Journal of Positive School Psychology http://journalppw.com
2022, Vol. 6, No. 6, 6978-6985

Data Analytics Using Machine Learning For Iot-Enabled Healthcare Systems

Dr. S. Lokesh[1] , Dr. S. Aramuthakannan[2] , Darshan B D[3] , Firdous Ahmad Lone[4] , C M Velu[5] , Yadala Sucharitha[6]

[1]Associate Professor, Department of Computer Science and Engineering, PSG Institute of Technology and Applied Research, Coimbatore, Tamilnadu, India.
[2]Associate Professor, Department of Mathematics, PSG Institute of Technology and Applied Research, PSG Institute of Technology and Applied Research, Coimbatore, India.
[3]Assistant Professor, Department of Electronics and Communication Engineering, SJB Institute of Technology, Bangalore, Karnataka, India.
[4]Faculty, Department of Computer Skills, Common First Year, King Saud University, Riyadh, Saudi Arabia
[5]Professor, Department of CSE, Savertha School of Engineering, Saveetha University, SIMATS, Chennai, Tamilnadu, India.
[6]Associate Professor, Department of Computer Science and Engineering, CMR Institute of Technology, Hyderabad, TS state , India

Abstract

One of the cutting-edge technologies that is gaining traction throughout the world is the Internet of Things. We can connect at any time, anywhere, and with any network or service because to the enormous power and capacity of IoT. The Internet of Things (IoT) is growing to be a powerhouse for next-generation machines, and its effects may be seen in the present corporate landscape. IoT is assisting businesses or researchers in the development of solutions. By integrating the current internet infrastructure for the efficient use of resources, they communicate with smart devices and smart objects. Additionally, it has the ability to expand services and advantages for intelligent systems. Beyond M2M (machine-to-machine) situations, the interests at stake include serial communication between the network and devices for delivering extreme services. An intelligent hybrid classification algorithm for an unbalanced ECG dataset based on the Internet of Things has been discussed in this study. The AD8232 heart rate sensor, the NodeMCU ESP32, and an intelligent hybrid classification algorithm for data categorization have been presented for an IoT-based ECG monitoring system.

Keywords: Node MCU, IoT, Electrocardiogram, M2M, ECG, Smart device.

1. Introduction

Cardiovascular diseases (CVD) are one of the greatest dangers of civilization around the world. Every year majority of the fatalities, owing to CVD are noticed globally. Most fatalities from CVD are abrupt and the patients don't have any opportunity to obtain medical care on time. Thus, there is an overwhelming necessity for such a real-time smart system that can continually monitor the cardiac-related activities of heart patients. The Internet of Things (IoT) enabled systems are one of the options for real-time data monitoring. The statistical analysis of real-time data is one of the biggest breakthroughs in the smart healthcare paradigms, which may equip physicians with speedier, effective, and smarter techniques of diagnosis, in the near future. IoT based smart healthcare includes a range of applications such as Electrocardiography (ECG) monitoring, Heart-rate (HR) monitoring, Blood Pressure (BP) monitoring, etc.

In classification difficulty, the imbalanced nature of data is one of the largest challenges and it has grown more significant in the healthcare arena since all the treatment rely upon classification outcome[1]. Thus, in the healthcare arena, categorization of the imbalanced dataset is an open topic of study. From time-to-time, numerous scholars have given their views in the form of algorithms and theoretical perspectives[2]. Various class balancing methods in the form of hybrid paradigms have also been created [3]. Two kinds of data balancing approaches are being frequently employed, first one is under-sampling and second is oversampling [4]. In under-sampling strategy, data samples are removed from the majority class for balancing the class, however, in over sampling approach, fake samples are introduced to the minority class for addressing the issue of class imbalance. Public health well-being is always a tough endeavor but it gets more complex when we are dealing with the world's one of deadliest illnesses (i.e. CVD) in real-time data paradigms. Consequently, there is an enormous necessity of the algorithmic techniques which will play a vital part in minimizing the total risk of CVD by its effective categorization. Holding these limits in the mind, we start experimenting with the basic classification models, which are neither very accurate nor capable of coping with the class imbalance issue. After multiple trials, we identified our suggested an intelligent hybrid classification model for the categorization of an unbalanced ECG dataset.

2. Literature Survey

The Internet of Things (IoT) is one of the developing technologies which is stretching its wings day by day. The smart objects in the IoT system are the final building blocks employed in the creation process of the IoT based smart ubiquitous frameworks. Healthcare is one of the crucial and well-known application sectors of IoT technology. The IoT is providing new structure to the current healthcare system, which is characterized as the Internet of Healthcare Things (IoHT) with competent technical, social, and economic potential. This , analyzed major improvements in the Internet of Healthcare Things (IoHT) technologies such as topologies, platforms/architectures, taxonomies, services and applications, industry trends, and the status of IoHT-based solutions. This report evaluated the current developments on the Internet of Healthcare Things (IoHT) research and exposes the numerous concerns and obstacles that demand suitable attention for integrating healthcare technology with IoT modernization. The IoHT networks are one of the key and highly critical aspects of the IoHT infrastructure, which functions as a backbone for IoHT by facilitating healthcare communication, data transfer, and data reception among the numerous smart devices. In-depth discussion on the IoHT topology, IoHT architecture, and IoHT platform has been undertaken in this part and is provided in figure.1.

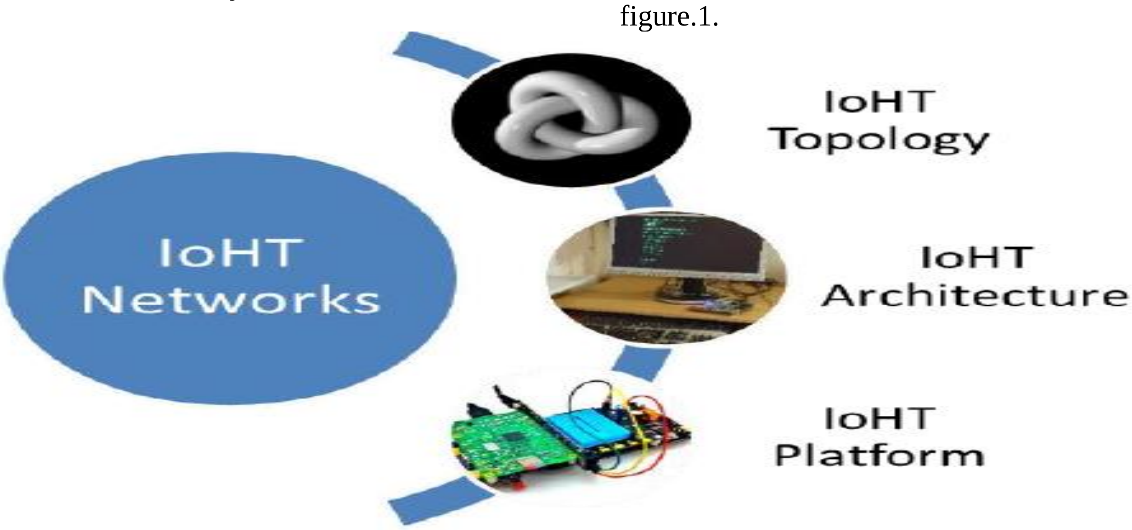

Figure.1: Typical IoHT Networks

To put it simply, it is a crucial component of the IoHT infrastructure. It is a collection of activities, such as setting up the equipment in their proper physical configuration and ensuring that they are suitable for the intended use case, among other things. The Internet of Healthcare Things (IoHT) is, as is well known, a network of disparate medical devices all linked together by a health server. One may choose between a wired and wireless connection. By coordinating their actions within the same area of application, smart health devices create the IoHT topology. Several medical devices may be part of the IoHT infrastructure, all collaborating to do their task at the same time through the communication network. These lines of communication allow for the recording of the data transfer and response. These lines of contact link up with the service providers in question[5]. This means that the administration of these channels rests with a number of different service providers. Service providers like this ensure that the network via which communications take place is safe and secure. Because this information is part of an individual's electronic health record (eHR), it is very important that the IoHT network remain secure. A service provider receives data from a wide variety of health devices, processes and interprets that data, and then makes that analysis and data available to the proper authorities or user. The sensors, their activities, and their workflow make up the usual topology of the IoHT. Smart gadgets based on sensors exchange data with one another across wired or wireless networks. Figure.2. shows the IoHT topology, which consists of the data, control, and resource networks operated by the three service providers.

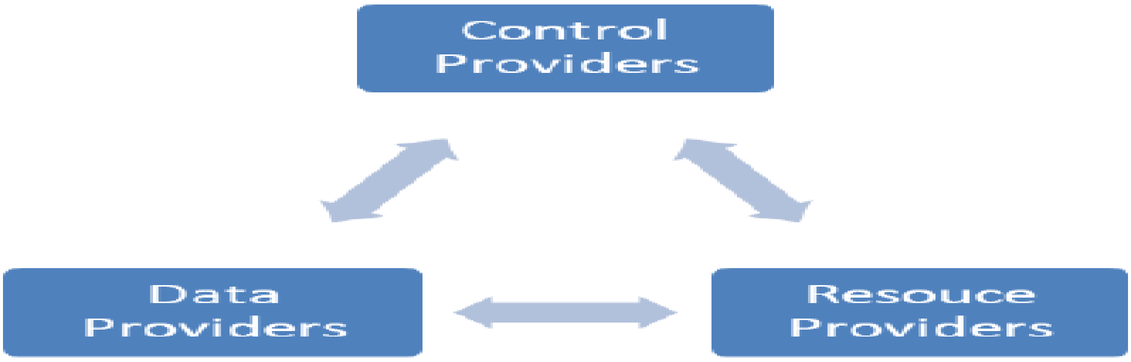

Figure.2. IoHT Topology

Patients' data is referred to as the "data provider," whereas anyone or whatever is in charge of the data is called the "control provider." When we talk about "the resource provider," we're referring to anyone or whatever is supplying us with the means to do the analysis. In certain cases, the control provider and the resource supplier will be the same party, allowing for just bidirectional communication[6]. In addition, this architecture allows for constant surveillance and management of data. Any lag in the smart system might be quite worrisome in the healthcare system because of how important it is to manage time effectively. Therefore, we must construct a comprehensive system that prioritises real-time data processing and offers a robust, safe means of communication. Connected Home and Telecomm. To put it simply, it is a crucial component of the IoHT infrastructure. Construction of an appropriate hierarchical model for the application-centric healthcare domain is one of the many activities that make up this design. Figure 3 depicts the fundamental architectural model for the IoHT.

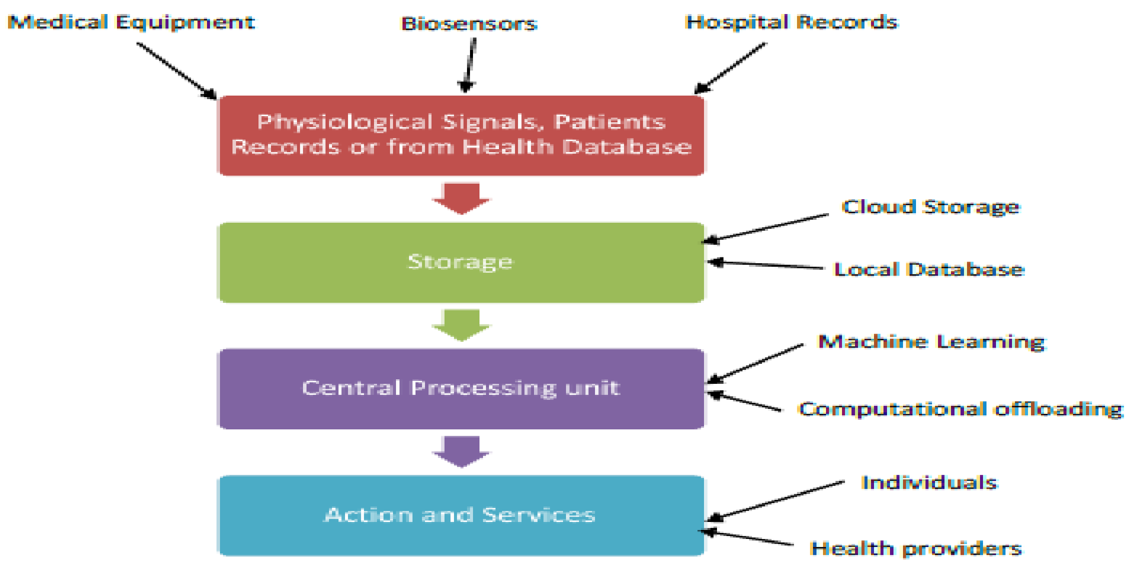

Figure.3. IoHT Architecture

Data in this basic form of an IoHT network is gathered from a wide variety of smart or sensor-based nodes. Input data may be obtained from a wide variety of sources, including but not limited to medical devices, biosensors, wearable sensors, smart devices, and electronic medical records. These elements come from the health database, patient records, and psychological signs. A local or cloud-based storage mechanism stores an identical duplicate of the message regardless of whether it originated from the device or the health records. The data is then sent to the CPU, which is responsible for the actual calculation and/or result finding[7]. Machine learning algorithms or computation offloading techniques are used to carry out the computation. When a computing job is finished, the outcome is shared with either the healthcare professional or the patient[8]. Because of the potential for significant harm to both the smart healthcare system and the individual's health, it is imperative that appropriate security mechanisms be in place at every stage, from sensing or collecting level data to the service level. Therefore, we need sufficient security from the physical layer to the application layer to ensure the privacy of patient information and the use of the IoHT network. The IoHT platforms are a crucial component of the overall IoHT infrastructure. It makes it easier to do things like configure the system or library, run applications, and more. The platform's duty is to bring archetypes to life by providing a suitable framework in the healthcare sector. Without a proper platform that can execute the software and allow all the fundamental features of the system, making blueprints and operating such a large network would be impossible[9]. The physical layer through the accessing layer and into the application layer should all be supported by the platform. The platform is necessary because it will allow us to connect all of our smart gadgets and lines of communication under one roof. The processing is carried out in a logical setting. However, all smart devices and computer systems are set up differently depending on their intended use.

3. Taxonomy of IoHT

To properly categorise and characterise the IoHT infrastructure, taxonomies are required. Figure.4 is a taxonomy of IoHT derived from a number of different sources.

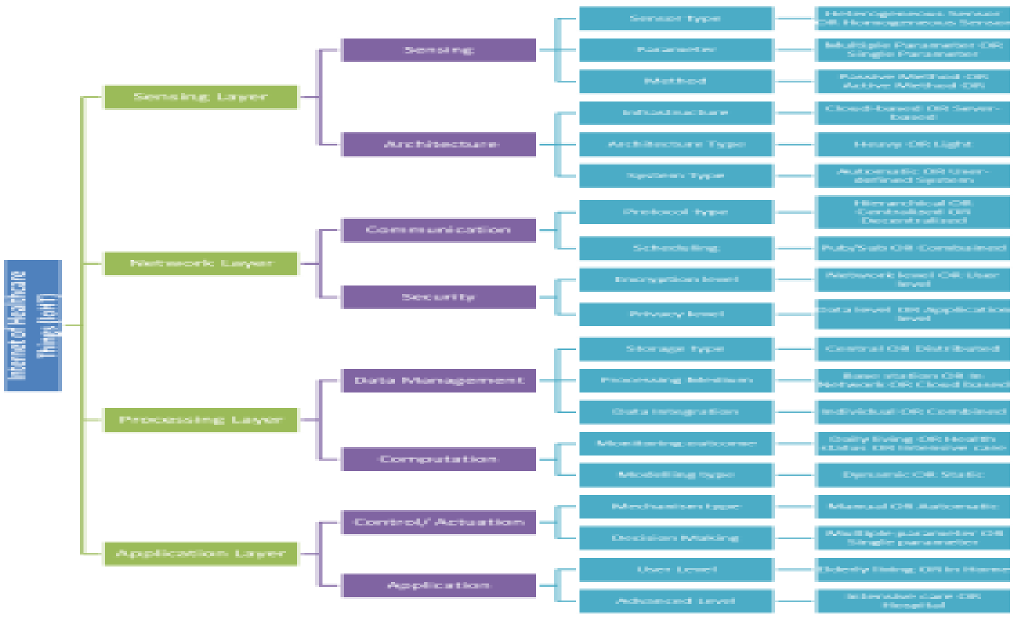

Figure.4. Taxonomy of IoHT

The sensing and architectural components make up the IoHT's initial layer, the sensing layer. In this layer, all operations involving sensing are carried out. All that goes into detecting is picking the right sensor and installing it on the right prototype. The architecture of an IoHT system is crucial to its efficiency and reliability. To enable the IoHT-based smart applications, an architecture that can also assist system integration is needed in the medical domain[10]. The second tier of the IoHT architecture is the network layer, which includes the subsystems responsible for communication and security. Here, tasks like picking protocols with sufficient security measures are carried out, as well as anything else that has to do with communication or security. Protecting the privacy and confidentiality of patients' health information is a major ethical and legal problem. Thus, we must pay close attention to data privacy and security when planning the IoHT architecture for healthcare applications. The third tier of an IoHT system is called the processing layer, and it consists of two sub-layers: data management and computing. Activities linked to data management and computation are carried out here[11], including data extraction from their original source and the application of computation tasks to data using a variety of data analytics tools. The computation definition is crucial in determining which methods are necessary for an IoHT-based application to function. Features like real-time remote patient monitoring are invaluable to medical professionals. The computational capabilities of the healthcare system have been bolstered by this real-time tracking and monitoring capability. Incorporating cloud computing increases the scope and complexity of possible computations. Integration of mobile devices, high-performance computers, a variety of operating systems, etc. are all possible thanks to cloud computing.

4. ECG Data Generation

Our ECG data generation system primarily included an ESP32 NodeMCU and a cardiac sensor (AD8232). The nine electrodes are placed as follows: E1 in the right fourth intercostal space, E2 in the left fourth intercostal space, E3 in the middle of leads E2 and E4, E4 in the fifth intercostal space, midclavicular line; E5 in the left anterior axillary line, mid axillary line, right arm, inner wrist, left arm, inner wrist, right side of scapula; and E9 on the right side of the scapula

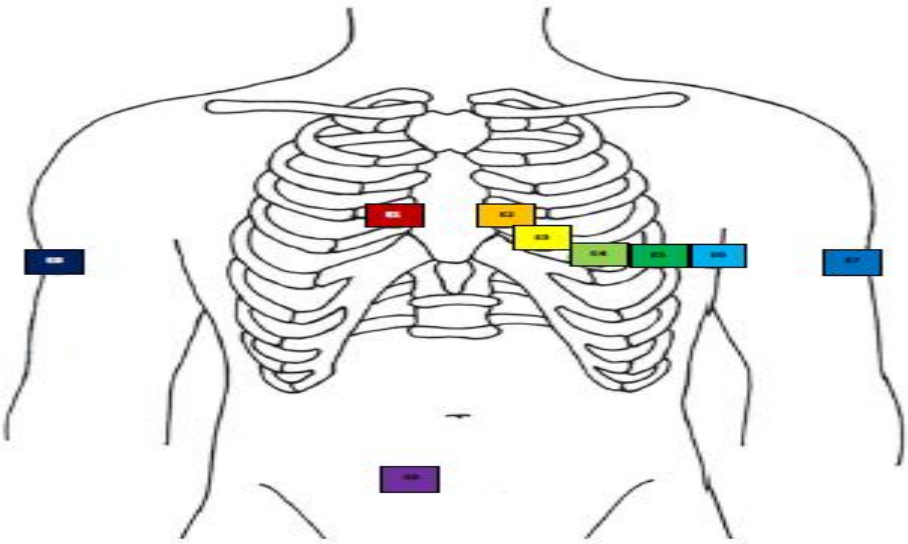

Figure.5. ECG Data Generation Electrode Placement.

The information is produced in real time and sent over TCP to cloud storage (Ubidots) using the HTTP POST command. Using a Wi-Fi connection, the produced data is uploaded to the cloud instantly[12]. Electrocardiogram (ECG) data obtained by an AD8232 heart rate sensor and a Node MCU have been utilised in experimental analyses (ESP32). From the cloud, we have downloaded the ECG data to analyse on our local PC. In order to collect this information, nine electrodes (E1-E9) have been attached to various parts of the human body[13]. The whole activity takes place in front of the 50 participants in a just 150 seconds. Class 1 patients represent the healthy population, while class 2 patients represent the heart unwell population in our dataset [14,15]. There are 1700 samples in this collection, each with 10 properties. The ECG dataset (nine channels with class level) is shown graphically in Figure.6.

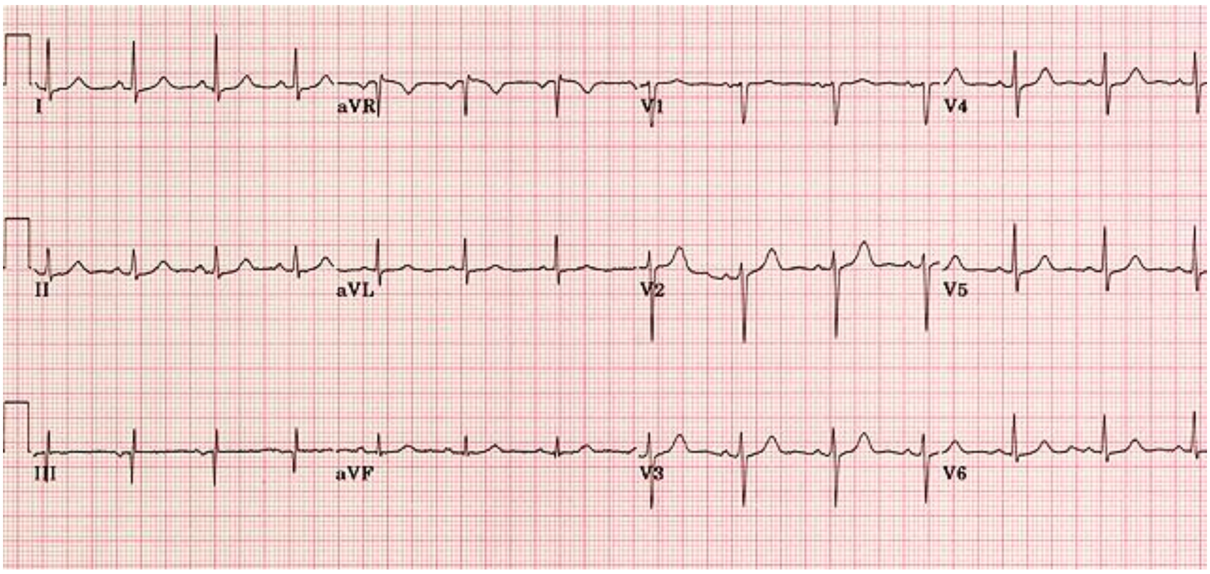

Figure.6. Visualization of the ECG Dataset

5. Results and Discussion

One of the challenging yet novel issues in IoT-based smart healthcare paradigms is accurate model identification. The study's overarching goal is to contribute to the development of a robotics-based solution for societal well-being by providing an intelligent hybrid categorization model for addressing the class imbalance issue with higher precision. Five existing models have been compared in detail using two, three, five, and ten-fold assessment criteria to determine the efficacy of the suggested model. The conditions for this experiment were set at 70% and 30%. (i.e., 70 percent for training, and the rest 30 percent for validation). Four performance indicators have been generated to validate the categorization findings (i.e., f1-score, recall, precision, and accuracy). The experimental assessment shows that the suggested hybrid model outperformed other well-established classification models in terms of accuracy across the board. Electrocardiogram (ECG) data were collected using the heart rate sensor (AD8232) and NodeMCU for the experimental analysis (ESP32). From the cloud, we have downloaded the ECG data to analyse on our local PC. There are two types of individuals included in this dataset: those who are healthy and those who are suffering from heart illness. Six classification models (SVM, KNN, RF, BAG, ADB, and a suggested hybrid model) have been evaluated using these four statistical measures: accuracy, precision, recall, and f1-score. Figure.7 shows the average accuracy of the categorization models across the whole experiment. The experimental evaluation demonstrates that the proposed hybrid model is effective at resolving the class imbalance issue in the electrocardiogram dataset, leading to improved performance for both classes and ultimately facilitating the development of an IoT-based, smart and accurate healthcare system. The suggested hybrid model's performance is evaluated by contrasting it with that of a standard classification algorithm.

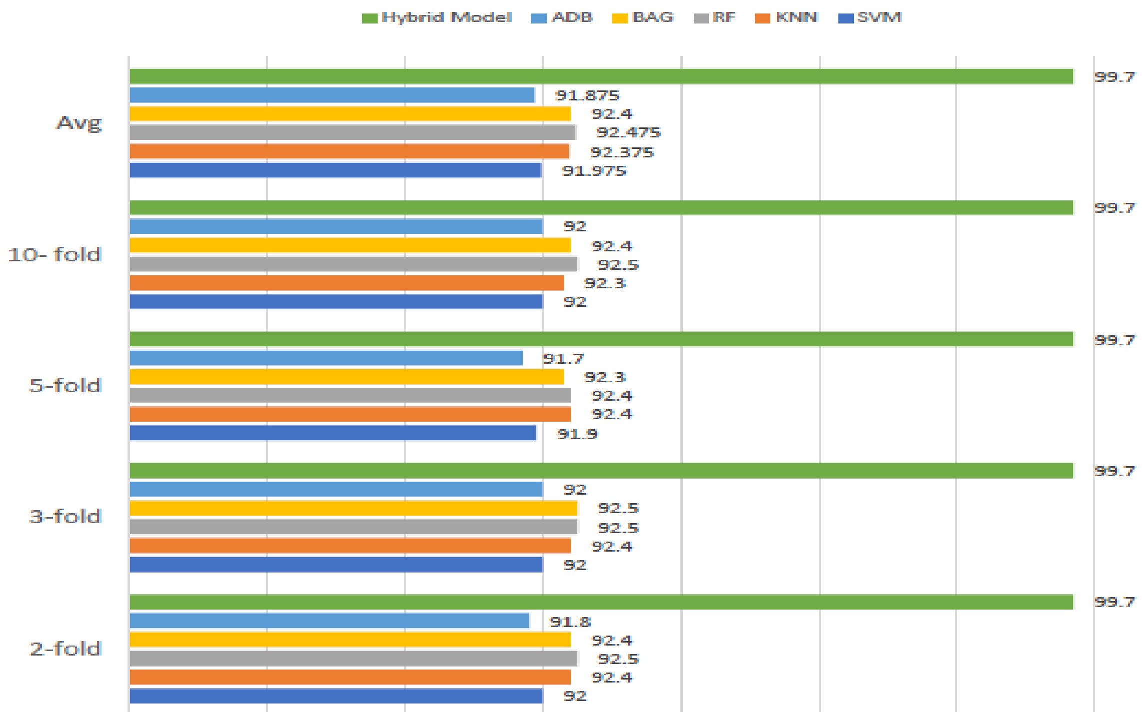

Figure.7. Results of Classification Models

6. Conclusion

One of the greatest threats to human civilization on a global scale is cardiovascular disease (CVD). As a result, there is a pressing need for continuous analysis of cardiac status. In IoT-based smart healthcare paradigms, determining the appropriate model is a challenging but potentially fruitful next step. Electrocardiography (ECG) monitoring, heart rate (HR) monitoring, blood pressure (BP) monitoring, etc. are just a few examples of the many uses for Internet of Things (IoT) in smart healthcare. In order to create the data (using the heart rate sensor AD8232 and NodeMCU ESP32), this study offers an IoT based ECG monitoring system, and to classify the data, an intelligent hybrid classification model is proposed. In order to more accurately address the class imbalance issue, this research aims to provide a smart hybrid categorization model that will be crucial in developing a robotics-based answer to improving social welfare. The experimental assessment shows that the proposed hybrid model outperforms the state-of-the-art classification models for both classes and obtains the greatest accuracy across all experiments using different validation criteria (2-fold, 3-fold, 5-fold, and 10-fold cross-validation policy).

References

1. Arney, D., Fischmeister, S., Goldman, J.M., Lee, I. and Trausmuth, R., Plug-andplay for medical devices: Experiences from a case study. Biomedical Instrumentation & Technology, 43(4), pp.313-317, 2009.
2. Bazzani, M., Conzon, D., Scalera, A., Spirito, M.A. and Trainito, C.I., Enabling the IoT paradigm in e-health solutions through the VIRTUS middleware. In 2012 IEEE 11th international conference on trust, security and privacy in computing and communications (pp. 1954-1959). IEEE, 2012, June.
3. Bocca, M., Toivola, J., Eriksson, L.M., Hollmén, J. and Koivo, H., Structural health monitoring in wireless sensor networks by the embedded Goertzel algorithm. In 2011 IEEE/ACM Second International Conference on Cyber-Physical Systems (pp. 206-214). IEEE, 2011, April.
4. Chawla, N.V., Bowyer, K.W., Hall, L.O. and Kegelmeyer, W.P., SMOTE: synthetic minority over-sampling technique. Journal of artificial intelligence research, 16, pp.321-357, 2002.
5. Chung, W.Y., Lee, Y.D. and Jung, S.J., A wireless sensor network compatible wearable u-healthcare monitoring system using integrated ECG, accelerometer and SpO 2. In 2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (pp. 1529-1532). IEEE, 2008, August.
6. De la Iglesia, D.H., De Paz, J.F., Villarrubia Gonzalez, G., Barriuso, A.L. and Bajo, J., A context-aware indoor air quality system for sudden infant death syndrome prevention. Sensors, 18(3), p.757, 2018.
7. Djenna, A. and Saïdouni, D.E., Cyber attacks classification in IoT-based-healthcare infrastructure. In 2018 2nd Cyber Security in Networking Conference (CSNet) (pp. 1-4). IEEE, 2018, October.
8. Elish, M.O., Aljamaan, H. and Ahmad, I., Three empirical studies on predicting software maintainability using ensemble methods. Soft Computing, 19(9), pp.2511-2524, 2015.
9. Hu, F., Xie, D. and Shen, S., On the application of the internet of things in the field of medical and health care. In 2013 IEEE international conference on green computing and communications and IEEE Internet of Things and IEEE cyber, physical and social computing (pp. 2053-2058). IEEE, 2013, August.
10. Sujihelen L, Boddu R, Murugaveni S, Arnika M, Haldorai A, Reddy PC, Feng S, Qin J. Node Replication Attack Detection in Distributed Wireless Sensor Networks. Wireless Communications and Mobile Computing. 2022 May 31;2022.
11. Reddy, P.C., Sucharitha, Y.A.D.A.L.A. and Narayana, G.S., Development of Rainfall Forecasting Model Using Machine Learning With Singular Spectrum Analysis. IIUM Journal of Engineering, 23(1), pp.172-186.
12. Reddy, P.C. and Sureshbabu, A., 2019. An adaptive model for forecasting seasonal rainfall using predictive analytics. International Journal of Intelligent Engineering and Systems, 12(5), pp.22-32.
13. Shaker Reddy, P.C. and Sureshbabu, A., 2020. An enhanced multiple linear regression model for seasonal rainfall prediction. International Journal of Sensors Wireless Communications and Control, 10(4), pp.473-483.
14. Balamurugan, D., Aravinth, S.S., Reddy, P., Rupani, A. and Manikandan, A., 2022. Multiview Objects Recognition Using Deep Learning-Based Wrap-CNN with Voting Scheme. Neural Processing Letters, pp.1-27.
15. Imadali, S., Karanasiou, A., Petrescu, A., Sifniadis, I., Vèque, V. and Angelidis, P., eHealth service support in IPv6 vehicular networks. In 2012 IEEE 8th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob) (pp. 579-585). IEEE, 2012, October.