] Khan S, K. Muhammad, S. Mumtaz, S. W. Baik and V. H. C. de Albuquerque, "Energy- Efficient Deep CNN for Smoke Detection in Foggy IoT Environment," in IEEE Internet of Things Journal, vol. 6, no. 6, pp. 9237-9245, Dec. 2019, doi: 10.1109/JIOT.2019.2896120.

[15] Loubet.G, A. Takacs and D. Dragomirescu, "Implementation of a Battery-Free Wireless Sensor for Cyber-Physical Systems Dedicated to Structural Health Monitoring Applications," in IEEE Access, vol. 7, pp. 24679-24690,2019, doi: 10.1109/ACCESS.2019.2900161.

[16] Mehmood et al. I, "Efficient Image Recognition and Retrieval on IoT Assisted Energy-Constrained Platforms from Big Data Repositories," in IEEE Internet of Things Journal, vol. 6, no. 6, pp. 9246-9255, Dec. 2019, doi: 10.1109/JIOT.2019.2896151.

[17] Niitsu et al. K, "A Self-Powered Supply-Sensing Biosensor Platform Using Bio Fuel Cell and Low-Voltage, Low-Cost CMOS Supply Controlled Ring Oscillator with Inductive- Coupling Transmitter for Healthcare IoT," in IEEE Transactions on Circuits and Systems Regular Papers, vol. 65, no. 9, pp. 2784-2796, Sept. 2018, doi: 10.1109/TCSI.2018.2791516.

[18] Rafique W, X. Zhao, S. Yu, I. Yaqoob, M. Imran, W. Dou, An Application Development Framework for Internet-of-Things Service Orchestration, IEEE Internet of Things Journal, Vol. 7 (5), pp. 4543-4556, May, 2020.

[19] Razzak M I, M. Imran, G. Xu, Big Data Analytics for Preventive Medicine, Neural Computing and Applications, Vol. 32, pp. 4417–4451, Apr, 2020.

[20] Rehman M H U, E. Ahmed, I. Yaqoob, I. A. T. Hashem, M. Imran and S. Ahmad, "Big Data Analytics in Industrial IoT Using a Concentric Computing Model," in IEEE Communications Magazine, vol. 56, no. 2, pp. 37-43, Feb. 2018, doi:10.1109/MCOM.2018.1700632.

[21] Rizwan et al. A, "A Review on the Role of Nano-Communication in Future Healthcare Systems: A Big Data Analytics Perspective," in IEEE Access, vol. 6, pp. 41903-41920, 2018, doi: 10.1109/ACCESS.2018.2859340.

International Journal of Science, Engineering and Technology

An Open Access Journal

[22] Raza M, M. Awais, N. Singh, M. Imran, S. Hussain, Intelligent IoT Framework for indoor healthcare monitoring of Parkinson's Disease Patients, IEEE Journal on Selected Areas in Communications, 2020.

[23] Sundaravadivel P, K. Kesavan, L. Kesavan, S. P. Mohanty and E.Kougianos, "Smart- Log: A Deep-Learning Based Automated Nutrition Monitoring System in the IoT," in IEEE Transactions on Consumer Electronics, vol. 64, no. 3, pp. 390-398,Aug.2018, doi:10.1109/TCE.2018.286.

[24] Santos, M. A. G., Munoz, R., Olivares, R., Filho, P. P. R., Ser, J. D., & Albuquerque V. H. C. de. "Online Heart Monitoring Systems on the Internet of Health Things Environments: A Survey, a Reference Model and an Outlook". Information Fusion, doi: 10.1016/j. inffus.2019.06.0

[25] Silveira, F., Neto, I. R., Machado, F. M., and da Silva, M. P. (2019). "Analysis of industry 4.0 technologies applied to the health sector: Systematic literature review". Occupational and Environmental Safety and Health.

[26] Sodhro, S. Pirbhulal, Z. Luo and V. H. C. de Albuquerque, "Towards an optimal resource management for IoT based Green and sustainable smart cities", in Journal of Cleaner Production, Vol. 220, 2019, pp. 1167-1179, doi: 10.1016/j.jclepro.2019.01.188.

[27] Zhang. Y, L. Sun, H. Song and X. Cao, "Ubiquitous WSN for Healthcare: Recent Advances and Future Prospects," in IEEE Internet of Things Journal, vol. 1, no. 4, pp. 311-318, Aug. 2014, doi: 10.1109/JIOT.2014.2329462.

[28] Zhang. Q, L. T. Yang, Z. Chen, P. Li and F. Bu, "An Adaptive Dropout Deep Computation Model for Industrial IoT Big Data Learning with Crowdsourcing to Cloud Computing," in IEEE Transactions on Industrial Informatics, vol. 15, no. 4, pp.2330- 2337, April 2019, doi: 10.1109/TII.2018.2791424.

[29] Zhang, Yin; Gravina, Raffaele; Lu, Huimin; Villari, Massimo; Fortino, Giancarlo. "PEA: Parallel electrocardiogram-based authentication for smart healthcare systems", Journal of Network and Computer Applications, 2018, v 117, pp 10-16, doi 10.1016/j.jnca.2018.05.007.