Fog-Driven Heart Attack Prediction from Wearable Edge Devices

Manya K Ravindranathan
Department of Computer Science and Engineering,
National Institute of Technology Puducherry,
Karaikal, India
manya080501[at]gmail.com

Sendil Vadivu D
Department of Computer Science and Engineering,
National Institute of Technology Puducherry,
Karaikal, India
ashasendilvadivu[at]gmail.com

Narendran Rajagopalan
Department of Computer Science and Engineering,
National Institute of Technology Puducherry,
Karaikal, India
narendran[at]nitpy.ac.in

2024 International Conference on Integrated Circuits, Communication, and Computing Systems (ICIC3S) | 979-8-3503-6408-8/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICIC3S61846.2024.10603131

***Abstract*—Cardiovascular diseases, such as heart attacks, are a significant global health concern, responsible for a great deal of annual mortality. The introduction of wearable edge devices with advanced sensors has enabled continuous real-time monitoring of physiological data. This research aims to use fog computing, a decentralized computing approach, to introduce a system for predicting heart attacks based on data from these wearable devices. The system features a custom Deep Learning (DL) model at the fog layer, allowing real-time analysis of health data without relying on centralized cloud processing. The model obtained an accuracy of 90% which is a significant improvement than the traditional models. This work contributes to the field of cloud computing in healthcare, showcasing the potential of fog-based solutions for timely and context-aware heart attack prediction. Successful outcomes could lead to scalable and decentralized healthcare systems, supporting proactive cardiac care and improving overall patient well-being.**

***Index Terms*—Cloud Computing, Fog Computing, Heart Attack, Deep Learning, Edge device**

I. INTRODUCTION

Cardiovascular diseases, including heart attacks, remain a significant cause of illness and mortality on a global scale. An obstruction of the blood supply to a portion of the heart muscle results in a myocardial infarction, often known as a heart attack. Plaque accumulation in the coronary arteries frequently causes this blockage, which deprives the heart tissue of oxygen and nutrients. Based on the "Accidental Deaths & Suicides in India" (ADSI) [1] data from the National Crime Records Bureau (NCRB) up to 2022, in India, the yearly death toll from heart attacks has topped 25,000 for the previous four years and has stayed over 28,000 for the last three.

Human resource shortages are posing significant hurdles to healthcare organizations, impeding their ability to rapidly visit patients during critical moments. Additional factors contributing to delays in patient care are the laborious manual measurement and recording of health markers and the time-consuming data transfer between systems. This inefficiency makes it difficult to deliver interventions on time because it wastes a large amount of important time. It is critical to address these problems, and wearable edge devices with built-in sensors have shown promise as effective means of tracking health. These gadgets provide a steady supply of real-time health data, minimizing the need for human intervention and expediting the procedure as a whole. Crucially, by using the data they gather to forecast heart illnesses, they have the ability to completely transform the healthcare industry. This predictive capacity enables hospitals and individuals to make well-informed decisions, allowing for early intervention and eventually improving health outcomes. In addition, the incorporation of wearable technology highlights the significance of data security and privacy, guaranteeing the protection of private health information at a time when digital health is essential to patient care.

We introduce a resilient and advanced system that utilizes DL techniques for the early prediction of heart attacks. By utilizing wearable edge devices, this innovation makes a substantial contribution to the field of remote health monitoring. By integrating various devices, real-time health data may be continuously collected, providing a comprehensive and dynamic view of an individual's cardiovascular well-being. By leveraging the power of DL, as models get exposed to new data, they can continuously learn and adapt, which enables them to increase in predicting accuracy over time. In dynamic healthcare applications, where underlying patterns and risk factors may vary over time, this is especially advantageous.

The proposed work combines the benefits of fog and cloud computing to enhance the forecast accuracy and streamline the computational processes. Fog computing lowers latency and ensures quick analysis of vital health metrics by extending the cloud paradigm to the network edge, increasing adjacency to the data source. Cloud computing simultaneously offers the infrastructure required for complicated DL model training and reliable, large-scale data storage. Through a smooth integration of fog and cloud computing, the solution not only guarantees data processing efficiency but also tackles issues related to scalability and storage.

We also investigate the works in fog computing and healthcare, highlighting the gaps in existing research conducted on cardiovascular diseases in particular.

This study makes the following significant contributions:

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- Introduction of a wearable edge device and fog computing system for heart attack prediction.
- Employing wearable edge devices to monitor physiological data continuously and in real-time, hence decreasing need on centralized cloud processing.
- Creation of a custom DL model at the fog layer for real-time health data analysis for promoting patient well-being and preventive cardiac treatment.
- Enhancement above conventional models, demonstrating the possibilities of fog-based heart attack prediction systems.

This work is motivated by the pressing need to address cardiovascular diseases. The need for timely monitoring and analysis of health data, compounded by human resource shortages and manual recording of health markers causing delays in patient care, drives the introduction of a novel approach that combines wearable edge devices and fog computing to enable early detection and treatment of heart attacks.

In summary, the primary motive of this research is to introduce a novel approach that enables both individuals and healthcare professionals to detect and treat heart attacks early by utilizing the creative combination of fog computing technologies and wearable edge devices.

II. Literature Review

Previous studies that propose fog computing for healthcare are covered in this section. Fog computing being a relatively new field, especially in healthcare, there is an ongoing exploration of its applications in this area.

Priyadarshini et al. (2018) proposed a fog-based deep neural network-based classifier [2] to predict hypertension levels, diabetes, and stress type classification. They were able to handle heterogeneous and multi-dimensional data from various sources. They used the KMeans clustering algorithm for leveling the data instances and feature selection at fog. The cloud was used only for data storage. However, the model did not handle noisy data and achieved an average accuracy of 80.29% for diabetes over 20 iterations, which is low.

Tanwar et al. (2020) [3] proposed an architecture using Bayesian network classifier and thread protocol for the prediction of arthritis. The use of thread protocol enhanced inter-device connectivity between the smart device and fog gateway, and between the fog system and the cloud for security and reliability. They captured the rotational and translational movements of the patients via smart gloves. The fog system was used to analyze any emergency situation and take apt action, and the cloud to store data from the fog.

Roy et al. (2021) [4] proposed Bilateral-Branch Network (BBN) Framework for the prediction of the outbreak of dengue fever. The demographic data was gathered from the individuals using their mobile phones along with environmental data from sensors. The fog layer was used for classification using BBN and for time-based alert generation. They also used the cloud for data storage and Global Positioning System (GPS) based alert system.

TABLE I
SUMMARY OF RELATED WORKS ON FOG-BASED HEART ATTACK PREDICTION

Sl. No.	Source	Disease Monitored	ML/DL model	Data/Dataset	Enhacements(+)/ Limitations(-)
1	[6]	Cardiac Arrhythmia	One dimensional Convolutional Neural Network (CNN)	Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) dataset	(+) Used only 2 1-D convolutional layers, Accuracy = 99.46%; (-) No feature selection
2	[7]	Diabetes, Cardio	Artificial Neural Network (ANN) and Fuzzy Logic (Adaptive Neuro-Fuzzy Inference System)	diabetes and heart disease dataset	(+) Use of blockchain for semi-centralization & secure storage; (-) Purity values for diabetes & heart disease are low (77% & 81%)
3	[8]	Heart disease, Diabetes, Blood pressure	Bidirectional Long Short-Term Memory (LSTM)	PIMA Indians dataset, MIMIC II (Medical Information Mart for Intensive Care) dataset	(+) Accuracy = Diabetes: 92% and Heart disease = 94%; (-) Resource allocation time increases with number of edge devices, Power consumption increases with increase in number of worker nodes
4	[9]	Heart disease	Hybrid neural network	Cardiovascular disease dataset by Kaggle	(+) Data cleaning, Alert generation, Backscatter & Active communication used for data transfer; (-) Diagnosis rate = 67.18%, Does not concentrate on the classification in cardiovascular disease
5	[10]	Heart disease	ANN, Naive Bayes (NB), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest (RF)	Data sources such as Cleveland Clinic Foundation, Long Beach, Hungarian Institute Zurich, Switzerland University Hospital Basel, and Statlog	(+) Data pre-processing (missing values replacement, data normalization), Data encoding; (-) No hyperparameter tuning, No feature selection
6	[11]	Heart attack	Deep Neural Network (DNN)	Dataset for heart disease from UCI Machine Learning Datasets Repository	(+) Higher performance metrics than KNN, Decision Tree (DT), RF; (-) No data pre-processing, No processing to avoid overfitting

Devarajan et al. (2021) [5] proposed the use of the J48Graft classifier to predict the level of danger of diabetes in individuals. They captured the patients' data using sensors along with environmental and location-related data. The fog layer was used to perform encryption, feature selection, and classification. The cloud was used for data storage, patient information sharing with authorized individuals, and apt recommendations. However, the J48Graft classifier can exhibit a bias towards dominant classes in imbalanced datasets.

Table I provides a list of research papers that have developed cardiovascular disease prediction models in fog computing. Additionally, it describes the datasets used and the models (Machine Learning (ML) or DL) introduced by the respective authors. It also includes the enhancements and the limitations of each work.

Cheikhrouhou et al. (2021) used a network of 2 1-D convolutional layers to analyze Electrocardiogram (ECG) dataset for monitoring of cardiac arrhythmia patients [6]. The architecture introduced provided data storage, pre-processing, and decision-making at the fog, and information sharing and model training at the cloud layer.

Shynu et al. (2021) developed a secure application for the prediction of diabetes and cardio diseases [7] with the help of a blockchain network. The fog nodes were enhanced with blockchain property to ensure safe data storage and transfer. The authors used Fuzzy Logic (Adaptive Neuro-Fuzzy Inference System) for disease prediction.

Javaid et al. (2021) classified heart disease, diabetes, and blood pressure using a Bi-LSTM model [8]. They used the PureEdgeSim framework to deploy the model and also used public cloud services such as Amazon Web Services (AWS) and Microsoft Azure.

Liu et al. (2022) [9] introduced a medical system for the purpose of diagnosing heart disease. The authors implemented data processing, anomaly detection, and alert generation along with a neural network with shallow depth at the fog layer, while the cloud with the deep neural network was used for storage and decision-making. The combination of backscatter and active communication was used for data transmission for enhancement of reliability and stability.

Chakraborty et al. (2022) [10] proposed ML algorithms such as NB, KNN, SVM, RF, and ANN employed at the fog layer for predicting heart disease. The authors collected patient data from IoMT medical sensors along with their demographics. The predicted data from the fog layer was sent to the user and also to the cloud storage for further use.

Xhaferra et al. (2022) introduced a DNN model for predicting heart attack at the fog layer [11]. The database module was introduced at the fog layer for the extraction of information from raw data. The authors were able to achieve higher accuracy than supervised ML approaches of KNN, DT, and RF.

III. Materials and Methodology

A. Dataset

The dataset used for training the model is the Heart Disease dataset (Cleveland) available at UCI MACHINE LEARNING [12]. The dataset contains 14 features and 303 data records, including age, sex, old peak, chest pain type, blood pressure, cholesterol, etc.

B. Proposed Workflow

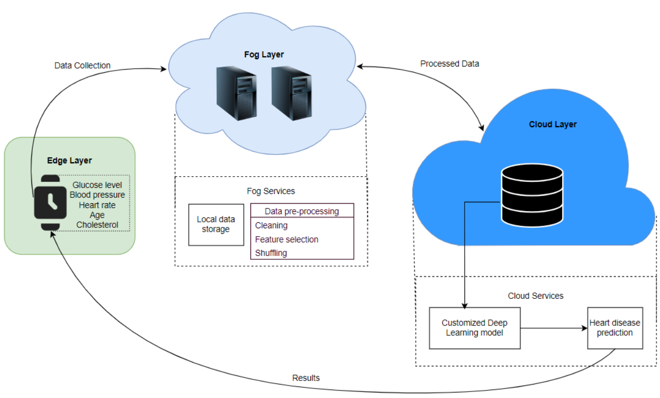

Fig. 1. Proposed Workflow

Fig. 1 shows the workflow for the heart disease prediction. A customized DL model for heart disease prediction is trained and stored at the cloud layer. It is trained with the data from patients who have heart disease and do not have the disease. This model is also stored at the fog layer. The fog nodes update their cached model regularly. At the edge layer, the smartwatch obtains important information from the users such as glucose level, blood pressure, heart rate, cholesterol level, and more, and sends it to the fog nodes. This data is stored and used for early prediction of heart disease by the model. Also, the patient data is transferred to the cloud layer for long-term storage, and for improving the model by re-training it using the newly arrived data.

C. Physical topology

The physical topology is simulated on iFogSim simulator. It is a fog environment simulator that models and simulates different IoT devices, fog nodes, and cloud servers using the Java programming language [13]. The iFogSim application logic has been enhanced with a Graphical User Interface (GUI) to allow for the description of the physical network architecture. Through the GUI, users have the ability to sketch various physical components including actuators, sensors, fog devices, and connections. These drawn configurations can be saved and loaded by transforming them into JSON file format. Additionally, physical topologies can be programmatically generated using Java APIs, alongside GUI-based creation.

The suggested fog-based design includes several devices, including sensors in smartwatches, fog nodes, a proxy server, and a cloud server. In the proposed architecture, the users with smartwatches are widely distributed in different geographical areas. The fog nodes are placed close to them. These fog nodes communicate with the proxy server in between before reaching the cloud server for any update in the stored prediction model.

Fig. 2 shows the physical topology analyzed in iFogSim tool.

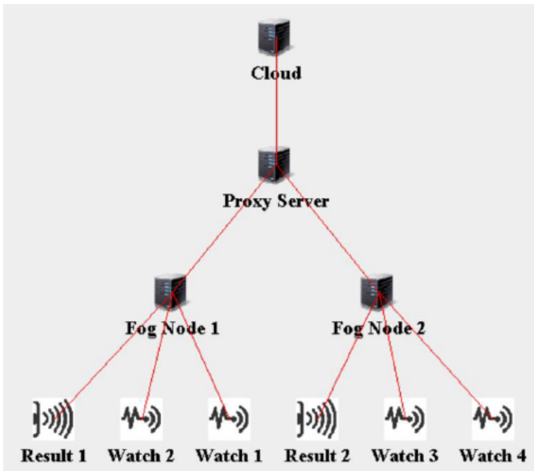

Fig. 2. Physical Topology

The fog, proxy, and cloud server setup parameters [14] that were set during the iFogSim simulation are shown in Table II.

TABLE II
VALUE OF CONFIGURATION PARAMETERS OF CLOUD, PROXY, AND FOG

Parameter	Cloud	Proxy	Fog
RAM (MB)	40000	4000	4000
CPU length (MIPS)	44800	2800	2800
Level	0	1	2
Uplink bandwidth (MB)	100	10000	10000
Downlink bandwidth (MB)	10000	10000	10000
RatePerMIPS	0.01	0	0
Idle power (Watt)	1332	83.4333	83.4333
Busy power (Watt)	1648	107.339	107.339

D. DL Model Implementation

A neural network-based approach is used for the detection of heart disease after suitable data pre-processing. The missing and unknown values are cleaned and the data is standardized. The data is then fed into a dense layer of 128 units, fully connected, with ReLU activation. Following that is a dropout layer, which helps to avoid overfitting by arbitrarily deactivating some input units to zero during the process of training. Before sending the data to the subsequent LSTM layer, which expects input data in the shape of (sequence_length, features), the data is re-shaped. Then again, a dense layer and a dropout layer are added, before finally adding the output layer.

Fig. 3 shows the model summary.

```
Layer (type)                Output Shape              Param #
=================================================================
dense (Dense)               (None, 128)               1792

dropout (Dropout)           (None, 128)               0

reshape (Reshape)           (None, 128, 1)            0

lstm (LSTM)                 (None, 64)                16896

dense_1 (Dense)             (None, 32)                2080

dropout_1 (Dropout)         (None, 32)                0

dense_2 (Dense)             (None, 1)                 33

=================================================================
Total params: 20801 (81.25 KB)
Trainable params: 20801 (81.25 KB)
Non-trainable params: 0 (0.00 Byte)
```

Fig. 3. DL model summary

IV. RESULTS

A. Evaluation in iFogSim

The comparison between the scenarios with and without the fog layer in iFogSim reveals significant advantages in favor of incorporating fog computing. In the fog-based scenario, the latency between layers is notably reduced to 3.92 ms compared to a substantially higher latency of 105.25 ms in the absence of fog nodes. Additionally, the network usage in the fog-enabled environment is considerably lower, standing at 11039.92 KB, as opposed to the markedly higher network bandwidth usage of 166345.96 KB without fog. These findings underscore the efficiency and performance benefits of deploying fog computing, as it effectively minimizes latency and optimizes network resources. Therefore, the utilization of fog computing emerges as a superior choice, demonstrating its capacity to enhance system responsiveness and resource utilization, making it a compelling solution for improved overall performance.

B. Performance of the DL model

The proposed heart attack prediction model was evaluated using a dataset collected from wearable edge devices. The model gave an overall accuracy of 90%. To benchmark the performance of the suggested model, we contrasted it to traditional cutting-edge models based on precision, recall and f1-score, as per the findings of Cina et al., 2022, as shown in Fig. 4. The KNN model achieved 79% accuracy, the RF model also achieved 79% accuracy, and the DT model attained an accuracy of 80% [11].

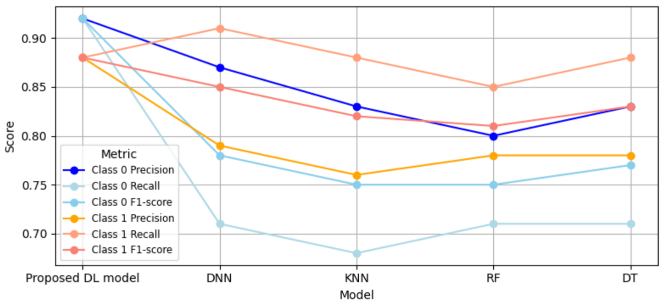

Fig. 4. Comparison of Models by Classification Metrics

V. CONCLUSION

This research proposed a robust system that predicts heart attacks using DL techniques through wearable edge devices while leveraging the abilities of fog and cloud computing. The comparative analysis of scenarios with and without the fog layer in iFogSim underscores the substantial advantages associated with the integration of fog computing. These findings distinctly highlight the efficiency and performance benefits inherent in the deployment of fog computing, as it not only minimizes latency but also optimizes network resources. Consequently, the adoption of fog computing emerges as a superior choice, demonstrating its capacity to enhance system responsiveness and resource utilization. This substantiates its position as a compelling solution for achieving improved overall performance in distributed computing environments. The DNN model was contrasted with various cutting-edge techniques and models from other research publications in order to assess the suggested architecture. According to the result metrics, the proposed model works better than traditional methods and offers a 90% classification accuracy for patients at risk of suffering a heart attack. The superior accuracy exhibited by our model underscores its effectiveness in reliably predicting the danger of heart attacks, positioning it as a cutting-edge solution in the realm of cardiovascular health. The envisioned framework has the potential to extend its applicability to real-world settings, such as hospitals or clinics that use IoT and fog computing to provide healthcare services.

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