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[1]Arthi R
[2]Krishnaveni S

ETL-FEXIC Model For Secured Heart Rate Abnormality Healthcare Framework

Abstract: In traditional methods, it is critical for an effective continuous pulse monitor for humans prone to heart rate abnormalities. This paper proposes a secured heartrate abnormality detector which continuously monitors human pulse rate and SpO2 level. The current studies proposes that machine learning (ML) models performs well in classification; also, TinyML model shows better performance for data from resource constrained IoT devices. Hence, the research first analyses abnormal heart rate detection and spam data identification using standard ML algorithms such as SVM, Random Forest, Decision Tree, and TinyML. Though ML models are superior in classification, deep learning approaches outperforms them in feature learning. Hence, our proposed framework combines the merits of both ML and DL models. In our approach, the generated healthcare dataset is fed to DL models such as ANN, and autoencoder and also to SHAP XAI (eXplainable Artificial Intelligence) for feature extraction and learning. These learnt features are fed to ML models for classification. In this experiment, the proposed ETL-FEXIC (Enhanced Tiny Machine Learning with Automated Feature Extraction) outperforms the other ML models where the extracted features from XAI is fed to optimized TinyML classification model.

Keywords: TinyML, XAI, Healthcare monitor system, Machine Learning, Feature extraction

I. INTRODUCTION

In the field of healthcare, continuous monitoring of vital signs plays a crucial role in the detection and prevention of health problems, particularly in the case of people who are more likely to have abnormal heart rates. The capacity to screen heart rate and oxygen saturation levels (SpO2) [1] consistently and successfully is significant for early mediation and opportune clinical help. This has always been a problem, especially in environments with limited resources and limited access to cutting-edge medical equipment. However, recent technological advancements, particularly in the areas of machine learning (ML) and deep learning (DL) [2][3], have opened up new opportunities for the creation of sophisticated monitoring systems that are able to function effectively even on devices with limited resources.

TinyML transforms classification processes on IoT devices with limited resources by installing lightweight machine learning models directly on these devices, doing away with the requirement for continuous data transfer to centralised servers. TinyML[4][10] focuses on being efficient and using little power. It allows for real-time decision-making and inference at the edge, which cuts down on delay and improves privacy. TinyML makes sure that even devices with limited memory and processing power can handle complex machine learning tasks by using optimised algorithms and model compression methods. This makes a huge range of uses possible, including predictive maintenance, finding strange behaviour, and keeping an eye on the environment in IoT settings. TinyML also lets edge devices change and learn from data locally, without needing to be connected to cloud servers all the time. This makes it perfect for situations where internet access is spotty or not available at all. To put it simply, TinyML brings the power of machine learning to the edge, letting smart decisions be made in places with few resources. Though TinyML is better for classification it requires manual feature selection from the generated dataset. Hence, there is a need for algorithms to automatically extract and learn features from the dataset.

XAI [11]extracts and learns features from datasets in a disruptive manner. XAI uses powerful algorithms to automatically extract and analyse meaningful features from raw data, unlike laborious feature engineering. XAI improves model accuracy and interpretability by revealing dataset patterns and correlations. XAI can find intricate, nonlinear correlations that manual inspection may miss. XAI approaches like SHAP (SHapley Additive exPlanations) [12] reveal how each feature affects model performance by analysing their contributions to model predictions. By providing human-readable model decision explanations, XAI makes machine learning models more understandable. This builds model trust and lets domain experts assess and improve learned features.

[1] *Corresponding author: Arthi R, ar7862@srmist.edu.in, Department of Computational Intelligence, SRM Institute of Science and Technology, Kattankulathur, Tamil Nadu India 603203
[2] Krishnaveni S, krishnas4@srmist.edu.in, Department of Computational Intelligence, SRM Institute of Science and Technology, Kattankulathur, Tamil Nadu India 603203

By utilising the merits of machine learning (ML) and deep learning (DL) models, we improve the efficacy of healthcare data analysis within the proposed framework. By integrating the generated healthcare dataset into DL models such as Artificial Neural Networks (ANN) [15] and autoencoders, and employing SHAP XAI (eXplainable Artificial Intelligence) for feature extraction and learning, we achieve the desired results. Then, machine learning models employ the acquired features to perform classification. Our proposed framework, ETL-FEXIC (Enhanced Tiny Machine Learning with Automated Feature Extraction), exhibits superior performance compared to standard machine learning models . This is apparent when the SHAP XAI-extracted features are incorporated into optimized TinyML [16] model which attains improved precision and effectiveness in the classification of healthcare data.

II. PAPER ORGANIZATION

The paper is organized as follows:
Section II provides a literature review of the proposed system with the current systems. Section III provides the proposed methodology and the components required for the research. Section IV provides the results obtained from the proposed work and a discussion about the performance of the proposed work. Section V provides the conclusion and future works of the research.

III. RELATED WORKS

The author in [5] proposes conventional transformation techniques, methods that make use of Wigner-Ville Transform (WVT) and Two-Dimensional Fast Fourier Transform (2-D FFT) for time-frequency representations. These approaches use Convolutional Neural Networks (CNNs) to accomplish impressive results in challenges related to Human healthcare monitor. But there has been a big change since deep learning (DL) became popular. For example, a CNN-LSTM model with an adaptive batch size has been developed to effectively handle non-normalized data and imbalanced classes. The CapsLSTM model is another noteworthy development. It makes use of spatiotemporal information to identify numerous human activities and demonstrates resilience in situations where data is poor.

Furthermore, in [6], a semi-supervised deep learning (DL) framework has been shown that effectively leverages weakly labelled sensor data using an intelligent auto-labeling strategy based on deep Q-network (DQN) and a multi-sensor data fusion mechanism in a reinforcement learning (RL) approach. To further improve the interoperability of health monitor tasks without adding extra computing loads, a temporal-aware and modality-aware (TAMA) attention mechanism has been devised, highlighting the significance of various temporal steps or modalities.

The author in [7] depicts the use of wireless fidelity (WiFi) channel state information (CSI) using orthogonal frequency division multiple access (OFDMA) sub-carriers CSI which is another significant development. Using CSI measures, a DL based model known as attention-based bidirectional LSTM (ABLSTM) has demonstrated better performance. This model significantly improves recognition performance by giving different weights to learned features.

Moreover, in [8] generative adversarial networks (GANs) combined with multi-modal generators have been applied to tackle the problem of non-uniformly distributed unlabeled data. This novel method increases the variety of data that is produced, which improves the identification of certain activities in a range of environmental contexts. These developments indicate a positive trajectory and hint at possible future improvements.

As we move towards TinyML technologies, in [9] [14] a number of creative methods have been developed to strike a balance between the demand for data and the utilisation of available resources. These include lightweight ANN designs created especially for heart rate monitor, binarized neural networks, and adaptive neural networks. Furthermore, efforts have been made to use frameworks like BandX to save network traffic and optimise DL models for wearable devices.

Subsequent research endeavours are examining the effective implementation of deep learning models on devices with limited resources. Research is being done on methods like TensorFlow Lite compression and TinyML integration with edge computing [13][20] through different sensing solutions. Notwithstanding these developments, issues like data shortages and privacy concerns continue to exist. Transfer Learning (TL), which efficiently uses knowledge from related jobs to enhance human monitor applications, has become an important solution. TL provides an effective way to deal with issues with data privacy, data collecting and annotation, and precise cross-domain knowledge transfer.

Our objective in this work is to leverage TL to expedite TinyML development by tackling issues like model adaption, inference rate, and fast deployment. By utilising TL approaches, we want to expedite model deployment and improve IoT application performance by making resource-intensive ML models easier to implement on edge devices. We also explore the possibilities of TinyML, highlighting TFLite-µ's contribution [17][18][19] to this paradigm change. Additionally, building on previous efforts, our analysis examines the effectiveness of TL in improving the accuracy of proposed models trained on sparsely labelled data, as well as its impact on edge inference performance.

IV. Proposed Methodology

From data collection to model evaluation, Figure 1 and Figure 2 explains the methodology for identifying abnormal heart rates, with a focus on combining machine learning and explainable AI techniques for enhanced interpretability and accuracy.

Dataset collection and Preparation: The procedure begins with collecting heart rate data, through the MAX30102 sensor [13][14] connected with Arduino microcontroller. The ThingSpeak cloud platform is then used to store this data, allowing for centralised access and storage. After that, the data is cleaned and made ready for analysis, making sure it is well-organized and structured.

Feature Extraction and Model Training: The proposed ETL-FEXIC model is used to extract features from heart rate data. In order to extract features from the raw data and identify patterns of abnormal heart rate, this model probably uses hybrid approaches.

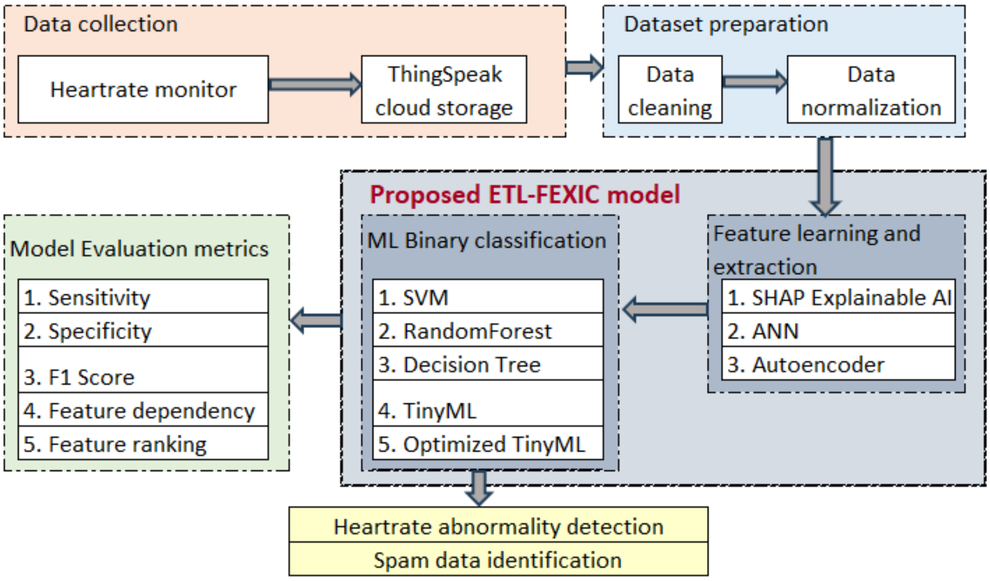

Figure 1: Proposed ETL-FEXIC framework

Evaluation of TinyML Models: The data is supplied into TinyML models for assessment after feature extraction. TinyML describes machine learning models that are optimised for resource-constrained devices, such as wearables or medical monitoring. This makes them appropriate for deployment in edge computing contexts. A number of ML models are evaluated, including an Optimised TinyML model, RandomForest, Decision Tree, Support Vector Machine (SVM), and TensorFlowLite.

Evaluation Metrics and Explainable AI: Each TinyML model's performance is measured using metrics including sensitivity, specificity, and F1 Score. The rate at which true positives are accurately identified is measured by sensitivity, and the rate at which true negatives are correctly identified is measured by specificity. The F1 Score provides a fair evaluation that takes precision and memory into account. Furthermore, the procedure integrates interpretable AI methods for feature dependency analysis, ranking, and interpretability, including SHAP (SHapley Additive exPlanations) and ANN (Artificial Neural Networks).

Interpretability and Feature Learning: Understanding the variables affecting model predictions is made possible by employing interpretable AI approaches such as SHAP and ANN. Better comprehension and confidence in the model's judgements are fostered by SHAP values, which offer insights into each feature's contribution to the model's output. Furthermore, higher-level representations of the input data are extracted using feature learning techniques like Autoencoder, which improves the interpretability and performance of the model.

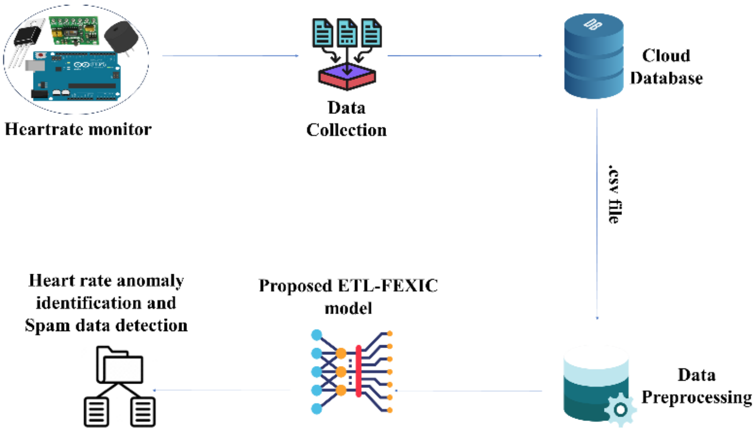

Figure 2: Proposed model conceptual architecture

Improved TinyML Model: With better sensitivity, specificity, precision, and F1 Score than any of the current algorithms, the Improved TinyML model identifies irregular heart rate patterns while reducing false positives and negatives.

V. Results And Discussion

The results of the proposed framework is obtained by (I) directly training various ML models with the raw features and classifying the data; (II) extracting features from autoencoder, ANN, and XAI-apply extracted features to various ML models for classification.

A. Classification without feature extraction

Table 1 provides the performance of different ML models in two different classification tasks: spam data recognition and abnormal heart rate detection. With F1 scores of 0.76 and 0.80, respectively, Decision Tree and TensorFlowLite performs well in the category of abnormal heart rate detection. These table values show an interconnection with accuracy and recall, which is important for reducing the number of false positives and negatives when diagnosing problems. The Optimised TinyML model produces a precision of 0.85, which shows that it correctly spots irregular heart rates while still having a good recall rate of 0.83.

The Optimised TinyML model produces an F1 score of 0.84 when it comes to spam data identification. This means that it depicts the difference between spam and user-generated data, with as few false positives and negatives as possible. Even though the SVM and Random Forest models perform better with F1 scores between 0.73 and 0.76, they still need improvement.

Overall, the results show that machine learning models, especially the Optimised TinyML model, work well in both healthcare and defence. The accuracy, recall, and F1 scores of these models shows that they could be used to improve medical diagnosis and internet safety.

Table 1: ML models classification performance

ML Model	Heartrate abnormality detection			Spam data identification		
	Precision	Recall	F1 score	Precision	Recall	F1 score
SVM	0.73	0.77	0.73	0.74	0.75	0.74
Random Forest	0.76	0.74	0.73	0.77	0.76	0.76
Decision Tree	0.77	0.76	0.76	0.80	0.80	0.79
TensorFlowLite	0.81	0.82	0.80	0.83	0.82	0.81
Optimized TinyML model	0.85	0.83	0.83	0.86	0.85	0.84

B. ML classification with feature extraction:

In this method, the collected dataset is trained with feature AI models such as ANN, autoencoder, and XAI. The models first acquire the dataset, learn the features, and extract the important features as in Figure 3 while training. The extracted features are saved and fed to the machine learning models for classification.

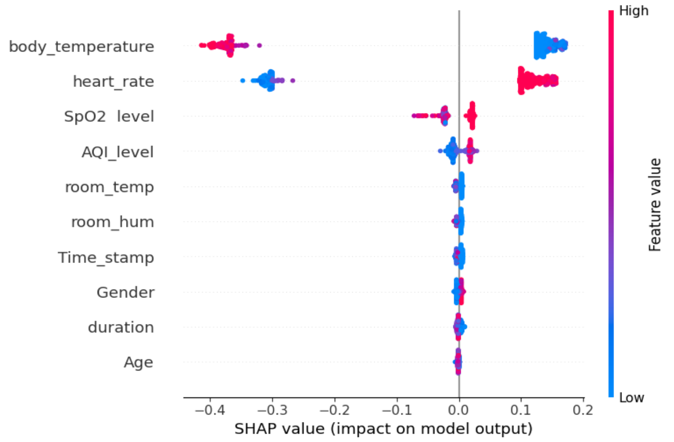

Figure 3: SHAP XAI feature ranking

C. Heartrate abnormality detection

Table 2 shows the different machine learning model performance when combined with ANN to find irregular heart rates. The ANN + Optimised TinyML model shows the best performance, with a sensitivity score of 0.92, a precision score of 0.91, and an F1 score of 0.91, which means accurate spotting with a low false discovery rate.

Table 2: ANN feature extraction with ML heartrate abnormality detection

ANN + ML Model	**Sensitivity**	**Specificity**	**Precision**	**False Discovery Rate**	**Accuracy**	**F1 score**
ANN + SVM	0.81	0.81	0.83	0.06	0.81	0.80
ANN + Random Forest	0.86	0.85	0.85	0.07	0.85	0.85
ANN + Decision Tree	0.89	0.87	0.88	0.07	0.90	0.89
ANN + TensorFlowLite	0.89	0.90	0.89	0.07	0.89	0.89
ANN + Optimized TinyML model	0.92	0.89	0.91	0.08	0.92	0.91

ANN + TensorFlowLite, Decision Tree, and Random Forest are some other combinations that also perform better. Overall, these results show that ANN combined with machine learning models, especially Optimised TinyML, accurately and reliably finds heart rate problems in healthcare monitors.

Table 3: Autoencoder feature extraction with ML heartrate abnormality detection

Autoencoder + ML Model	**Sensitivity**	**Specificity**	**Precision**	**False Discovery Rate**	**Accuracy**	**F1 score**
Autoencoder + SVM	0.77	0.76	0.76	0.07	0.78	0.76
Autoencoder + Random Forest	0.81	0.80	0.81	0.07	0.80	0.81
Autoencoder + Decision Tree	0.84	0.86	0.87	0.08	0.88	0.86
Autoencoder + TensorFlowLite	0.89	0.90	0.88	0.08	0.89	0.88
Autoencoder + Optimized TinyML model	0.91	0.90	0.92	0.09	0.91	0.91

Table 3 shows the different machine learning models working when combined with autoencoders to find irregular heart rates. In general, adding autoencoders improves the model performance. A pair of functions is the same as an autoencoder. We need an assignment in order to assess its quality. A reference probability distribution defines a task. The training loss function of the autoencoder is defined below.

$$Loss(\partial, p) := E_{x\sim\mu_{ref}}\left[d\left(x, D_\partial\left(E_p(x)\right)\right)\right]$$

$$\min_{\partial,p} Loss(\partial, p), where\ L(\partial, p) = \frac{1}{N}\sum_{i=1}^{N} \| x_i - D_\partial\left(Ep_\phi(x_i)\right) \|_2^2$$

The Autoencoder + Optimised TinyML model has the best sensitivity (0.91), specificity (0.90), accuracy (0.92), and F1 score (0.91). This means that it correctly finds things and doesn't find many false ones. Autoencoder + TensorFlowLite, Decision Tree, and Random Forest are some other combinations. These results show that using autoencoders along with machine learning models, especially Optimised TinyML, finds abnormal heart rates more accurately and reliably.

Table 4: XAI feature extraction with ML heartrate abnormality detection

XAI + ML Model	**Sensitivity**	**Specificity**	**Precision**	**False Discovery Rate**	**Accuracy**	**F1 score**
XAI + SVM	0.80	0.82	0.80	0.05	0.84	0.82
XAI + Random Forest	0.89	0.87	0.88	0.06	0.89	0.88
XAI + Decision Tree	0.91	0.90	0.92	0.06	0.91	0.90
XAI + TensorFlowLite	0.93	0.92	0.92	0.07	0.93	0.93
XAI + Optimized TinyML model	0.93	0.92	0.94	0.05	0.95	0.94

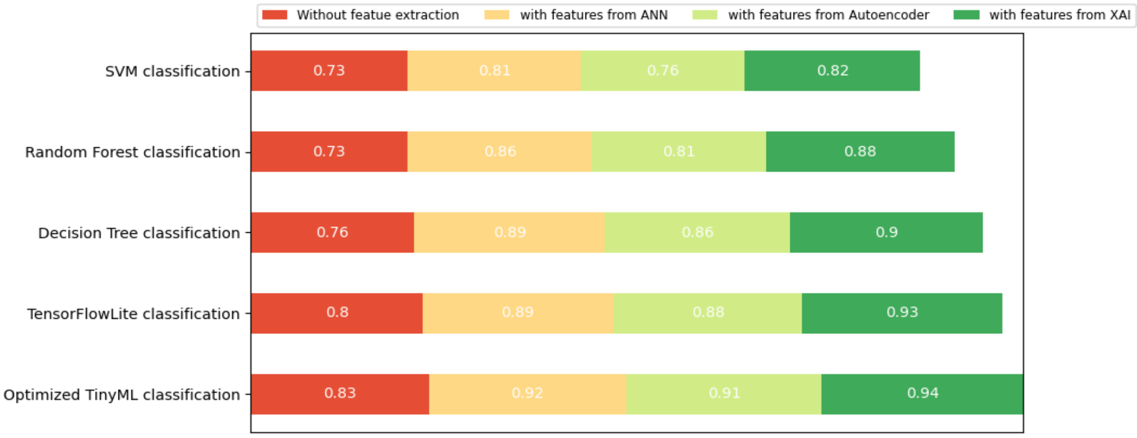

Figure 4: ML model comparative study of heartrate abnormality detection

Table 4 and Figure 4 shows the different machine learning models working when combined with XAI methods for finding abnormal heart rates. XAI makes models easier to understand and better at what they do in all combos. The XAI + Optimised TinyML model has the best sensitivity (0.93), specificity (0.92), precision (0.94), and F1 score (0.94), which means it finds things correctly and rarely makes false findings. These results show that using XAI techniques, especially with Optimised TinyML, finds abnormal heart rates in healthcare apps that are accurate and easy to understand.

D. Span data identification

The proposed healthcare framework introduces attacks such as DDoS, phishing attacks, and other routing attacks. The classification performance of various ML models with different feature extraction methods are explained below.

Table 5: ANN feature extraction with ML spam data identification

ANN + ML Model	**Sensitivity**	**Specificity**	**Precision**	**False Discovery Rate**	**Accuracy**	**F1 score**
ANN + SVM	0.83	0.87	0.83	0.06	0.87	0.83
ANN + Random Forest	0.86	0.84	0.83	0.06	0.84	0.83
ANN + Decision Tree	0.84	0.85	0.84	0.07	0.85	0.84
ANN + TensorFlowLite	0.87	0.86	0.86	0.07	0.86	0.86
ANN + Optimized TinyML model	0.89	0.89	0.90	0.06	0.90	0.89

Combinations of features taken from ANN using different machine learning models are included in Table 5 for the purpose of spam identification. Notably, the Optimised TinyML model combined with ANN yields the best results in terms of F1 score, sensitivity, specificity, accuracy, and precision. Competitive outcomes are also shown by other combinations, such as Random Forest, Decision Tree, and ANN + TensorFlowLite. All things considered, using ANN features in conjunction with machine learning models particularly the Optimised TinyML model offers a viable strategy for efficient spam identification. These results are important for improving communication channel cybersecurity with dependable and effective spam filtering systems.

Table 6: Autoencoder feature extraction with ML spam data identification

Autoencoder + ML Model	**Sensitivity**	**Specificity**	**Precision**	**False Discovery Rate**	**Accuracy**	**F1 score**

Autoencoder + SVM	0.82	0.83	0.83	0.06	0.84	0.84
Autoencoder + Random Forest	0.83	0.84	0.83	0.06	0.84	0.84
Autoencoder + Decision Tree	0.89	0.87	0.88	0.07	0.87	0.87
Autoencoder + TensorFlowLite	0.88	0.89	0.88	0.08	0.89	0.89
XAI + Optimized TinyML model	0.91	0.91	0.90	0.08	0.91	0.90

The performance of autoencoder based feature extraction combined with different machine learning models for spam detection is shown in Table 6. The detection accuracy is increased when autoencoders and machine learning models are combined. High sensitivity (0.89), specificity (0.87), and F1 score (0.87) are notable results of the Autoencoder + Decision Tree combo, suggesting accurate spam identification with few false positives. Additionally, Autoencoder + TensorFlowLite performs good. But the XAI + Optimised TinyML model performs better than the others, displaying the highest F1 score (0.90), precision (0.90), specificity (0.91), sensitivity (0.91), and recall (0.91). These results indicate strong detection capabilities with a balanced precision and recall.

Table 7: XAI feature extraction with ML spam data identification

XAI + ML Model	**Sensitivity**	**Specificity**	**Precision**	**False Discovery Rate**	**Accuracy**	**F1 score**
XAI + SVM	0.79	0.79	0.80	0.07	0.82	0.80
XAI + Random Forest	0.88	0.86	0.87	0.08	0.87	0.86
XAI + Decision Tree	0.89	0.88	0.88	0.08	0.90	0.89
XAI + TensorFlowLite	0.92	0.91	0.91	0.09	0.92	0.92
XAI + Optimized TinyML model	0.93	0.92	0.92	0.09	0.93	0.92

The effectiveness of XAI methods in conjunction with several machine learning models for spam detection is shown in Table 7 and Figure 5. In every scenario, XAI improves detection precision. It is noteworthy that the XAI + Optimised TinyML model earns the highest scores for F1 (0.92), specificity (0.92), precision (0.92), and sensitivity (0.93), showing balanced and accurate identification of spam with few false positives. Strong performance is also shown by other combinations, such as Random Forest, Decision Tree, and XAI + TensorFlowLite. These results highlight that XAI approaches is effectively integrated for trustworthy and comprehensible spam identification in communication channels, especially when combined with the Optimised TinyML model.

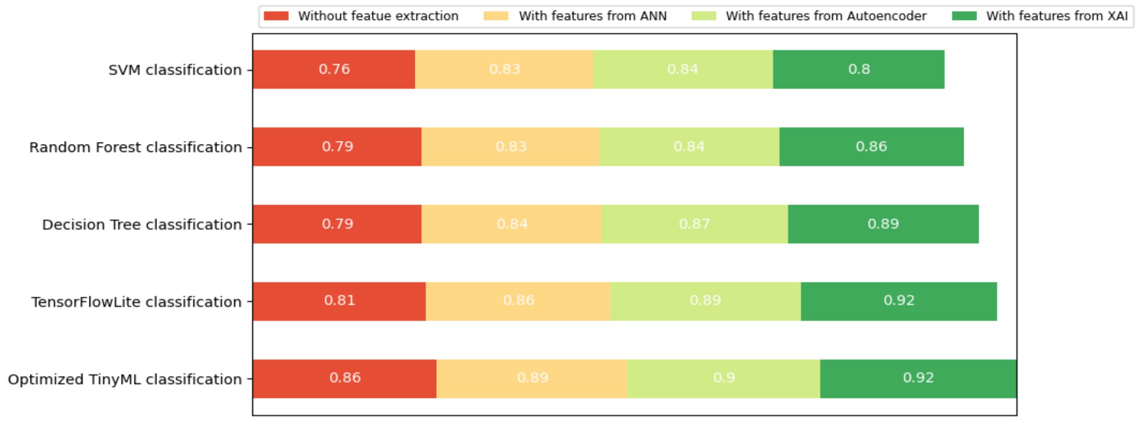

Figure 5: ML model comparative study of spam data identification

The performance of several feature extraction techniques and machine learning algorithms for spam identification and abnormal heart rate categorization is displayed in the tables. Better outcomes are consistently obtained when XAI features are integrated with the proposed optimised TinyML model. This combination outperforms all other combinations in terms of sensitivity, specificity, accuracy, precision, and F1 score in both tasks. These results emphasise the superiority of the Optimised TinyML model in accurate and dependable classification across several domains, such as spam detection and abnormal heart rate classification, and demonstrate the high performance of XAI features is integrated with the model.

CONCLUSION

The proposed method presents a comprehensive framework, ETML-FEXIC (Enhanced Tiny Machine Learning - Feature Extraction and Interpretability Combiner), aimed at advancing abnormal heart rate monitoring systems using TinyML. By harnessing the capabilities of TinyML and transfer learning (TL), our approach enables the deployment of sophisticated ML models directly on resource-constrained edge devices, thereby alleviating concerns related to data privacy, latency, and energy consumption associated with cloud processing.

Through a systematic methodology involving data collection, feature extraction, and evaluation of TinyML models augmented with explainable AI techniques, we have demonstrated significant advancements in abnormal heart rate detection. Our findings highlight the efficacy of the Optimised TinyML model, particularly when combined with feature extraction methods such as autoencoders and explainable AI approaches. Notably, this combination exhibits superior performance in both abnormal heart rate detection and spam data identification tasks, showcasing its potential for real-world applications across various domains. Moreover, our research underscores the importance of transfer learning in enhancing the efficiency and reliability of heart rate monitoring systems.

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