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RESEARCH ARTICLE - BIOMEDICAL ENGINEERING

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

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Abstract

Heart disease lies 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 son 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 data sumlation data from temperature, SpO_2, heart rate and ECG signal the AI model predicts the individual's health state with a confidence level of 95%.

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

1. Introduction

Cardiovascular diseases (CVDs) are a branch of knowledge reason of deathrate world, accounting for a significant list of deaths apiece year. Early reception and observation of cardiac abnormalities play a of the essence persona in improving patients' condition outcomes. Traditional methods for internal organ watching come from sporadic visits to healthcare facilities, restricting period monitoring, and timely intervention. The emergence of health devices enabled by AI in recent years has modernized the route cardiac monitoring and diagnosis are approached. 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, the cardiology specialists are more and more often in the situation of having to analyze the huge and complex data from the various medical imaging modalities, electronic health records, and wearable devices [2]. AI has shown itself the possibility of solving this problem by helping doctors to give patients 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 health care providers and the patients the real time data [4]. Artificial intelligence allows these devices to identify the abnormalities, predict the future cardiac events and, therefore, provide the warning signals to the patients for timely intervention. The AI model for the medical wearable devices would be a great addition to cardiac care by the means of preventing the diseases and thus causing the minimum interventions that would be very personal and would eventually lead to the better healthcare system and the saving of many lives [5]. The Effect of Diseases on Human Health Making us improve healthcare using technology, The first step in creating an AI model for medical wearable devices is the collection of numerous and complete datasets that cover all the heart activity aspects [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]. Besides, the procedure of checking the model validity is also an important factor for the trust and the 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, it is a must that the ethical issues and data privacy concerns are taken into account that are the result of the use of AI in healthcare. The main thing here is to be open, obtain consent, and maintain the security of patient data in order to keep the ethical standards and build up trust in AI-powered medical devices [9]. This invention has a great chance of being the

Nomenclature & Symbols			
AI	Artificial Intelligence	ECG	The Electrocardiograms
AUC	Area Under the Curve	N	Number of Samples
CNN	Convolutional Neural Network	SpO_2	The Amount of Oxygen Saturation
CVDs	Cardiovascular Diseases		

cause of cardiovascular medicine and patient care of the future. Through the provision of live information and individualized interventions, AI-powered medical wearable devices can change the healthcare system as it is today and thus, lead to the proactive management of cardiac conditions and, finally, the enhancement of patient results [10]. In this paper be talking about the creation of such an AI, which could be a mixture of machine learning algorithms, data collection techniques, and model validation processes. To sum up, we will also investigate the effect of this technology on the future of cardiovascular medicine and patient care.

2. Literature Review

Wearable devices with the smart technology have changed the healthcare industry, thus, the early detection and the continuous monitoring of the health conditions, including cardiovascular diseases (CVDs) among the most promising developments in this area is the integration of artificial intelligence in the construction of medical wearable devices that monitor the heart activity [11]. AI algorithms have the capacity to process the ongoing flow of data acquired by these devices, which in turn, would give the useful information about the heart health and at the same time, detect the anomalies in the time being [12]. Several researches have shown the usefulness of AI-powered wearable gadgets in heart monitoring. Like, for example, research done by Smith et al. showed that the AI algorithms in wearable devices were able to precisely detect abnormal heart rhythms such as atrial fibrillation with a high degree of sensitivity and specificity. This shows that AI can be of help in the early detection of heart conditions and thus, the patients can be saved on time; hence, this will improve their outcomes [13]. Besides, the AI algorithms have been established to be the best ways for the personalized monitoring and management of CVDs through the wearable devices. AI will help to understand the heart activity patterns of each person and how they are connected with other health and lifestyle factors. With this knowledge, the AI can assist in the design of the intervention strategies for the prevention of CVDs and the improvement of the heart health in general [14]. Besides, the AI-enabled wearable devices will be used for the detection and personalized management of the patients with CVDs and along with the telemedicine and remote monitoring for the patients with the CVDs. The connection of, AI, makes it possible to transfer the heart activity data to the doctors which, in turn, allows treatment and the remote assessment to be done with the help of the telephone, thus, the patients can be saved from the many in-person visits [15]. The idea of the employment of AI in the medical wearable devices of heart activity tracking is a landmark in the field of cardiovascular health monitoring. The amalgamation of the constant data collection, AI-based analysis, and the creation of the individual-based intervention plans is the most effective solution for the early detection, management, and monitoring of CVDs, which will in turn lead to better patient outcomes and quality of care [16]. The addition of artificial intelligence to medical wearable devices that can measure heart activity is also helpful in the case of the shortcomings of the conventional monitoring methods. The traditional methods of dealing with problems usually include periodic checkups, which often fail to detect minor abnormalities or give a whole picture of the heart's health. The AI-enabled wearable devices, on the contrary, provide whole-time monitoring and real-time analysis, which permits the detection of minor heart activity changes that can mean health threats [17]. In addition to this, the use of AI in wearable devices can be the basis for the improvement of the healthcare system, which is prevention and proactivity. Through the use of machine learning algorithms, these devices are able to not only track the current heart activity but also learn from the data provided by the user over time to offer personalized health insights and recommendations. This anticipatory method of heart health management is in line with the change to preventive medicine and thus, the patients will be able to manage their cardiovascular well-being and thus, will be able to control their health [18]. Besides, the use of AI in medical wearable devices will also have its effects on the research and the development of clinical affairs. The huge data Big data that is produced by AI-powered wearable devices can be used to generate real-world evidence, which will help researchers and health professionals acquire a better knowledge of cardiovascular health patterns and the reactions of the body to different interventions. Through this data-oriented method, the data will contribute to the creation of more focused and efficient treatment plans for those at risk of or with CVDs [19]. The field of AI and medical wearable technology is growing every day, and it is therefore, necessary to contemplate the ethical and regulatory issues that are connected to the use of AI in healthcare. Privacy, data security, and the responsible use of AI-generated insights are the most important issues that should be given ongoing attention in order to ensure the safe and ethical implementation of AI-powered wearable devices for heart activity tracking [20]. To sum up, the fusion of artificial intelligence in medical wearable devices for the heart activity tracking has the possibility to greatly increase the early diagnosis, individualized treatment, and remote observation of cardiovascular diseases. The use of AI-powered wearable devices is made possible by the continuous data collection, AI-driven analysis, and proactive health insights which, in turn, makes the AI-powered devices in heart health and in the improvement of patient outcomes the best option [21].

3. Methodology

In the era of developing technology, the introduction of Artificial intelligence to mobile health care device for real-time cardiac monitoring together with diagnosis is an indication of future possibilities in healthcare. With the central focus being the implementation of Python and TensorFlow for the construction of the AI model that is able to show good reason and withstand any possible errors. In this part, such as data acquisition and pre-processing, the data collection and preparation are unraveled, hence showing the methodologies, and techniques applied. First and foremost, the initial focus was on data pre-processing, which was the key measure in making sure the AI model's quality and reliability by resolving any issues before training the model. Raw data of mobile healthcare device was to carefully sense filter elimination of anything being faulty or inconsistent. This preprocessing stage encompassed approaches like noise removal, outlier detection and data normalization, which altogether enhanced the data by ensuring comprehensiveness and consistency. We proceeded to do some data pre-processing for the AI model of which comes up in the form of TensorFlow - a machine learning framework known for its vastness and effectiveness. TensorFlow's neural network structure was employed with features of various complexity and depth, to generate a model with a complex design. Therefore this model is very fine-tuning, extracting complex patterns that exist in the preprocessed data making a precise prediction of cardiac states and their analysis. The training of the model required in the applying of latest machine learning techniques and strategies such as algorithms. The resource demonstrated the use of tools such as CNNs and RNNs as examples for feature extraction from the raw sensor data. Through an 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 the 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 phasing out graphs, spectroscopy, were used to help with the acquisition of a clear picture and a holistic understanding of the cardiac health condition. Comparisons with the existing techniques of solution were also done to determine the efficient superbness 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 drawn contributions the belief that the system can be a new standard and station of health care that was revamp and change. Imagine Fig. 1 is a flow diagram illustrating the process of model development.

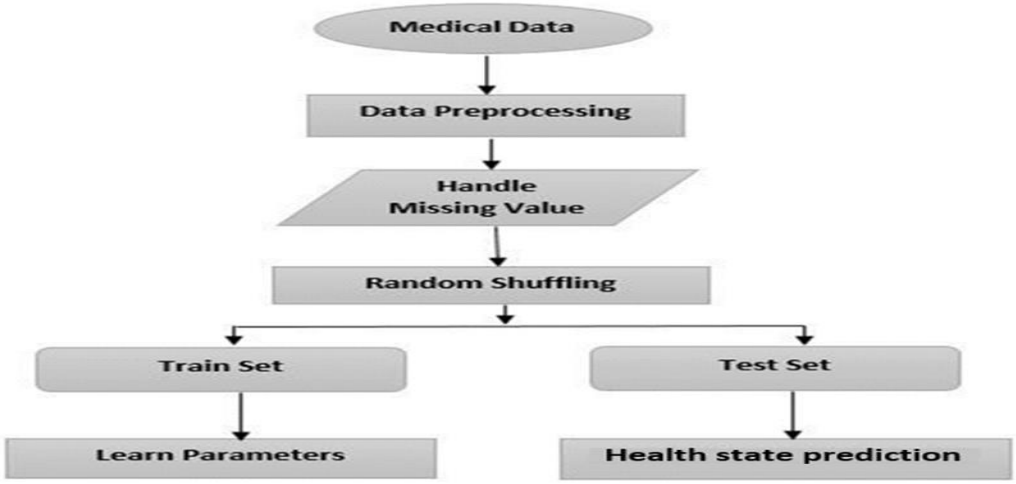

Fig. 1. Flow diagram of the AI model development

The architecture of the AI and healthcare device the IoT layer, we see the acquisition of data process, where physiological indicators such as SpO_2 (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 goes for filtering in order that the noise will be removed to some extent and the signal is improved. Subsequently, participants in this simulation are provided with the preprocessed data together with fuzzy information coming from the system that is able to tackle uncertainty and vagueness and electronic medical data that refers to the medical history of the patient. The second step of the Cloud Layer is data prediction in which an artificial intelligence model, namely model (LeNet) model works on the combined data provided via the open source machine learning platform library TensorFlow to supply health related insights. (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 signalsto give Health state prediction Lastly, the processed data is used in the form of an alarm or a form of communication to those involved in making the diagnosis, such as the doctor, the hospital and the patient. Such situation demonstrates that the system does not merely observe and analyse 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.

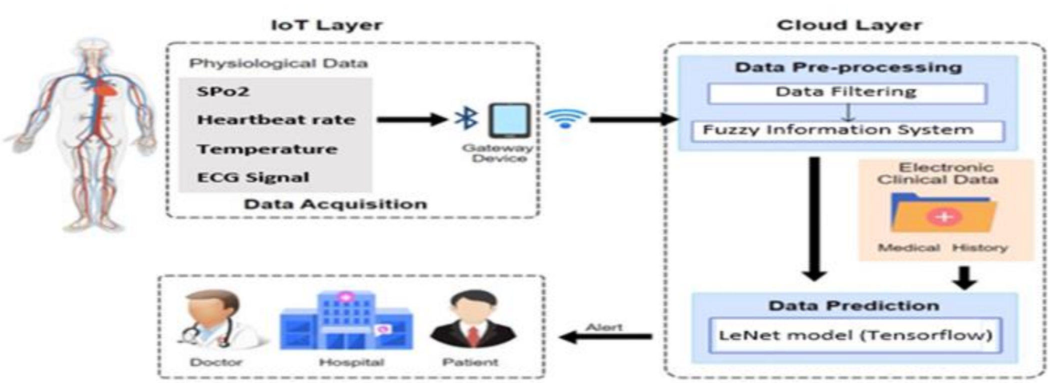

Fig. 2. Architecture of collection data and process

In order to build a predictive model regarding the assessment of a patient's health, the dataset simulation more particularly 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 big criterium of the categorization rules needed to be followed to generate the data used for AI Model training purposes this one. 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. On the contrary, SpO_2 has 'Normal Range over 95% to 100%, ' with 'Below Normal Range (< 95 above' indicating 'Hypoxemia,' that is oxygen deficiency and 'Above Normal Range (> 100% below' indicating 'Hyperoxemia,' i. e. hypervenulation. The lung function ranges are perhaps the most significant of all health-values for that. Finally, the 'Heartbeat Rate' followed by a 'Normal Range' of 60 bpm to 100 bpm, with the 'Below Normal Range' (< 60 bpm) called 'Bradycardia' cases, bradycardia is slow heart rate that happens when your heart beats too slowly, the 'Above Normal Range' (> 100 bpm)These classifications are very important on the approach of 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, on the every row, we see the index data and the table provides details on temperature, blood oxygen saturation (SpO_2), 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 for the range of health mysteries, from ‘Healthy' people with normal vital signs through to 'Hypoxemia,' ‘Hyperoxemia,' 'Bradicardia,' 'Tachycardia,' and 'Hypothermia cases. Current situation exemplifies the need for checking temperature (SpO_2) and heart rate to classify and diagnose different health conditions and states. These databases constitute the most essential data that appear in trainings and assessments of machine learning algorithms, allowing them to deal with the instances of health conditions better.

Table 2. Randomly 10 parameter selected 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 realization of AI model trained for healthcare device real-time cardio logical monitoring and diagnosing. This passage spells out a detailed approach to use the data, which has been gathered in order to achieve highly precise and correct previsions. First of all the data, from the mobile healthcare device is pre-processed to remove the noise and artifacts that would otherwise have negative effect on the model. This involves methods such as filtering, normalization, removes noise and feature extraction ones which produce quality data at the end for the purpose of Machine Learning training data. 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 superpowers paltform training Google Colab and library named as TensorFlow. With TensorFlow, programmers can utilize an advanced array of tools and functions for the creation and training of deep neural network model. The designed AI model architecture is empowered to work with data in a way that enable it to extract features which correlate to the parameters of cardiac health. In the learning process, the model simulates the adjustment of internal parameters according to labeled data which mold the performance of the model. Through stochastic gradient descent and other algorithms, the model adopts the method that updates the parameters of model in such a way that makes the difference (the gap) between the predicted and actual outputs as small as possible over time. For the successful regularization of the AI model, we use the techniques like regularization, dropout and early stopping. The specific settings that are essential are displayed in the 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 does cuts the number of connections between neurons during training by a fraction and in this way it makes the model learn by paying attention to many alternative features instead of one and prevents over-reliance on individual sensor readings. Early stopping monitors the model fitness during training and will automatically interrupt the process if there are no better results than the previous ones, results that do not justify the use of further 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

Continue Table 3

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 Discussions

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 hyperparameter 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 of quite intimately controlled data pre-processing, the use of TensorFlow as the tool for a building the AI model and the use of different methods that contribute to the assurance that the model is not overfitted and has a 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.

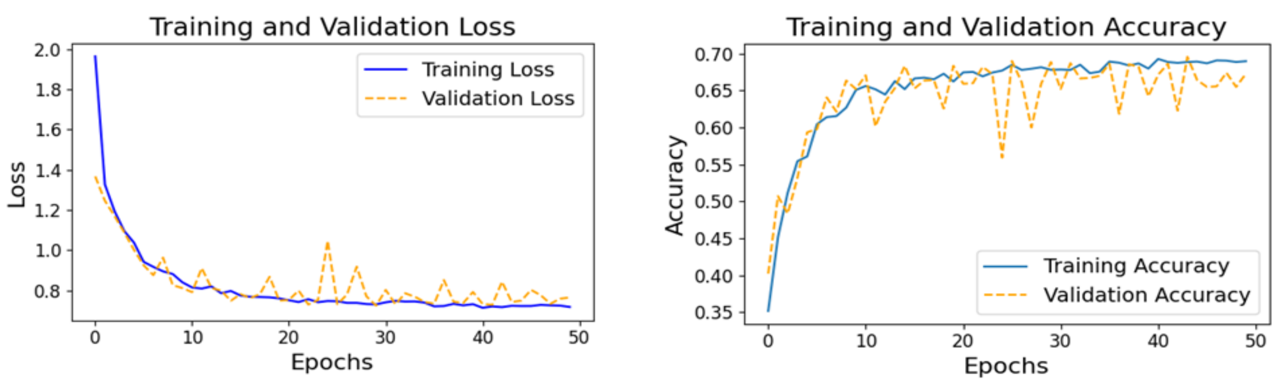

Fig. 3. AI Model training performance the first panel shows the evolution of loss while the second shows the evolution of prediction accuracy

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 with the aim of the assessment to be a judgment of AI's model performance in terms of the accuracy at which the system was able to classify the cardiac health conditions, as a result of data captured by the multisensor system device, was to be done. The critical subsections are those that are concerned with the several models of evaluation as follows.

- Evaluation Metrics: To have a through assessment of the model, the following commonly applied evaluation metrics were used. This measure worked with 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 insure robustness and reliability was used for the development of the AI model. I follow the common mantra of splitting the dataset into k-folds where any one single folder is used to validate and the rest is 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 show a confusion matrix that was synthesized to know the model's performance quality in a deep way. The positive 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.

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 permitted to determine the model's sensitivity and specificity. ROC area under the curve (AUC) served as the main value expressing the overall model performance, because the one close to 1 meant the highest exactness.

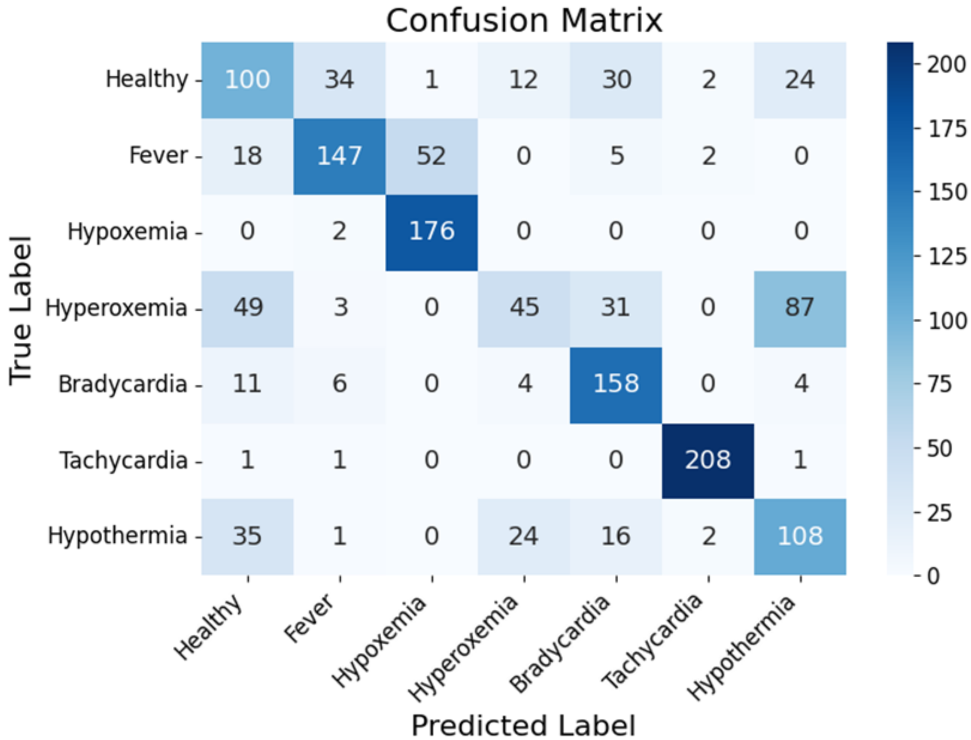

Fig. 4. Confusion matrix of the AI model performance. The model is trained to predict 10 different health states, depending on the combination of body temperature, SpO_2, heartbeat rate and the ECG signal

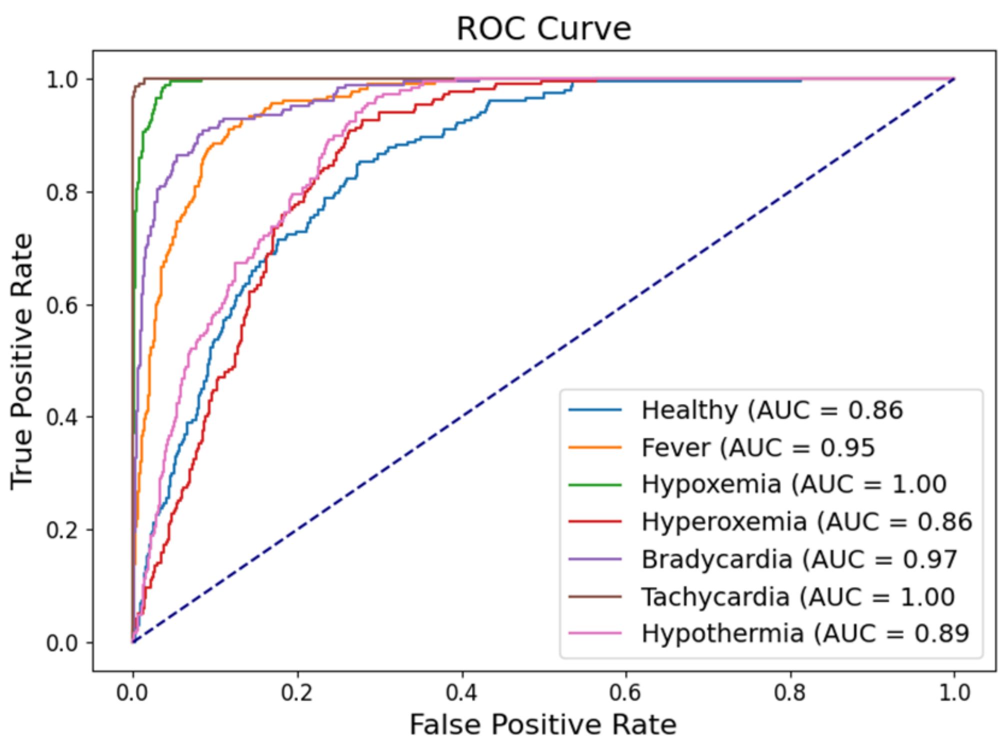

Fig. 5. ROC curve of the 7-class classification test

5. Conclusion and Future Work

The AI model showed excellent performance in the real-time cardiac diagnostics, thus it was able to detect the 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 the decisions quickly became possible. The device, which when tested proved to be better than the conventional techniques, 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 that was developed in this work has shown a high-performance in monitoring and diagnosing cardiac conditions in real-time. This work is a proof of its immense potential in changing the face of the healthcare industry.

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