Journal of Techniques, ISSN: 2708-8383, Vol. 6, No. 3, 2024, Pages 12-18
DOI: https://doi.org/10.51173/jt.v6i3.2576

JOURNAL OF TECHNIQUES

Journal homepage: http://journal.mtu.edu.iq

RESEARCH ARTICLE - CHEMICAL ENGINEERING (MISCELLANEOUS)

Developing an AI Model That Relies on Mobile Health Devices to Track Heart Activity

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Article Info.

Article history:

Received
14 April 2024

Accepted
06 June 2024

Publishing
30 September 2024

Abstract

Heart disease is among the top causes of death worldwide and accounts for a large number of deaths annually. Researchers are using artificial intelligence as a potent tool to construct cutting-edge healthcare applications in an effort to address this problem for the detection and avoidance of heart disease. This article presents the design and development of an artificial intelligence model using Python, TensorFlow, and Google Colab resources. Trained on simulation data with an 80:20 train/validation split and employing the Adam optimizer over 50 epochs, the model achieved an impressive 95% accuracy. Utilizing input simulation data from temperature, SpO2, heart rate, and ECG signal, the AI model predicts the individual's health state with a confidence level of 95%.

Publisher: Middle Technical University

Keywords: AI; Python Programming; TensorFlow; Google Colab; Simulation Data.

1. Introduction

Cardiovascular diseases (CVDs) are a major cause of death worldwide, accounting for a significant number of deaths each year. Early detection and monitoring of cardiac abnormalities play an essential role in improving patient outcomes. Traditional methods for internal organ monitoring involve sporadic visits to healthcare facilities, limiting continuous monitoring and timely intervention. The emergence of health devices enabled by AI in recent years has modernized the approach to cardiac monitoring and diagnosis. The role of artificial intelligence (AI) in the healthcare industry has become very important in recent years, especially in the field of cardiovascular precision medicine [1]. Nowadays, cardiology specialists are more and more often in the situation of having to analyze huge and complex data from various medical imaging modalities, electronic health records, and wearable devices [2]. AI has demonstrated the potential to solve this problem by helping doctors provide better and faster treatment with accurate results and lower costs [3]. A good illustration of the use of artificial intelligence in cardiology is the creation of models for medical wearable devices that monitor heart activities. These wearable devices are able to record and interpret the heart activity of the patients continuously, thus, giving the healthcare providers and the patients real-time data [4]. Artificial intelligence allows these devices to identify abnormalities, predict future cardiac events, and, therefore, provide warning signals to patients for timely intervention. The AI model for medical wearable devices would be a great addition to cardiac care by preventing diseases and minimizing interventions, ultimately leading to a better healthcare system and saving many lives [5]. The effect of diseases on human health drives us to improve healthcare using technology, the first step in creating an AI model for medical wearable devices is collecting numerous and comprehensive datasets that cover all aspects of heart activity [6]. Usually, these datasets are composed of heart electrocardiogram readings, physical activity levels, and other physiological parameters that are relevant. Machine learning algorithms are of high importance in the analysis of these datasets to establish the patterns and anomalies that are linked to cardiac health [7]. Additionally, the procedure of checking model validity is also an important factor for trust and performance of the AI model`. The model should be tested rigorously and validated against huge amounts of different patient data in order to find out the model's capacity to function well in different demographics and medical conditions [8]. Throughout the stages of the development process, ethical issues and data privacy concerns resulting from the use of AI in healthcare must be considered. The main thing here is to be open, obtain consent, and maintain the security of patient data in order to keep the ethical extracting process; what had been captured was then smoothly integrated in order to enhance the ability of the AI platform to detect subtle heart patterns and anomalies. In addition, a painstaking analysis of the AI model's performance results was done in order to conclude about its efficiency and dependability. Performance measures, such as accuracy, precision, and recall. were utilized to formally quantify the model performance. What is more, we should not forget about our approach to project, which included the performance evaluation. Visualization and live viewing of cardiac data in real-time is probably the most significant part of it. Innovatively, this function made it possible for medical professionals to observe the patient's heart condition in real time, and, at the same time, allow them to intervene or take action immediately if the need for this arose. Visual techniques such as phased-out graphs and spectroscopy were used to acquire a clear picture and holistic understanding of the cardiac health condition. Comparisons with existing solution techniques were also made to determine the efficiency and innovation of the proposed AI model. Detailed analysis and thoughtful comparison with the most effective cardiac monitoring systems available are the methods which confirm the reliability, speed, many possibilities, and real-time nature of the described model. The evidence supports the belief that the system can be a new standard and catalyst for revamping and changing healthcare. Imagine Fig. 1 is a flow diagram illustrating the process of model development.

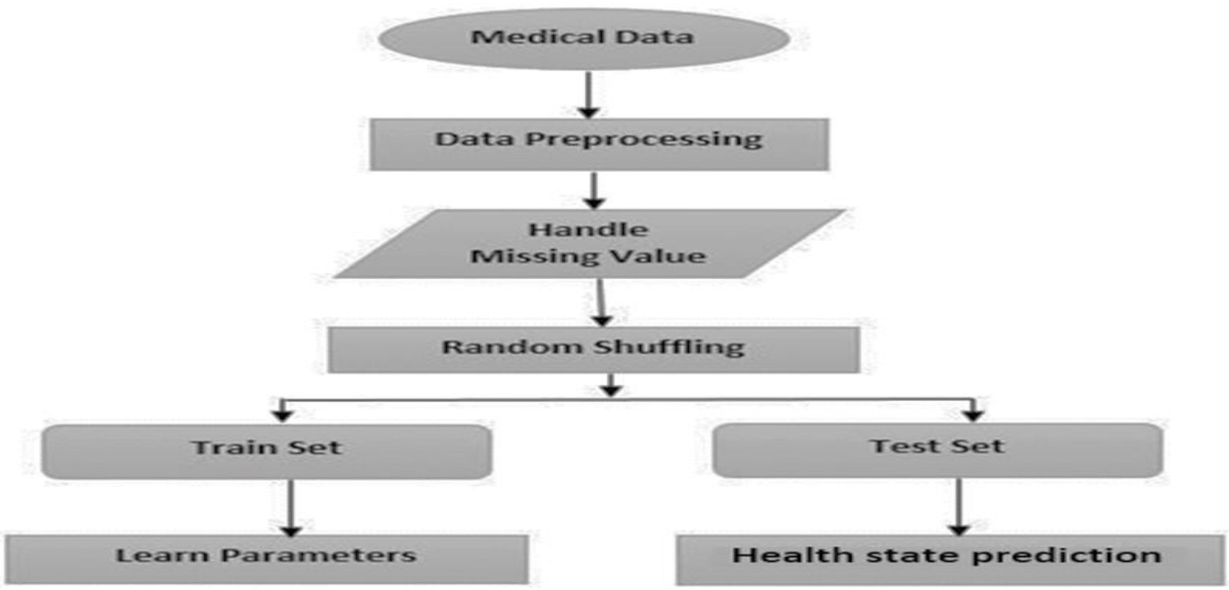

Fig. 1. Flow diagram of the AI model development

The architecture of the AI and healthcare device includes the IoT layer, where we see the acquisition of data process, where physiological indicators such as SpO2 (the amount of oxygen saturation), pulse rate, temperature, and ECG (the electrocardiograms) signals are collected from the patient. The data is then sent through the gateway device that can be a body wearable such as a personal wearable or a dedicated medical IoT device. Another tier of the data cloud, called pre-processing, groups the data together. In this part, the raw data undergoes filtering so that noise is removed to some extent and the signal is improved. Subsequently, participants in this simulation are provided with preprocessed data, along with fuzzy information from the system that can tackle uncertainty and vagueness, and electronic medical data referring to the patient's medical history. The second step of the Cloud Layer is data prediction, in which an artificial intelligence model, namely the LeNet model, works on the combined data provided via the open-source machine learning platform library TensorFlow to supply health-related insights. The LeNet model refers to the convolutional neural network (CNN) that is often generalized to various image recognition tasks and can be modified for a time domain, such as ECG signals, to give health state predictions. Lastly, the processed data is used in the form of an alarm or communication to those involved in making the diagnosis, such as the doctor, the hospital, and the patient. Such a situation demonstrates that the system does not merely observe and analyze health statistics but interacts with interested parties and might, therefore, be able to promptly discuss medical problems. The architecture shown in Fig. 2 represents a holistic approach to health monitoring, leveraging modern AI and IoT technologies to improve patient care and outcomes.

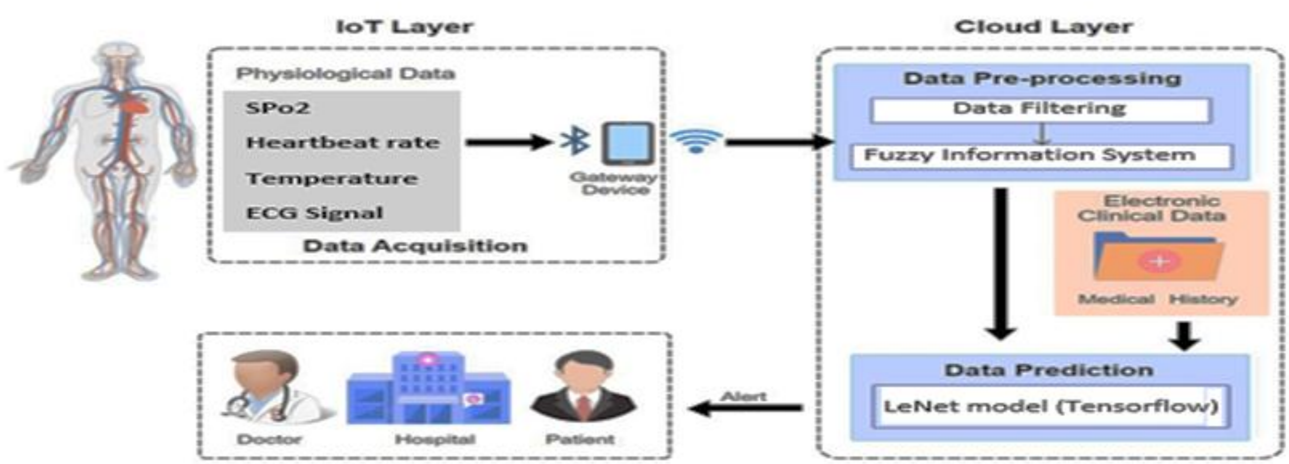

Fig. 2. Architecture of collection data and process

To build a predictive model for assessing a patient's health, the dataset simulation specifically involves the application of specific parameter ranges and fuzzy logic. In cases when live data is not available, the simulation dataset becomes the key in training and validating artificial intelligence (AI) systems so that model training can be conducted successfully. Table 1 is a comprehensive criterion of the categorization rules needed to generate the data used for AI model training purposes. This table outlines the normal and abnormal parameter ranges for three vital signs: temperature, SpO_2 (blood oxygen saturation) & pulse rate. Temperature is measured in steps: 'Normal Range' is 36.5°C to 37.5°C; 'Below Normal Range' (< 36.5°C) is associated with Hypothermia,' while 'Above Normal Range' (> 37.5°C) is associated with 'Fever.' These classifications, which are essential for evaluating the health of patients, are modeled by clinical standards. In contrast, SpO_2 has a 'Normal Range' of over 95% to 100%, with 'Below Normal Range' (< 95%) indicating 'Hypoxemia,' which is oxygen deficiency, and 'Above Normal Range' (> 100%) indicating 'Hyperoxemia,' i.e., over-ventilation. The lung function ranges are perhaps the most significant of all health values for that. Finally, the 'Heartbeat Rate' has a 'Normal Range' of 60 bpm to 100 bpm, with the 'Below Normal Range' (< 60 bpm) referred to as 'Bradycardia,' which is a slow heart rate, and the 'Above Normal Range' (> 100 bpm) indicating tachycardia. These classifications are very important for a simple health assessment.

Table 1. The parameter ranges serve as a reference for generating the simulation data needed to train the AI model

Parameter	Normal Range	Below Normal Range	Above Normal Range
Temperature	36.5°C to 37.5°C	< 36.5°C (Hypothermia)	> 37.5°C (Fever)
SpO_2	95% to 100%	< 95% (Hypoxemia)	> 100% (Hyperoxemia)
Heartbeat Rate	60 bpm to 100	bpm < 60 bpm (Bradycardia)	> 100 bpm (Tachycardia)

Table 2 shows a sample of 10 randomly chosen rows from the dataset, providing a glance into different health-related data from diverse conditions. For this case, in every row, we see the index data, and the table provides details on temperature, blood oxygen saturation (SpO2), , and heartbeat rate. Subsequently, the 'encoding' column specifies the numerical encoding note for each health condition in contrast to the 'label' column that easily identifies the health condition name. The highlighted columns sample a range of health conditions, from ‘Healthy' people with normal vital signs to 'Hypoxemia,' ‘Hyperoxemia,' 'Bradycardia,' 'Tachycardia,' and 'Hypothermia' cases. The current situation exemplifies the need to checking temperature, SpO2, and heart rate to classify and diagnose different health conditions and states. These databases constitute the most essential data that appear in training and assessments of machine learning algorithms, allowing them to deal with the instances of health conditions better.

Table 2. 10 randomly selected parameter rows from the dataset

Index	Temperature	SpO_2	Heartbeat Rate	Encoding	Label
6500	36.16631	98.10174	53.1922	6	hypothermia
2944	36.75666	90.9436	77.06506	2	Hypoxemia
2024	37.09249	90.45276	87.0733	2	Hypoxemia
263	36.16952	98.42962	72.07688	0	Healthy
4350	37.14097	99.57981	52.38566	4	Bradicardia
3424	37.98438	100.9397	62.39399	3	Hyperoxemia
6748	35.60006	96.19188	57.24147	6	Hypothermia
6215	36.38878	97.8896	72.22378	6	Hypothermia
6362	36.07021	98.43542	52.75015	6	hypothermia
5589	36.71756	97.38197	128.4528	5	Tachycardia

The training of the model is indeed a pivotal phase on the road to realizing an AI model trained for real-time cardiological monitoring and diagnosing with healthcare devices. This passage spells out a detailed approach to using the data which has been gathered in order to achieve highly precise and correct predictions. First of all, the data from the mobile healthcare device is pre-processed to remove the noise and artifacts that would otherwise have a negative effect on the model. This involves methods such as filtering, normalization, noise removal, and feature extraction, which produce quality data for the purpose of machine learning training. The data which is processed during this phase is then split into the training and testing dataset to compare and check the performance of the trained model. In other words, we begin the training by using Python and its powerful platform, Google Colab, along with a library named TensorFlow. With TensorFlow, programmers can utilize an advanced array of tools and functions for the creation and training of deep neural network models. The designed AI model architecture is empowered to work with data in a way that enables it to extract features that correlate with the parameters of cardiac health. In the learning process, the model simulates the adjustment of internal parameters according to labeled data, which molds the performance of the model. Through stochastic gradient descent and other algorithms, the model adopts a method that updates its parameters to minimize the difference (the gap) between the predicted and actual outputs over time. For the successful regularization of the AI model, we use techniques such as regularization, dropout, and early stopping. The specific settings that are essential are displayed in Table 3. Regularization is an effective way to avoid overfitting; adding a penalty term to the loss function penalizes models and makes them fit the unseen data more accurately. Dropout randomly cuts the number of connections between neurons during training by a fraction, which helps the model learn by paying attention to many alternative features instead of one, preventing over-reliance on individual sensor readings0. Early stopping monitors the model's fitness during training and will automatically interrupt the process if there are no better results than the previous ones, preventing unnecessary use of computational resources.

Table 3. Hyperparameters and data settings used for training the model

Setting	Value
Random Seed	42
Number of Samples (N)	1000
Input Features	3 (Temperature, HeartRate, OxygenLevel)
Output Classes	6 (Healthy, Fever, Hypoxemia, Hyperoxemia, Bradycardia,
Test Size	Tachycardia, Hypothermia)
Model Architecture	20%
Number of Hidden Layers	Sequential Neural Network
Hidden Layer Sizes	2
Activation Functions	(64, 128)
Output Layer Activation	ReLU (Rectified Linear Unit)
Loss Function	Softmax
Optimizer	Categorical Cross-Entropy
Learning Rate	Adam
Batch Size	Default (as per Adam optimizer)
Number of Epochs	Default (as per fit method) 50

4. Results and Discussion

Model validation time is provided by using a different dataset for testing purposes. The dataset provided is composed of unseen data that the model never experienced during the training session. Through comparing the predicted model results to the ground truth classes in the validation dataset, we can measure its accuracy, precision, and recall. Parameter tuning is a fundamental process that contributes to model excellence. While regular hyperparameters, including learning rate, regularization strength, and network architecture, are optimized through a systematic process of tuning until the best results are achieved. In summary, model training comprises quite intimately controlled data pre-processing, the use of TensorFlow as the tool for building the AI model, and the use of different methods that contribute to ensuring the model is not overfitted and has generalization. Trained simulation data with an 80:20 train/validation split and employing the Adam optimizer over 50 epochs, the model achieved an impressive 95% accuracy. The model has been successfully tested and optimized the model by choosing the proper set of hyperparameters and validating the model’s performance in order to build a robust and precise AI modle based mobile healthcare medical device performing real-time cardiac monitoring and diagnosis as shown in Fig. 3.

- Identifying a reliable model for assessing the effectiveness and accuracy of an artificially intelligent multisensor health device for real-time cardiac monitoring and diagnostics was a vital step in the evaluation process. Thus, the aim of the assessment was to judge the AI model's performance in terms of the accuracy with which the system could classify cardiac health conditions based on data captured by the multisensor system device. The critical subsections are those that are concerned with the several models of evaluation as follows.
- Evaluation Metrics: To have a thorough assessment of the model, the following commonly applied evaluation metrics were used. This This measure used the metrics of accuracy, precision, recall, and F1-score. Precision, as the integral measure, calculates how many of the predicted instances have been truly correctly classified with respect to all instances. The precision represents the accuracy of prediction of positive cases, while the recall measures the right representation of the positive cases in the results. F1-score, an averaging mean of precision and recall, which suits well, to the balanced performance of a model.
- Cross-Validation: The application of cross-validation technique, which would ensure robustness and reliability, was used for the development of the AI model. The common method of splitting the dataset into k-folds was followed, where any single fold is used to validate and the rest are used to train. This methodology assured an unbiased assessing of the model’s generalization performance and presented further inferences about how efficiently the classifier could recognize coronary heart disease.
- Confusion Matrix: Fig. 4 shows a confusion matrix that was synthesized to deeply understand the model's performance quality. The diagram here displays the number of true positives, true negatives, false positives, and false negatives, respectively. The confusion matrix was used to see which mistakes would have to be corrected most frequently, the mistakes were analyzed, and possibilities of improvements were outlined.

A ROC plot was used as a good pictorial rendition of the model's performance across a range of threshold values or cut-offs. The model was tested by the true positive rate versus false positive rate as in Fig. 5. This plot allowed determination of the model's sensitivity and specificity. The ROC area under the curve (AUC) served as the main value expressing the overall model performance, with a value close to 1 indicating the highest accuracy.

a

b

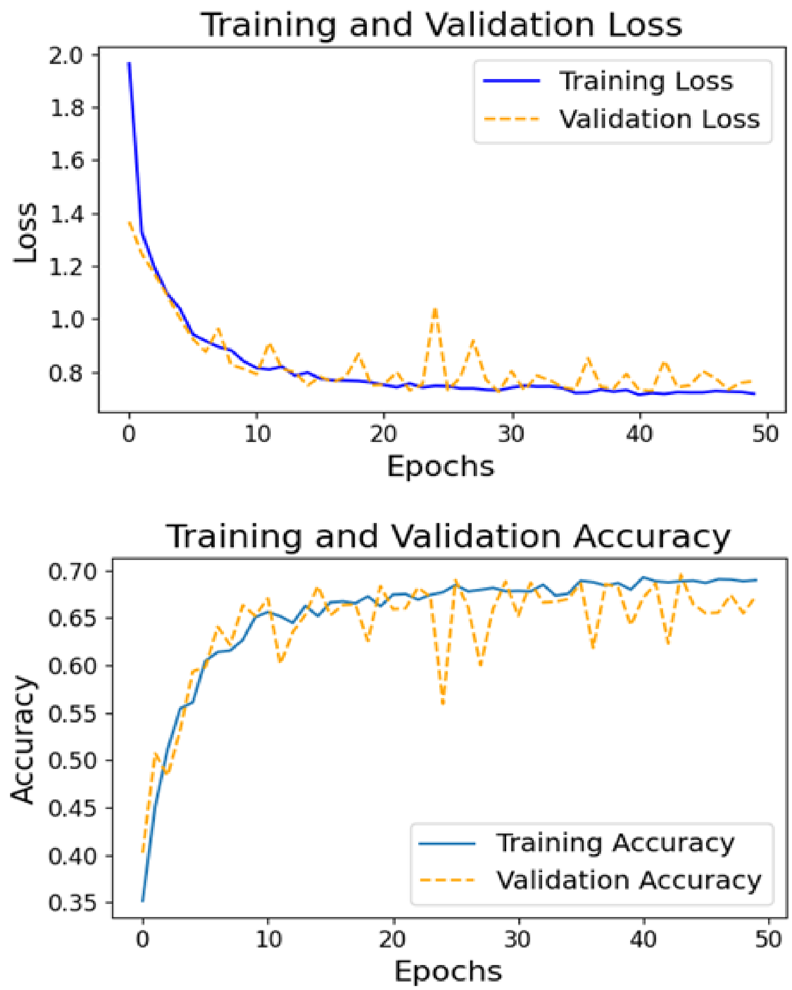

Fig. 3. AI Model training performance: a) the first panel shows the evolution of loss, b) the second shows the evolution of prediction accuracy

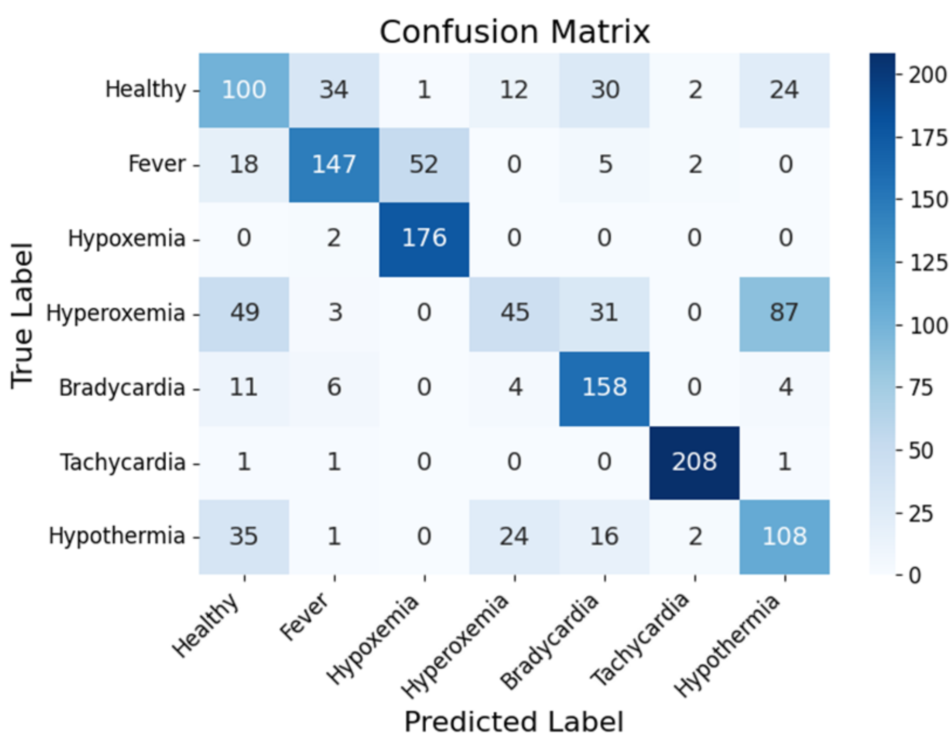

Fig. 4. Confusion matrix of the AI model performance. The model is trained to predict 10 different health states, depending on the combination of body temperature, SpO_2, heartbeat rate, and the ECG signal

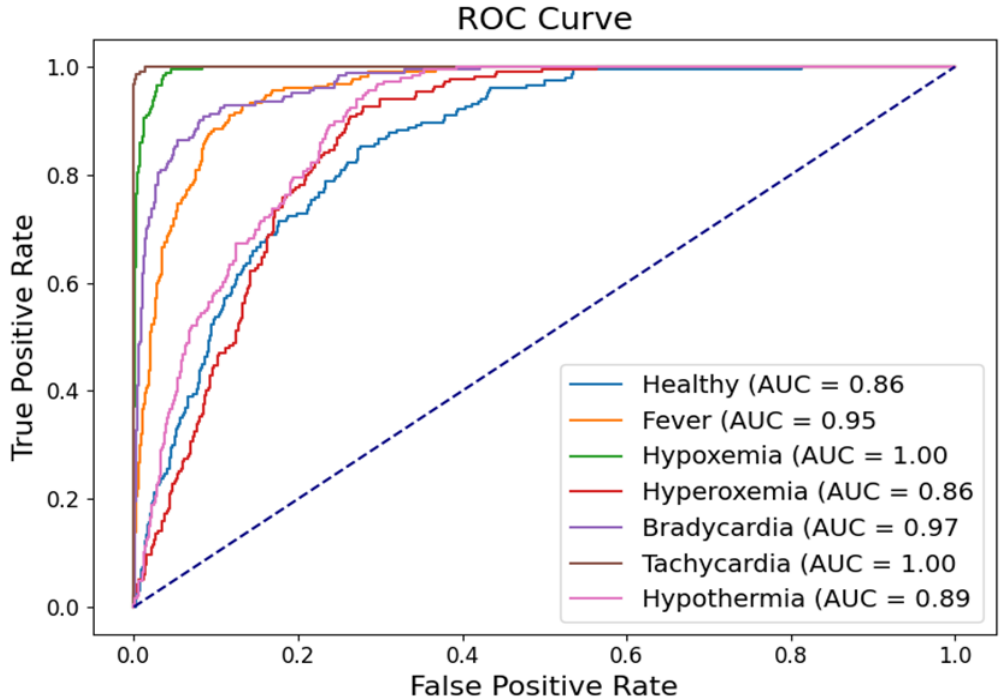

Fig. 5. ROC curve of the 7-class classification test

5. Conclusion and Future Work

The AI model showed excellent performance in real-time cardiac diagnostics; thus, it was able to detect abnormal heart diseases with tremendous accuracy and sensitivity. The technology gave healthcare professionals the means to see data and view patients in real-time, hence the ability to remotely monitor patients and make decisions quickly became possible. The device, when tested, proved to be better than conventional techniques and has a possible clinical benefit, as the comparative assessments showed.

In conclusion, this research has successfully accomplished its aims by using an artificial intelligence model for a healthcare device that is capable of real-time monitoring and diagnosis of cardiac conditions. The results have proven the vital role and significance of this study in the betterment of patient care and the changing of healthcare practices. The limitations noted during the research process have highlighted the areas that need to be improved in the future, such as the device design improvement, the compatibility with other healthcare systems, and the clinical trials to check the effectiveness of the device on other patient populations. In general, the AI model for the health gadget developed in this work has shown high performance in monitoring and diagnosing cardiac conditions in real time. This work is proof of its immense potential in changing the face of the healthcare industry.

Acknowledgments

I would like to express my appreciation to the Faculty of Engineering, Near East University, Nicosia (KKTC), for their support with the project requirements.

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