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Predicting Resting Heart Rate Anomalies Using Heart Rate Data And Explaining The Predictions With XAI

[1]Asmita Goyal , [2]Anima Sharma, [3]Manju Vyas, [4]Deepika Bansal, [5]Radhika Kanwar Rajawat,
[1,2,3]Artificial Intelligence & Data Science Dept., JECRC, Jaipur
[4]Information Technology Dept., JECRC, Jaipur
[5]Computer Science & Engineering Dept., JECRC, Jaipur

Abstract:
The rapid integration of artificial intelligence into our regular lives has made its way into various sectors, including healthcare. However, the current AI models do not give any explanations for the answers and solutions they provide. In diagnostic medicine, it is important to know the decision-making process of any AI. This article presents an understanding of eXplainable AI and the current research in the area with respect to remote healthcare and diagnostic medicine. Further, we conduct an experiment with a kaggle dataset conducted in Harvard in 2020 for apple watches and predict stress levels in the heart using heart rate data and explain the random forest model's predictions using XAI techniques. We conclude that we can explain an AI's decisions and which features contributed to the final answer to provide better clarity in the AI's decisions.
Keywords: XAI, Black-Box models, Diagnostic Medicine, Smartwatches, Remote Healthcare.

1. Introduction

With the advancement of digital transformation in healthcare, the integration of smart technology and artificial intelligence in diagnostic medicine and remote healthcare is rapidly speeding up. As of 2025, The number of smartwatch users has reached 454.69 million, a 476.52% increase from the 97.63 million users in the year 2020.[1] This rapid increase suggests the growing concern for healthcare among the population, as these smartwatches can track health metrics such as breathing rate, heart rate, as well as activity metrics such as the number of steps, distance, calories burned, sleep patterns.

These smartwatches are excellent for keeping track of your daily health. By integrating Artificial Intelligence in these smartwatches, we can detect early signs of diseases and provide warnings so that appropriate measures can be taken. [7] However, it is extremely important that the decisions made by the AI are comprehensive and the decision – making process can be understood by at least medical professionals, if not the general public. XAI for ubiquitous and wearable computing will help in developing advanced solutions for healthcare and diagnostic medicine.

A. Black-Box Models

The most famous AI models as of 2025 such as ChatGPT, DeepSeek, Google Gemini are based on various machine learning and deep learning models. Since these models learn on their own, forming complex neural networks, it becomes almost impossible to understand the thought process of such AI. Their internal working is a complex web which we cannot unravel once it is implemented. Hence these AI models are called "Black Box" models. The problem with these is that their decision-making process cannot be explained, making them non-interpretable, unreliable and untrustworthy. [2] To rectify this, the concept of XAI comes in.

B. What is XAI

eXplainable Artificial Intelligence or XAI systems are those which can provide a clear, understandable decision-making thought process for any particular task to human beings. With the ubiquitous integration of AI systems in everyday life, it is crucial to develop trust and interpretability of the thought process of an AI model. [6]

1) The need for XAI:

We have defined the following metrics to understand the correctness of any machine learning model:

- "Accuracy": The frequency of correct predictions in the outcome of the machine learning model
- "Confidence": A quantifier which indicates the probability of a machine learning model's prediction being correct.

While these metrics provide some insights into the working of AI models, we still do not have a gateway to understand how the ML model made its decisions on a primary level. While AIs learn by trial and error by training on new data, we cannot take that risk while dealing with life-threatening scenarios such as disease diagnosis, forecasting natural disasters or criminal-justice decision making. We need to know which feature contributed the most to the decision, relationship between different features and the target features, and more of the nitty-gritties of the diagnostic process. XAI comes as a solution to this skepticism against AI by providing clear understanding of their decisions and take actions according to our understanding of the situation, not taking black box models at their word.

C. Smart Technology In Healthcare

Smart technology combines Artificial Intelligence, Internet of Things and Cloud Computing technology to gather, analyze and act on data to perform intelligent tasks. These "smart" devices are ubiquitous, i.e., seamlessly integrated into everyday objects and devices so that they remain accessible at all places at all times.

To apply smart technology in remote healthcare, we need frameworks so that these ubiquitous devices can accurately select features which are relevant for automatic disease diagnosis. For instance, anomalies in heart rate can detect and diagnose various heart diseases, whereas abnormal breathing rates (too fast or too slow) can indicate underlying medical conditions.[5]

Although AI models are faster than humans, their non interpretability makes it difficult to trust them in clinical contexts, as treatment for inaccurate diagnosis may prove fatal. Hence, XAI techniques are crucial for further development in the integration of AI into diagnostic medicine.

2. Literature Review

The current research into eXplainable AI systems is still in the development and testing phase. Recently, ChatGPT (from GPT-3.5-turbo till more recent models) has included a "Reason" section in which the AI has a "chain of thought" process. We can see an example of it in *Figure 1*.

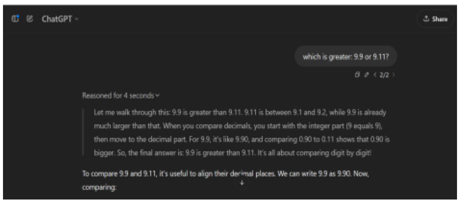

Fig. 1. ChatGPT Prompt to compare float values

Here, we can see the internal thought process of the AI as we ask a simple question: which is greater, 9.9 or 9.11?

[8]In previous models of ChatGPT, it was observed that the AI couldn't answer this question correctly, stating that since 11 is greater than 9, hence 9.11 is greater than 9.9. This mistake has been rectified here, as we can see that it correctly shows 9.9 > 9.11. We can clearly see its thought process here, which reinforces our trust in its decision-making abilities.

Even after such examples, a recent late-breaking paper has highlighted that less than 1% of Explainable AI papers validate explainability with humans.[3] This study further highlights the critical gap in the XAI literature in terms of evidence-based validation and human explainability.

3. Methodology

The following experiment aims to develop a machine learning model to predict the stress levels using heart rate data and explaining the predictions with XAI techniques. We will plot various graphs such as the SHAP summary plot, the LIME plot, importance score, partial dependency plots so that we can understand how much significance each feature from the dataset holds in the final prediction of resting heart rate anomalies.

Experiment: Predicting Stress Levels Using Heart Rate Data and Explaining the Predictions with XAI

This experiment's objective is to analyze the resting heart rate anomalies from smartwatch data using machine learning techniques and then explaining and visualizing the results using the concepts of XAI. The approach consists of the following stages:

1. Data collection
2. Data preprocessing
3. Model Building
4. Model Evaluation
5. Result Explanation (XAI techniques)

The tools and libraries used in the implementation are listed below:

- Python 3.10: Programming Language used for implementation
- Google Colab: Development environment
- Python libraries:
    - Pandas
    - Numpy
    - Sci-kit Learn
    - SHAP
    - Matplotlib
    - Seaborn
    - LIME

The dataset used for this experiment is available on Kaggle, which is part of a Havard study on predicting physical activity type with a reasonable accuracy[4]. While the objective of this dataset is fundamentally different from our purpose, it contains relevant features for resting heart rate anomaly detection which proved useful in conducting this experiment. We can simply remove the features which bear no weight on our experiment. However, here we have deliberately kept some non-relevant features in order to better understand the concept of feature contribution in explainable AI techniques.

4. Implementation & Results

To train the model, we have used the random forest classifier to classify each record as normal heart rate or deviating heart rate(anomaly).

```
RandomForestClassifier
RandomForestClassifier(random_state=42)
```

Fig. 2. Training the model using Random Forest Classifier

```
Accuracy: 1.00
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       885
           1       1.00      1.00      1.00       368

    accuracy                           1.00      1253
   macro avg       1.00      1.00      1.00      1253
weighted avg       1.00      1.00      1.00      1253
```

Fig. 3. Evaluating the model

5. Analysis of Results Using XAI

To explain the decision making of the model, we draw various plots to understand it better. Medical professionals can look at these to understand that the model took which features into consideration, and can make an informed decision regarding the treatment of their patient.

A. Importance Score

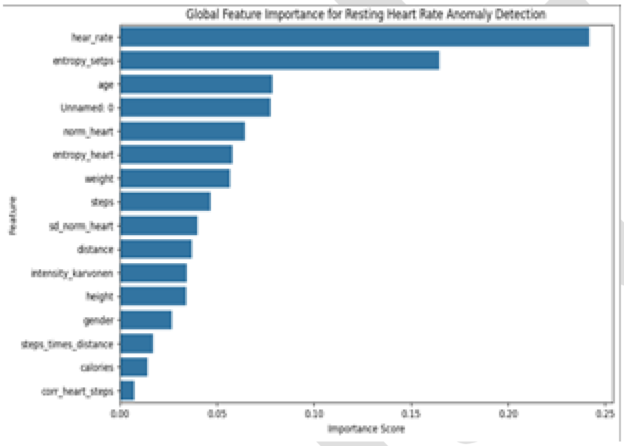

Fig. 4. Global Importance Feature from Random Forest

This bar plot ranks the features based on their overall contribution to the Random Forest model's ability to predict resting heart rate anomalies. The longer the bar, the more important the feature. We can clearly see that the model used heart_rate and entropy_setps as the most relevant features.

B. Partial Dependence Plots

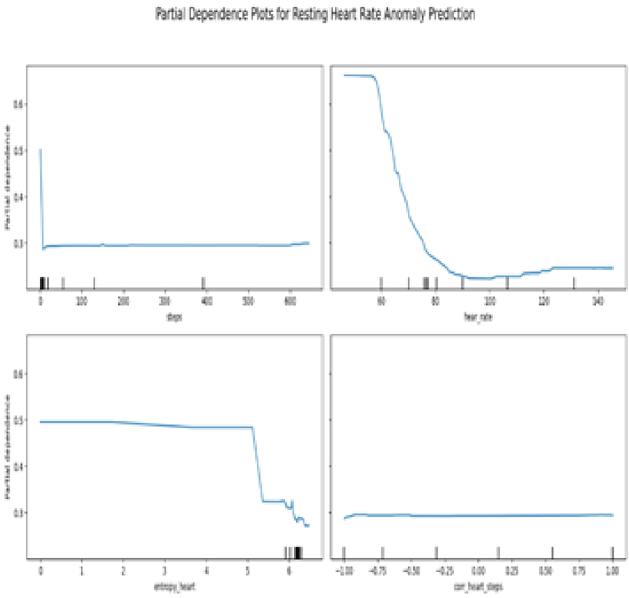

Fig. 5: Partial dependence of various features for resting heart rate anomaly prediction

These plots illustrate the average relationship between a single feature and the predicted probability of a resting heart rate anomaly, while holding all other features constant on average. We observe that features such as steps and corr_heart_steps are not deciding factors in the process, which is the expected outcome.

However, the heart_rate shows that higher values are associated with a lower probability of an anomaly, which is clearly wrong. A heart rate above 100 bpm can be indicative of various medical conditions or be a sign of stress, anxiety or exercise. This graph is particularly helpful as it shows us the lapse in judgement of the model's decision.

C. LIME Plot

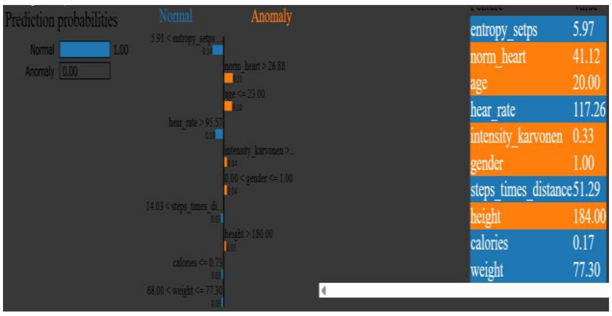

Fig. 6: LIME plot: Local Explanations

For a specific individual's data point, LIME provides a local explanation by highlighting which features contributed positively (pushed the prediction towards "Anomaly") and which contributed negatively (pushed towards "Normal"). This can help understand the model's reasoning on a case-by-case basis, which can be valuable for building trust in the model and potentially identifying real health events.[10]

We can see for this particular individual, whose heart rate was identified as "normal", which features contributed in it being "normal" and which predicted it as an "anomaly". Through this plot, we can analyse the model's decision on a case-by-case basis.

6. Discussion

A. Challenges Faced & Limitations

The main challenge faced during this experiment was moulding the dataset so that we can still use the heart rate parameter to our advantage despite the obvious drawback that the purpose of data collection was entirely separate from our agenda here. This challenge is also a limitation, as we cannot rely on this data for real life predictions. However, since this study is focused on exploring XAI techniques for feature selection, we can ignore this limitation.

B. Future Scope

Since the XAI techniques used here are somewhat rule-based, and we have to analyse the outcomes based on the visualization, we need to come up with better approaches to apply which are faster and more efficient for diagnosis of diseases. Especially in case of remote healthcare, there is the possibility of predicting heart rate anomalies and explaining the results so that even non professionals can understand it, believe it and take necessary measures.

C. Conclusion

In this paper, we explored the advent of Artificial Intelligence in the field of remote healthcare and its integration in smart devices, which makes AI ubiquitous in our lives. However, with the currently popular AI models being "black box" models, we cannot unravel the decision-making process making them unreliable. Hence, the insurgence of explainable AI is on the rise.

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