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Health fog: A deep learning approach leveraging Internet of Things and fog computing for real-time heart disease prediction

Angela Jennifa Sujana Jesudoss[1], Infant Mystica[1],
Jebasingh Jeremiah Rajesh[2], Krzysztof Stebel[3]

[1] Department of Artificial Intelligence and Data Science, Mepco Schlenk Engineering College, Sivakasi 626005, Virudhunagar, India
[2] Faculty of Electrical Engineering, Automatic Control and Informatics, Opole University of Technology, ul. Proszkowska 76, 45-758 Opole, Poland
[3] Faculty of Automatic Control, Electronics and Computer Science, Department of Automatic Control and Robotics, Silesian University of Technology, ul. Akademicka 16, 44-100 Gliwice, Poland
* Corresponding author's e-mail: krzysztof.stebel@polsl.pl

ABSTRACT

Real-time data available from IoT devices, allows predicting a patient's risk of heart disease using Health Fog. The proposed approach is economically affordable yet reliable, as it offers low-cost input devices to meet the necessary requirements. The goal achieved is accurate results with low latency. The reduction in latency time was achieved through fog processing. The Arduino UNO serves as an IoT device and the Raspberry Pi serves as a node in the fog architecture. The centralised cloud system has its limitations in terms of direct access, hence the use of a distributed multilayer model significantly improves the availability of computing resources locally where they are needed. Heart disease is predicted using a deep learning algorithm. The DNN algorithm is used by the model to improve performance. The data is sent and received by an Android mobile phone, a fog node that completes the forecast sends it back. Deep learning is accepted for predicting outcomes in the healthcare industry because it is characterised by precise results. Requests are sent between the client and server computers via the REST API. As a result, data is digitally stored in the cloud for later use. The model makes use of Bagging Classifier ensemble learning. Based on a deep learning algorithm, the user submitting input for heart disease prediction gets a result with high reliability.

Keywords: heart disease prediction, internet of things (IoT), fog computing, deep learning, edge computing, predictive analytics.

INTRODUCTION

The healthcare industry has experienced progress due to the rapid development of IoT technology, which has enabled real-time monitoring and data collection. Progress has facilitated the development of intelligent systems that can predict diseases, such as heart disease, which is still the leading cause of death worldwide. The use of IoT in healthcare-related research is being developed extensively, with a focus on real-time early diagnosis and monitoring capabilities. The benefits to healthcare systems of using IoT for accelerated diagnosis have been discussed by Ahmed et al. [1]. However, when these systems are based only on cloud computing systems, they often suffer from latency, limited resource capacity. Challenges and processes in cloud environments [2], emphasise the importance of decision making at the design level [3], in terms of dealing with uncertainty [4] and ensuring appropriate levels of trust [5]. Recent research [6] has provided interesting results in this area.

Technologies and sensors designed for direct contact with the human body are increasingly used in the healthcare industry to monitor patients' vital parameters and obtain other relevant health information. These devices continuously collect data that can be analysed by healthcare professionals. Data collected includes blood pressure, glucose levels and heart rate and more. The main concern of IoT in healthcare is the collection of large amounts of data, which can cause problems such as latency, network bandwidth and ensuring data privacy. IoT applications in healthcare have been the subject of many studies [7], the authors provided a comprehensive overview of IoT applications in medicine. The potential of the technology to improve patient health and healthcare services through timely intervention was highlighted. Management monitoring is also needed, highlighting the challenges of data security, which can be solved, for example, by combining IoT and dark computing. Fog computing extends cloud computing by bringing computing resources closer to the data source,. It is very beneficial for real-time data processing and analysis [8]. Such a model optimises data security, reduces latency and improves the efficiency of healthcare services. Local preprocessing and filtering of data by a fog node allows them to upload only relevant data to the cloud for further analysis and long-term storage. Fog computing has been used in the healthcare industry for several purposes, including real-time diagnostics, remote disease monitoring and emergency response systems. The authors in [9] explored how fog processing can be integrated into the IoT, emphasising how latency can be reduced and responsiveness increased.

The ability to extract knowledge from complex, over-dimensional information has made it popular in the healthcare industry. Deep learning models such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs) have shown encouraging results in predicting heart disease as well as bone fractures [10]. These mods provide accurate detection and prediction of heart disease by extracting complex patterns from large data sets. Miotto et al. [11] conducted a study that demonstrated the effectiveness of deep learning in predicting disorder outcomes through the use of digital medical records (EHRs). The study verified that by using large-scale information and periodically determining relevant features, deep learning can be more effective than conventional knowledge-based devices. Similarly, Acharya et al [12] used deep CNNs to automatically diagnose cardiovascular disease using ECG indices. They achieved exceptional accuracy and showed how machine learning can be used to predict ischaemic heart disease. Similar studies have been conducted for breast cancer detection [13]. The idea of "Health Fog" is to combine the advantages of Deep Learning, Fog Computing, and the Internet of Things to produce a strong framework for real-time heart disease prediction. The technique uses the idea of deep learning, fog computing and IoT devices to continuously monitor patients' health by pre-processing and verifying indicators locally. Rahmani et al [14] conducted a groundbreaking study in this area using the Fog Computing framework, which integrates data from different devices for local processing and providing results in fitness tracking applications. The study confirmed that Fog Computing can predict diseases with high accuracy, reduce latency and bandwidth consumption. Oussous et al [15] highlighted significant progress in big data technology in the healthcare sector, demonstrating the use of deep learning and fog computing to manage and analyse large volumes of health data produced by Internet of Things (IoT) devices. This paradigm facilitates processing data closer to its source, a concept rooted in fog computing, which serves as an extension of traditional cloud computing. The use of fog computing, reduces the challenges of latency and bandwidth constraints. According to Shi et al [16], this innovative approach not only improves data processing efficiency, but also enables real-time analytics and decision-making, ultimately improving patient care and health outcomes. Similarly, Yazisi et al. [17], conducted a study to compare fog processing with cloud computing in healthcare. They conducted that fog processing reduces latency and increases the efficiency of data analysis. Recently, machine learning and deep learning have been shown to be potential approaches for diagnostic analysis in cardiovascular disease. For example, the accuracy and reliability of these models in medicine was demonstrated by Rajput et al [18], who used deep neural networks (DNNs) to predict cardiovascular disease, demonstrating the complexity of the explanations. Furthermore, it has been shown that when multiple decision trees with different features were combined into a learning strategy - Bagging Classifier; the results improved significantly, as the average effect among learning components reduced over-fitting and generalisation performance increased [19]. Practical examples of the application of the state-of-the-art technologies discussed in this area can be found in the work of [20], among others. Also very interesting is the recent work of Varghese and Buyya [21], which illustrates how to provide high-quality, real-time medical records at lower cost. In addition, real-world applications have confirmed the need for intermediary devices such as Raspberry Pi and Arduino UNO for integration between IoT-Fog [22, 23].

The current paper builds on the findings to up to date [20–23] and proposes:
- the novel architecture for a health fog system that uses the Arduino UNO for IoT connectivity and the Raspberry Pi as the fog node,
- practical use of a bagging classifier to increase predicted accuracy along with an artificial neural network (ANN) model,
- health fog-based system for effective and timely prediction of heart disease using REST API-based data communication that meets immediate requirements to ensure timely and accurate medical care is implemented without delay.

Nowadays, such systems are used not only for health prediction but also for the detection of other threats, for example those related to crime [24]. This is therefore an important area in need of development.

METHODOLOGY

The solution to the posed problem of predicting heart disease in real time requires the adoption of a suitable and efficient architecture. The system based on IoT and Fog Computing must have the appropriate components to realise the full functionality as shown in Figure 1. On the one hand, the hardware part that ensures low latency is important. On the other hand, in order to achieve high prediction accuracy, the algorithms used are crucial. Both of these elements will be discussed in this chapter

Deep learning model

DNN (deep neural network) algorithm usually consists of more than two hidden layers other than the input and output layers. In this work, three hidden layers were decided to be used. The input layer consists of 13 dimensions as the input data contains 13 columns. Examples of heart patient data include: age, chest pain intensity, heart rate, ECG, etc. The output layer consists of a prediction of the binary classification in which a person has or does not have heart disease. To assess the patient's risk of disease, the output also includes the percentage chance associated with the possibility of heart disease. The model is trained by updating the weights of each assumed parameter until their final values are obtained. The dataset is split 80 percent to 20 percent between the teaching and testing data. After training, the model is

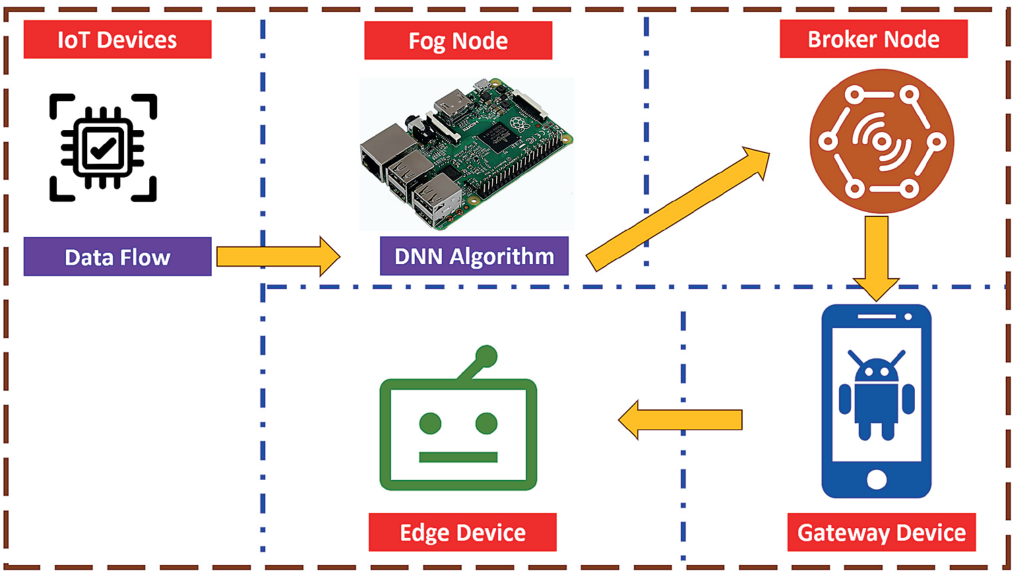

Figure 1. Real time heart disease prediction by DNN model – A schematic representation

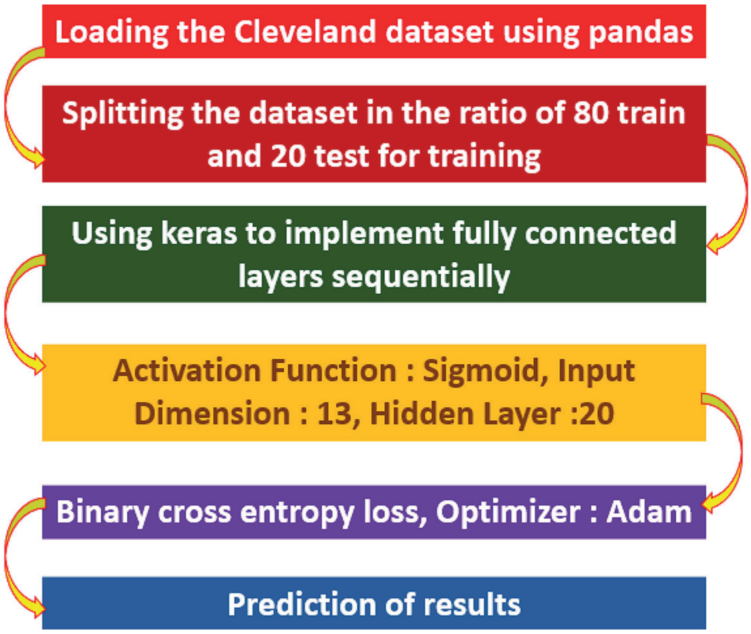

Figure 2. Flowchart of DNN algorithms

extracted as an H5 file and implemented on the raspberry pi. During testing, successive data sets are given as input and the prediction is given as a percentage. The DNN deep learning model is used, the steps of which are shown in Figure 2.

Hardware setup

The predictive heart hardware kit combines a number of parts and sensors to track vital parameters and send information for monitoring. The whole system includes many components like an Arduino UNO microcontroller, a Raspberry Pi module with a Bluetooth module, an electrocardiogram (ECG) sensor. The ECG device usually consists of three electrodes connected by an ECG module (e.g. AD8232). Electrodes are positioned appropriately on the patient's body to record electrical impulses from the heart. The ECG module processes these signals and sends the data to the Arduino UNO. The heart works at a specific beat and the ECG transmits data with an interval between 120 and 200 milliseconds. The heart rate sensor calculates the number of heart beats per minute and transmits it in a similar way. The patient's body temperature is measured using a temperature sensor, which serves as an important indicator of overall health. The oxygen sensor measures the oxygen saturation level of the patient's blood. This measurement is crucial for assessing lung efficiency and overall cardiovascular health. Each of the sensors described is placed on the patient's body and a reading is collected from it (Figure 3).

The Arduino UNO serves as the main wireless interface between the many sensors and the external systems, additionally prepares data for transmission be preprocesing it. The data is then sent via Bluetooth to an Adroid device where there is a corresponding app for predicting cardiac conditions. The application uses sensor data applying models and assumed algorithms to determine target health indicators. The computing node of the fog is the Raspberry Pi. It is responsible for performing complex data processing operations using a deep learning model. In this way, the probability of heart disease is determined by interpreting the data obtained from the broker node. The computing node of the fog is the Raspberry Pi. It is responsible for performing complex data processing operations using a deep learning model. In this way, the probability of heart disease is determined by interpreting the data obtained from the Broker Node. In this hardware configuration, the PC serves as both a broker node and a server. It manages the communication between the Raspberry Pi and the Arduino UNO. Via the REST API, the PC obtains data from the Arduino UNO and sends it to the Raspberry Pi for additional processing.

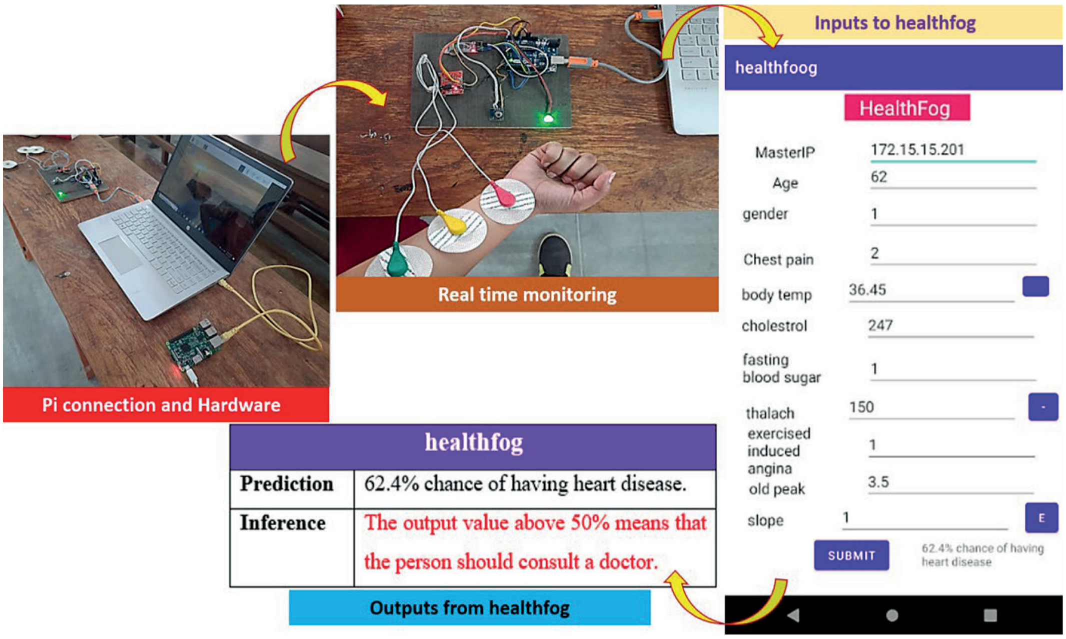

Figure 3. Prediction of heart disease by the hardware module

RESULTS AND DISCUSSION

The code for all the Android UI, Deep learning, Arduino and Rest API are run in various platforms and executed for finding the heart disease prediction (Figure 4). The accuracy from the deep learning is about 87% which is quite higher than the related research papers. The Predicted result is given in percentage of possibility for the user to get Heart Disease (Figure 3). Table 1 gives the execution details of deep learning model with comparison of outputs generated.

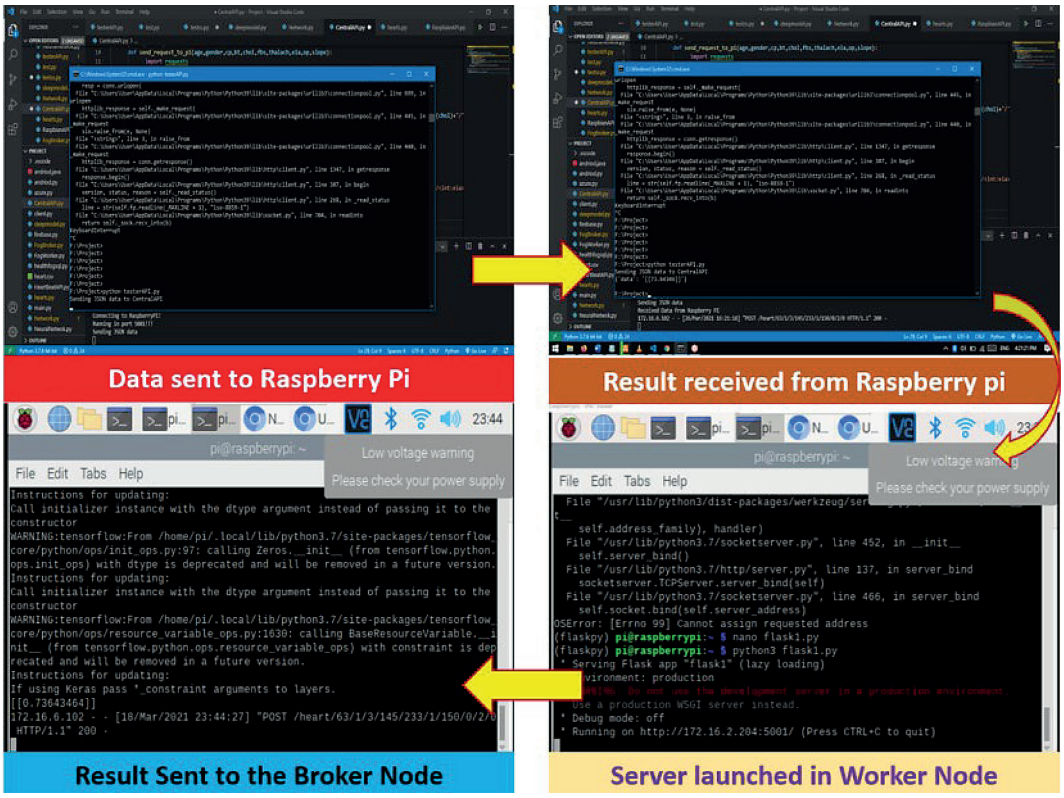

Figure 4. Execution of data by the developed codes

Table 1. Comparing the DL model with various functions

Activation function	Learning rate	Optimizer	Accuracy
sigmoid	0.01	Adam	83.61
sigmoid	0.0001	Adam	86.67
sigmoid	0.03	Adam	81.97
sigmoid	0.02	Adam	85.25
sigmoid	0.02	adagrad	81.97
sigmoid	0.02	RMSProp	80.33
sigmoid	0.001	RMSProp	81.97
sigmoid	0.3	RMSProp	49.18

Figure 5 shows the accuracy of a machine learning model both for training and testing datasets in over 1000 epochs 5). The x-axis represents the number of epochs through the training phase, i.e., iteration over entire dataset. The y-axis represents the accuracy of our model, how good this model can predict outcome accurately. The two lines shown across the graph represent respectively training dataset (blue) and testing datasets (orange). It is not uncommon to see the training accuracy increase during this phase of model as it learns from its training data, followed by plateauing.

The overall increasing graph of training and testing accuracies means the model is getting smarter as well over time. The accuracy first increases rapidly up to 200 epochs. This is to be expected as the model starts understanding underlying patterns in the data. You can see how this training accuracy (blue line) and validation testing fluctuate over epochs. This could happen for a few reasons, like Model overfitting on the training set and thus performance in testing vary largely variance or noise in the testing data. The training accuracy (blue line) is smoother compared to testing but too still volatile.

Around 400 epochs, the training accuracy plateaus and remains relatively stable thereafter; which means the model has learned almost every pattern in its ability from training set. Furthermore, the testing accuracy has stable intervals as well which is still fluctuating showing a concern of generalisation issues. The final accuracy of testing and training is sitting at around 0.8 (80%), showing that though better than random chance, the model still makes an adequate amount of mistakes. The increasing training accuracy indicates that the model is successfully learning from the training set. The range in testing accuracy suggests that either the test data is noisier or maybe could be believes as overfitting. While the training accuracy flattens, the variability in testing accuracy could be addressed by regularization or cross-validation (or more).

Figure 6 illustrates the accuracy scores of three different machine learning algorithms, support vector machine (SVM), random forest, and neural network. In the following chart, algorithms are indicated by along x-axis and accuracy scores on y- axis. The highest score is achieved by a neural network algorithm with an almost 80 accuracy rate. The below encircles the fact that among these 3 methods, Neural Network gives a higher accuracy when it comes to prediction or classification. The accuracy score of Random Forest is slightly less than the Neural Network at around 80. This means that in accuracy Random Forest algorithm is so close to Neural Network.

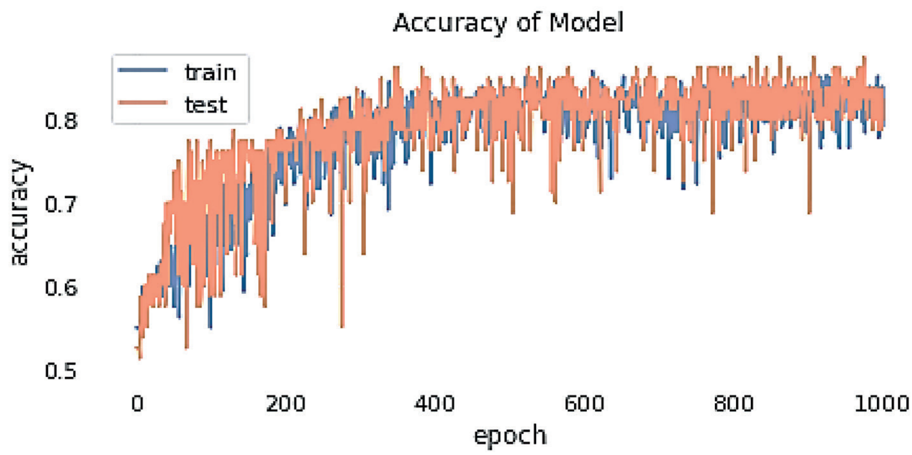

Figure 5. Comparing the training and testing data

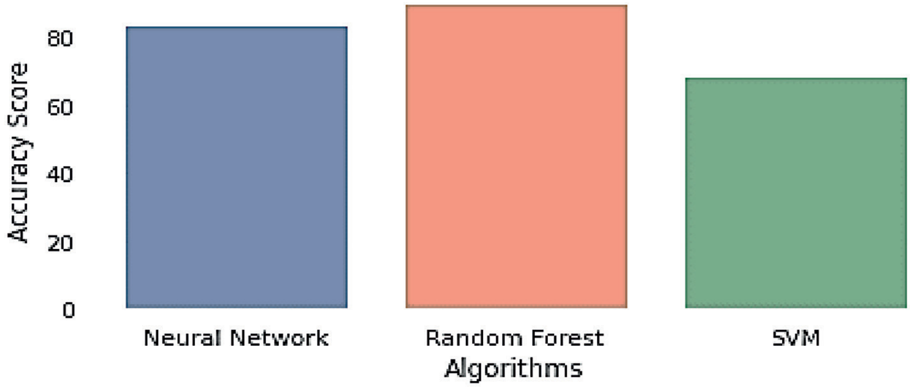

Figure 6. Comparing DNN, Random Forest and SVM

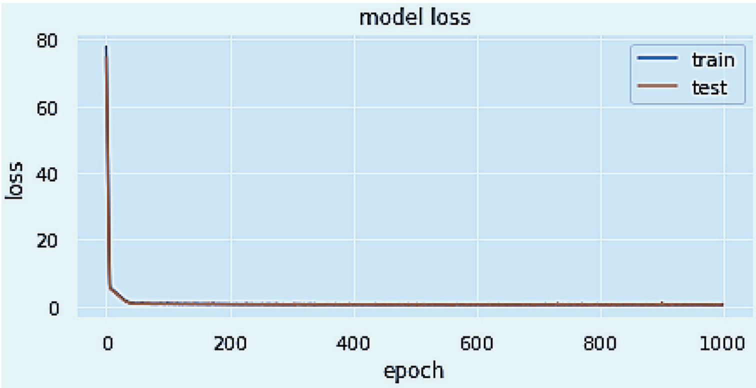

Figure 7. Line graph for training and testing

The SVM algorithm has a slightly over 60 as the lowest accuracy score among them.

The graph (Figure 7) shows that the model was trained successfully. The sudden drop in the values of the loss and its stabilisation afterwards indicates that it is learning well, as there are no signs of overfitting. This is an indicator that the model should consequently have low errors when making predictions on new data. The model learns well in its initial phases of training as evidenced with a significant drop to loss. Since the value of test loss goes linearly with how well it performed on training data, the numbers are low and stable. The low constant loss values of training and test datasets indicate that the model is learning from data as well as generalizing to new/unseen data appropriately.

CONCLUSIONS

In summary, Health Fog shows an efficient solution for heart disease prediction via the synergy between IoT devices and fog computing in tandem with deep learning. Health Fog, meanwhile is reportedly going to reduce latency by having data processed locally and in turn provide much quicker real-time health monitoring & decision making as well as increase the accuracy of predictions through several refined deep learning models. Leveraging these research opportunities, the potential for IoT and fog computing to completely transform healthcare delivery is significant — but more work must be done in terms of scalability (of both the solution itself as well as its provisioning), security enhancements etc., which we plan on continuing through future-oriented collaborations. Their study results indicate that an integration of deep learning and fog computing can be applied to design much more efficient heart disease prediction systems. Health fog is an example showing us how the latest computing paradigms can greatly improve healthcare outcomes with reduced latency and processing data closer to where it originates. It will push the envelope of patient care and optimize resource management in these healthcare institutions.

- health fog: It uses deep learning, fog computing and IoT devices to provide an optimized solution for heart disease prediction,
- reduces latency using the localized data processing and increase predictive accuracy by employing complex deep learning models which helps to improve real time healthcare monitoring & decision making,
- the key research focus in the future is to optimize this framework, e.g. by offering a better security and scalability solution,
- the research results demonstrate that coupling deep learning with fog computing significantly improves the accuracy and efficacy of heart-disease prediction systems,
- by reducing latency and processing data closer to the source, Health Fog illustrates how modern computational paradigms could benefit health outcomes as well as better resource management in healthcare settings.

The following suggestions for the future should be taken into consideration in order to further enhance the creation and use of health fog: Look on ways to extend the Health Fog architecture to accommodate more IoT devices and bigger datasets without sacrificing functionality. Create and put into place strong security measures to safeguard private health information and guarantee system integrity against online attacks. To improve data sharing and decision-making, investigate how to more effectively connect Health Fog with current healthcare systems and electronic health records (EHRs). Deep learning algorithms should be further improved to increase their precision and flexibility for a range of patient types and situations. To reduce fog computing nodes' power consumption and increase the longevity of IoT devices, investigate energy-efficient processing methods.

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