UNIVERSIDAD DE MURCIA

ESCUELA INTERNACIONAL DE DOCTORADO

TESIS DOCTORAL

Computational Learning for Sensor Signal Analysis

Aprendizaje computacional para análisis de señales de sensores

D. Arijit Ukil

2023

UNIVERSIDAD DE MURCIA

ESCUELA INTERNACIONAL DE DOCTORADO

TESIS DOCTORAL

Computational Learning for Sensor Signal Analysis

Aprendizaje computacional para análisis de señales de sensores

Autor: D. Arijit Ukil

Director/es: D. Leandro Marín Muñoz, D. Antonio Jesús Jara Valera

UNIVERSIDAD DE
MURCIA

DECLARACIÓN DE AUTORÍA Y ORIGINALIDAD
DE LA TESIS PRESENTADA EN MODALIDAD DE COMPENDIO O ARTÍCULOS PARA OBTENER EL TÍTULO DE DOCTOR
Aprobado por la Comisión General de Doctorado el 19-10-2022

D./Dña. Arijit Ukil

doctorando del Programa de Doctorado en

Programa de Doctorado en Informática

de la Escuela Internacional de Doctorado de la Universidad Murcia, como autor/a de la tesis presentada para la obtención del título de Doctor y titulada:

Aprendizaje computacional para análisis de señales de sensores

y dirigida por,

D./Dña. Leandro Marín Muñoz

D./Dña. Antonio Jesus Jara Valera

D./Dña.

DECLARO QUE:

La tesis es una obra original que no infringe los derechos de propiedad intelectual ni los derechos de propiedad industrial u otros, de acuerdo con el ordenamiento jurídico vigente, en particular, la Ley de Propiedad Intelectual (R.D. legislativo 1/1996, de 12 de abril, por el que se aprueba el texto refundido de la Ley de Propiedad Intelectual, modificado por la Ley 2/2019, de 1 de marzo, regularizando, aclarando y armonizando las disposiciones legales vigentes sobre la materia), en particular, las disposiciones referidas al derecho de cita, cuando se han utilizado sus resultados o publicaciones.

Además, al haber sido autorizada como compendio de publicaciones o, tal y como prevé el artículo 29.8 del reglamento, cuenta con:

- *La aceptación por escrito de los coautores de las publicaciones de que el doctorando las presente como parte de la tesis.*
- *En su caso, la renuncia por escrito de los coautores no doctores de dichos trabajos a presentarlos como parte de otras tesis doctorales en la Universidad de Murcia o en cualquier otra universidad.*

Del mismo modo, asumo ante la Universidad cualquier responsabilidad que pudiera derivarse de la autoría o falta de originalidad del contenido de la tesis presentada, en caso de plagio, de conformidad con el ordenamiento jurídico vigente.

En Murcia, a 23 de Febrero de 2023

Arijit

Fdo.: Arijit Ukil

Información básica sobre protección de sus datos personales aportados	
Responsable:	Universidad de Murcia. Avenida teniente Flomesta, 5. Edificio de la Convalecencia. 30003; Murcia. Delegado de Protección de Datos: dpd@um.es
Legitimación:	La Universidad de Murcia se encuentra legitimada para el tratamiento de sus datos por ser necesario para el cumplimiento de una obligación legal aplicable al responsable del tratamiento. art. 6.1.c) del Reglamento General de Protección de Datos
Finalidad:	Gestionar su declaración de autoría y originalidad
Destinatarios:	No se prevén comunicaciones de datos
Derechos:	Los interesados pueden ejercer sus derechos de acceso, rectificación, cancelación, oposición, limitación del tratamiento, olvido y portabilidad a través del procedimiento establecido a tal efecto en el Registro Electrónico o mediante la presentación de la correspondiente solicitud en las Oficinas de Asistencia en Materia de Registro de la Universidad de Murcia

I dedicate this thesis to my parents- Dipak Kumar Ukil, Rekha Ukil; my wife- Susmita Ukil and my daughter- Ahana Ukil.

Acknowledgements

This research work would not have been possible unless I received support, encouragement, motivation from large set of people. PhD is a long journey with triumphs, joys and periods of agony and somber feelings. Writing these words implies closing a cycle and I am certainly not the same person who started this doctoral program. I have learned a lot, not only on science, technology, but also to keep patience and perseverance throughout this period of time, which started in 2018.

First of all, I would like to thank my supervisors and directors, Leandro Marin and Antonio J Jara, because without you this would have not been possible. The positive energy, motivation, guidance and encouragement made my journey successful. Thanks once again for your continuous overwhelming support and relentless encouragements. Words cannot express my gratitude to my guides.

I am immensely grateful to K. Ananth Krishnan, Executive Vice President and Chief Technology Officer, Tata Consultancy Services (TCS) and Gautam Shroff, Senior Vice President and Head of TCS Research for the generous support and motivation to conduct this research work. I thank Preetha Rajiv and Haridas Menon U, Tata Consultancy Services for lending their helping hands towards completing my PhD program in University of Murcia, Spain.

I extend my sincere thanks and gratitude to Arpan Pal, Distinguished Chief Scientist and Research Area Head, Embedded Devices and Intelligent Systems, TCS Research for being the pillar of strength and inspiration throughout my PhD journey.

I thank Subhas Chandra Mukhopadhyay, Professor, Macquarie University, Australia for his continuous moral support, encouragement so that I can remain focused in my research work.

I thank my parents, my wife, and my daughter for their unwavering supports over the past few years. Their strong belief in me has kept my spirits and morale high during this process. I am indebted to them for the relentless fortitude that they have bestowed upon me for last few years through sacrificing many family occasions just to encourage my studies and to support my effort towards successful PhD.

I would also like to thank everyone who has been there for me emotionally and intellectually as I have worked on my coursework, my journal paper and dissertation preparation.

Preface

This doctoral thesis is presented as a compendium of publications in accordance with the rules for the regulation of official doctoral studies of the University of Murcia and with the approval of the thesis supervisors, the Academic Commission of The Doctoral Program in Computer Science and the General Committee for Doctoral Studies. This thesis is composed of three research studies ([50], [53], [52]) published in three international journals indexed in Journal Citation Reports (JCR). Additionally, this thesis provides a general introduction, which presents the studies and justifies the scientific unity of the thesis, and an overall summary of the aims of the research and the final conclusions along with discussion on the obtained scientific results.

Prefacio

Esta tesis doctoral se presenta como compendio de publicaciones de acuerdo con las normas para la regulación de los estudios oficiales de doctorado de la Universidad de Murcia y con la aprobación de los directores de tesis, la Comisión Académica del Programa de Doctorado en Informática y la Junta General para Estudios de Doctorado. Esta tesis está compuesta por tres estudios de investigación ([50], [53], [52]) publicados en tres revistas internacionales indexadas en Journal Citation Reports (JCR). Además, esta tesis proporciona una introducción general, que presenta los estudios y justifica la unidad científica de la tesis, y un resumen general de los objetivos de la investigación y las conclusiones finales junto con la discusión sobre los resultados científicos obtenidos.

Resumen en Español

Esta tesis doctoral se presenta como un compendio de publicaciones. Esta tesis se compone de tres trabajos de investigación (1. Sensor Data Uncertainty Principled Differential Privacy for User-controlled Privacy Preserving Model Construction for Heart Sound or PCG signal Analysis [50], 2. AFSense-ECG for Compact Model Construction for Atrial Fibrillation Detection Using Single Lead ECG Signals [53], and 3. When less is more powerful: Shapley value attributed ablation with augmented learning for practical time series sensor data classification [52]) publicados en revistas indexadas en Journal Citation Reports (JCR). Todos los artículos juntos constituyen una unidad científica en el campo del modelado computacional de señales de sensores. De hecho, el análisis computacional y el modelado de las señales de los sensores es uno de los factores de mayor importancia para comprender los eventos descritos por los sensores, así como para inculcar inteligencia en las aplicaciones que se construyen utilizando las señales de los sensores. El objetivo general es construir modelos de aprendizaje automático precisos para resolver desafíos prácticos como la escasez de datos de entrenamiento, la construcción de modelos compactos y la preservación de la privacidad de los datos para un conjunto diverso de tareas de análisis de señales de sensores. Con la proliferación de Internet de las cosas (IoT), los avances de las tecnologías de detección, las increíbles mejoras hacia el poder de cómputo junto con el progreso sobresaliente de los algoritmos y herramientas de inteligencia artificial (IA), los investigadores están encontrando nuevas vías para construir un gran número de diferentes aplicaciones útiles, así como nuevas direcciones de investigación. En este trabajo de investigación, nuestra visión es desarrollar un modelo único y unificado para construir un modelo de clasificación para señales de sensores de series temporales y abordamos los siguientes desafíos de investigación que son de gran importancia en la práctica:

- Un número menor de ejemplos de entrenamiento no tiene por qué ser un obstáculo para generar un modelo aprendido adecuado.
- El aprendizaje computacional independiente del tipo de aplicación y sensor es factible.
- Un solo modelo puede funcionar potencialmente cerca de los resultados de referencia (donde los resultados de referencia pueden ser aportados por una gran cantidad de algoritmos) consistentemente sobre un conjunto diverso de tareas de clasificación de series temporales de sensores.

Además, el modelo computacional de aprendizaje preferiblemente no debería requerir conocimiento externo o intervención humana. Es un modelo de aprendizaje automático totalmente automatizado sin personalización manual de funciones o selección de hiperparámetros. Este trabajo de investigación se centra en la construcción de modelos para el aprendizaje computacional de tareas de análisis que involucran diferentes tipos de señales de sensores como electrocardiograma (ECG), fonocardiograma (PCG), acelerómetro, medidor de energía, etc. Muchos sensores pueden considerarse como la micro-representación de la fisiología humana y la actividad humana en general, por lo que tales sensores contienen información sensible. Por lo tanto, nuestra tarea principal es la habilitación de técnicas de preservación de la privacidad como parte de los modelos de detección computacional que analizan las señales de los sensores e infieren decisiones críticas. Por ejemplo, el análisis computacional de las señales PCG puede revelar el estado de salud cardíaca de un ser humano. Se entiende que la atención médica remota es una de las aplicaciones críticas de IoT y resolvemos el problema de la protección de la privacidad de los datos al proponer la eliminación del riesgo de la gestión de datos confidenciales mediante la privacidad diferencial, donde se puede emplear la protección de privacidad controlada habilitada por el usuario en datos de atención médica confidenciales. El método de protección de la privacidad propuesto [50] ofusca los datos confidenciales como los datos PCG (PCG registra el sonido del corazón y puede indicar potencialmente una anomalía cardíaca) para garantizar que se realice una protección aceptable sin comprometer gravemente la utilidad, y que se realice el control de la habilitación de la privacidad. impulsada por el usuario. Nuestra contribución novedosa es proponer el principio de incertidumbre de los datos del sensor, de modo que se emplea la incertidumbre estadística controlada para la información sensible con la definición de protección de la privacidad de que las probabilidades a priori y a posteriori de encontrar información privada no cambian más allá de un umbral predefinido y la ganancia de acceso a los datos confidenciales por parte del adversario se vuelve insignificante. Por lo tanto, el aprendizaje computacional propuesto en las señales de los sensores cubre el análisis de privacidad, donde el requisito de privacidad y la cantidad de sensibilidad de las señales del sensor se estiman a partir de estadísticas teóricas de la información y se aplican técnicas relevantes de preservación de la privacidad para garantizar la preservación dinámica de la privacidad. Demostramos que con el enfoque apropiado de ofuscación de datos de sensores en el proceso de preservación de la privacidad de datos confidenciales, el rendimiento del análisis computacional se degrada considerablemente (se convierte en casi equivalente a un resultado aleatorio) de modo que los atacantes no obtienen ningún conocimiento al capturar dichos datos. La preservación de la privacidad está controlada por la distribución de datos del sensor de tal manera que la ofuscación mínima adecuada para garantizar que la protección de la privacidad se realice en las señales del sensor, lo que garantiza una pérdida mínima de información. Sin embargo, el motor de análisis del modelado computacional en [50] considera tres tipos de características hechas a mano que extraen propiedades estadísticas y de procesamiento de señales de la señal del sensor dado a través del algoritmo de aprendizaje automático de refuerzo basado en Adbaoost. La limitación de este trabajo [50] es que el algoritmo de aprendizaje automático que realiza la tarea de análisis requiere una ingeniería de funciones artesanal, que no solo restringe la escalabilidad del aprendizaje computacional, sino que también depende de lo costoso (a veces, prácticamente no factible) proceso de generación y selección de características asistida por expertos con conocimiento del dominio. De hecho, la ingeniería de requisitos requiere un amplio conocimiento del dominio, así como una importante intervención humana y un esfuerzo manual para generar el conjunto de características distinto y adecuado. Dichos procesos no solo son costosos, sino que tampoco son escalables para diversas aplicaciones y señales de sensores. Posteriormente, desarrollamos detección integrada de inteligencia que realiza tareas de clasificación supervisadas utilizando un método novedoso de aprendizaje profundo (DL) de red neuronal convolucional ajustada por hiperparámetros (CNN) sin necesidad de un gran esfuerzo en la ingeniería de requisitos [53]. De hecho, las arquitecturas de redes neuronales profundas exhiben excelentes capacidades de aprendizaje en aplicaciones de visión por computadora y ya alcanzaron un nivel de rendimiento similar al humano. En consecuencia, construimos un modelo computacional para interpretar la señal de EG para la condición de fibrilación auricular (un tipo de enfermedad cardiovascular crítica que se caracteriza por ritmos cardíacos irregulares, que eventualmente pueden provocar un derrame cerebral, coágulos de sangre en el corazón, etc.). La estimación de hiperparámetros propuesta a partir de las características de la señal de entrada facilita la construcción del modelo CNN compacto. Ponemos especial atención al hiperparámetro de longitud de zancada de la arquitectura CNN. Controles de hiperparámetro de longitud de zancada en el filtro de convolución que se utiliza para convolucionar los datos de entrenamiento de entrada. Establecimos el hiperparámetro de longitud de zancada de manera que se centre adecuadamente en las zonas morfológicas significativas de las señales de ECG de una sola derivación de entrada, para así capturar adecuadamente la región adecuada de interés clínico. De este modo, la capacidad de aprendizaje del modelo CNN mejora significativamente al incorporar los fundamentos morfológicos de ECG en sus amplificadores de características. Definimos el parámetro de densidad de muestra de una señal de ECG que indica la proximidad de los complejos QRS en las señales de ECG. La longitud de zancada del modelo se establece dinámicamente en función de la magnitud del parámetro de densidad de la muestra. Cuando la densidad de la muestra es alta, reducimos la redundancia en los mapas de características de la CNN al establecer un valor de longitud de zancada mayor y cuando la densidad de la muestra es baja, establecemos un valor bajo de longitud de zancada para capturar la información completa de las morfologías en los mapas de características de la CNN. Demostramos que el modelo propuesto supera constantemente los algoritmos de última generación relevantes para la tarea de aprendizaje computacional dada de detección de la condición de fibrilación auricular a partir de grabaciones de ECG de una sola derivación. De hecho, ambos trabajos de investigación [50] [53] resuelven los desafíos únicos del desarrollo de soluciones inteligentes para el cuidado de la salud , particularmente como una aplicación de IoT. En [52], ampliamos [53] para abordar el problema integral de la escasez de datos de entrenamiento en la generación de modelos DL. Se sabe que los modelos DL exigen ejemplos de entrenamiento sustanciales para la construcción confiable del modelo computacional. Sin embargo, las tareas prácticas de análisis de la señal del sensor a menudo se proporcionan con un número limitado de ejemplos de capacitación, principalmente debido a los costes asociados con la anotación de expertos (por ejemplo, cada uno de los registros de ECG debe ser anotado por un cardiólogo), lo que provoca un aprendizaje deficiente o una mayor generalización, lo cual supone una pérdida cuando se construyen algoritmos de clasificación de series de tiempo. De hecho, en una configuración de aprendizaje supervisado, la adecuación de los datos de entrenamiento es uno de los requisitos principales para generar un modelo entrenado bueno y confiable. En [52], proponemos un método novedoso de aprendizaje efectivo bajo la limitación de datos de entrenamiento utilizando el descubrimiento atribuido a Shapley de un subconjunto de entradas que influyen positivamente para construir un modelo DL basado en una red residual (ResNet). Proponemos una arquitectura DL push-pull única con ResNet como la arquitectura DL base. En primer lugar, se calcula la atribución del valor de Shapley para cada una de las entradas y la selección del subconjunto de entrada se realiza en función de esa atribución. El subconjunto de entrada, de hecho, empuja al modelo a aprender sobre un espacio de entrada de menor dimensión. Posteriormente, realizamos un entrenamiento contradictorio que mejora la capacidad de aprendizaje fuera de la distribución del modelo con el supuesto de una mejor capacidad de aprendizaje cuando se encuentra con datos no vistos. Nos basamos en la formulación de la teoría de juegos para estimar la contribución de cada una de las entradas en la previsibilidad del modelo con el cálculo de utilidad de características basado en el valor de Shapley para cada una de las muestras de entrenamiento de entrada por medio de axiomas de juegos de utilidad transferibles, a saber, "eficiencia" y "nulidad". axiomas del jugador. Además, proponemos un entrenamiento antagónico controlado del modelo utilizando las funciones de entrada efectivas seleccionadas. Por lo tanto, el modelo aprende con entrenamiento contradictorio de un subconjunto de entradas con la filosofía de aprender más con mejores ejemplos de entrenamiento. Nuestra noción de capacidad de aprendizaje mejorada y las mejoras del modelo propuesto se reflejan precisamente en los resultados obtenidos y el estudio empírico respalda sin ambigüedades nuestra afirmación de superioridad en el aprendizaje frente a datos de entrenamiento insuficientes. Demostramos un rendimiento superior para un conjunto diverso de tareas de clasificación de señales de sensores de series temporales en comparación con los algoritmos de última generación actuales. Además, representamos a través del estudio de ablación la eficacia del modelo push-pull con el método de entrenamiento contradictorio atribuido a características con respecto a los métodos de entrenamiento solo atribuidos a funciones y solo contradictorios. Por lo tanto, afirmamos con seguridad que el modelo propuesto mejora significativamente el rendimiento y que el modelo push-pull obtiene el apoyo empírico requerido.

Esta tesis doctoral está compuesta por los siguientes trabajos de investigación publicados (JCR)-

1. [50] Arijit Ukil, and Antonio J Jara, and Leandro Marin, "Data-driven automated cardiac health management with robust edge analytics and de-risking," Sensors, volume 19, number 12, 2019.
   https://doi.org/10.3390/s19122733
   https://www.mdpi.com/1424-8220/19/12/2733

2. [53] Arijit Ukil, and Leandro Marin, Subhas Chandra Mukhopadhyay, and Antonio J Jara, "AFSense-ECG: Atrial Fibrillation Condition Sensing from Single Lead Electrocardiogram (ECG) Signals," IEEE Sensors Journal, volume 19, number 12, 2022.
   10.1109/JSEN.2022.3162691
   https://ieeexplore.ieee.org/abstract/document/9743469

3. [52] Arijit Ukil, and Leandro Marin, and Jara, Antonio J Jara, "When less is more powerful: Shapley value attributed ablation with augmented learning for practical time series sensor data classification, volume 17, number 11, Plos One, 2022.
   https://doi.org/10.1371/journal.pone.0277975
   https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0277975

Abstract

Objective- The general objective is to build accurate machine learning models to solve practical challenges like training data scarcity, compact model construction and data privacy preservation for diverse set of sensor signal analysis tasks. With the proliferation of Internet of Things (IoT), advancements of sensing technologies, incredible enhancements towards computing power along with the outstanding progress of Artificial Intelligence algorithms and tools, researchers are finding new avenues to build different useful applications and novel research directions. The research work focuses on the construction of models for computational learning of analysis tasks involving different types of sensor signals from sensors like Electrocardiogram, Phonocardiogram, accelerometer, energy meter etc. In general, we can consider sensors as the micro-representation of our ambient world. Given that sensors capture near-human information, they usually contain sensitive data. Hence, our foremost task is the enablement of privacy preserving techniques as part of the computational sensing models that analyze the sensor signals and infer critical decision.
Methodology- It is understood that remote healthcare is one of the critical applications of IoT and we solve the problem of data privacy protection by proposing de-risking of sensitive data management using differential privacy, where user-enabled controlled privacy protection on sensitive healthcare data can be employed. We propose a novel data privacy preservation method that obfuscates the sensitive component of the sensor data while utility is not severely compromised, while user controls the quantum of privacy. The proposed machine learning algorithm requires subtly hand-crafted feature engineering, which not only restricts the scalability of the computational learning, but also depends on the expensive process of expert or domain-knowledge aided feature generation and selection. We develop intelligence-embedded sensing that does supervised classification tasks using novel deep learning (DL) method of hyperparameter-adjusted convolutional neural network without feature engineering efforts. We extend research to address the integral problem of training data scarcity in DL model generation. It is known that DL models demand substantial training examples for reliable construction of the computational model. Practical sensor signal analysis tasks are often provided with limited number of training examples mainly due to the costs associated with expert annotation. We propose a novel method of effective learning under training data

limitation using Shapley-attributed discovery of subset of positively influencing inputs to construct an effective Residual network-based DL model.
Results- Our novel privacy preserving method proposes sensor data uncertainty principle, such that controlled statistical uncertainty is employed to the sensitive information with the definition of privacy protection that the prior and posterior probabilities of finding private information does not change beyond a pre-defined threshold and the adversary's gain of sensitivity data access becomes insignificant. The proposed hyperparameter estimation from the input signal characteristics facilitates compact CNN model construction. We demonstrate that our model consistently performs superior over the relevant state-of-the-art algorithms for the given computational learning task of Atrial Fibrillation condition detection from single-lead ECG recordings. We propose an unique push-pull DL architecture, where, firstly Shapley value attributed input subset selection pushes the model parameters towards lower dimension and subsequently, we augment the learnability of the model through adversarial training. We demonstrate the efficacy of proposed model that empirically outperforms the current state-of-the-art algorithms in diverse set of time series sensor signal classification tasks.
Conclusion- We have proposed a holistic framework to solve the practical and research challenges of computational analysis of sensor signals including the data privacy preservation, deep learning algorithm for compact model generation, effective computational model under training data scarcity issue. In summary, the research work provides a unified approach to develop practical computational analysis for diverse set of sensor data.

Table of contents

List of figures

List of tables

Chapter 1

Introduction

1.1 Presentation and Scientific Unity

This doctoral thesis is presented as a compendium of publications. This thesis is composed of three research studies [50] [53] [52] published in Journal Citation Reports (JCR) indexed international journals. All the articles configure a scientific unity in the field of computational learning, particularly for the development sensor signal analysis using machine learning algorithms. Our focus is to build accurate machine learning models to solve practical challenges like training data scarcity, compact model construction and privacy preservation.
Sensor signals often being nearer to human being contain sensitive information. For example, Electrocardiogram (ECG), Phonocardiogram (PCG) signals contain cardiac activity signature, which is a direct health information of an individual. So, the first and foremost critical component of computational learning that generated data-driven model using machine learning algorithms is to ensure resistance against plausible privacy breaching attack. In study #1 [50], data sensitivity protection by derisking with sensitive data management using differential privacy method is employed such that strong predictive capability of machine learning algorithm to infer sensitive condition from sensor signal does not get misused for privacy beaching purposes. Firstly, we propose a data privacy protection scheme, which is functionally on-demand and that employs differential privacy method [16], where the profile of the destination is considered to ensure appropriate obfuscation on the shared sensitive data. Our proposed feature-engineered (feature selection is done using expert domain knowledge) Ada-boost [18]-based machine learning model infers decision from PCG signal whether the user is suffering from cardiac ailment or not. However, such prediction is sensitive and needs to be privacy protected. We propose sensor data uncertainty principle such that statistical uncertainty is incorporated into the sensitive information. Our privacy protection definition is that the prior and posterior probabilities of determining the sensitive private information

gets restricted within a pre-defined threshold. Let the prediction from a sensor signal $\boldsymbol{x}$ be $\mathbb{Y}$. When a privacy-breach attack is suspected, $\mathbb{Y}$ is transformed to controlled obfuscated form $\mathbb{Y}^{priv}$ and we have shown that the attacker receives $\mathbb{Y}^{priv}$, which effectively provides ransom outcome such that accuracy, sensitivity and specificity measures are $\rightarrow 0.5$, whereas the the prediction outcome of $\mathbb{Y}$ in terms of accuracy, sensitivity, specificity are more than 0.8 when validated by experimenting on large publicly available MIT Physionet Challenge 2016 database [36] containing PCG data. While the issue of privacy-preserved computational analysis is achieved in our study #1, the main limitation of study #1 is its reliance on expert-driven feature extraction. Human expert provided features are not only expensive, but also not scalable. The machine learning algorithm, Ada-boost [18] requires feature engineered inputs and classification model is generated from the provided hand-crafted features.

In study #2, [53] deep learning model based sensor signal like ECG classification algorithm is proposed, where external, domain expert-driven feature identification and selection are not required. Hence, we have eliminated the limitation of study #1 in study #2 by proposing AF-Sense, a hyperparameter-tuned (such that morphological feature of sensor signal, ECG gets incorporated into the feature maps) Convolution Neural Network (CNN) model with adaptive learning rate control that generates the required features for performing classification on its own. The paradigm shift from hand-coded symbolic expressions as features in machine learning algorithms to learned distributed representations in deep learning algorithm has not only demonstrated significant performance gain, but also eliminates the expensive requirement of hand crafting of features [7]. We closely examine ECG signals, which are quasi-periodic in nature with repeated QRS complexes, P-waves, T-waves that constitute its morphology. In CNN model, the long-range dependencies within the input ECG require larger receptive fields. We adjust the CNN receptive field with the knowledge of signal morphology to induce the domain characteristics into the CNN-generated feature maps. In CNN architecture, stride length hyperparameter controls how the convolution filter convolves the input space. In AFSense-ECG [53], we hypothesis that for a good representative feature map construction from ECG signals, the stride length hyperparameter is to be selected in proportion to sample density. Let us denote z_p as the sampling frequency and total s_p be the length of sample points that are captured by the ECG sensor. The sample density is defined as $\frac{z_p}{s_p}$. AF-Sense is an effective CNN model which outperforms the state-of-the-art models like [22, 48, 58, 41, 25] well as efficient (when model efficiency is measured through the number of trainable parameters or equivalently, the model size in Bytes). In study #1, 2435 number of training examples are present, in study #2, 8,528 number of training examples are used to model the classifier algorithm. However, in many real-world applications, the available number of training examples are often limited and small in size, (for e.g., the total number of

seen examples for the computational model is ≤ 200) mostly due to the cost associated with obtaining labeled sensor data.
We extended study#2 by addressing the practical issue of training data scarcity in typical sensor signal classification problem in study #3 [52] by proposing novel method of using Shapley ([42]) attribution to discover the subset of positively-influencing features in additively perturbed training for generating effective deep learning model using Residual network [23] architecture. Our proposed ShapAAL study 3 [52]s is a novel push-pull deep neural network architecture. Firstly, training augmentation aids the learn model to get trained over unseen data. Next, subset selection through Shapley value attribution is done that pushes the model to lower dimension so that apt selection to the augmented input space is performed. ShapAAL routinely outperforms the cutting-edge algorithms like [35, 17, 5, 45, 14, 38, 37, 55] over a variety of sensor data from a publicly available UCR time series archive dataset [4], which is one of the most renowned time series [20]. Further, we have established the efficacy of our proposed ShapAAL model with ablation study.
In summary, our research work starts with addressing the privacy-preservation aspect of sensor data analytics task with hand-crafted feature engineering based machine learning model (study#1). We eliminate the limitation of hand-crafting of features for machine learning by proposing CNN-based deep learning algorithms. However, study #1 and study #2 do not consider the practical problem of training data scarcity in developing effective classification model for computational learning of sensor signals. In study #3, we propose ShapAAL that addresses the problem of training data scarcity by Shapley-attributed input selection over augmented training data. Thus, the research work has holistically solve the challenges of computational learning of sensor signal analysis. This doctoral thesis is composed of the following works by published (JCR) research papers-

1. Arijit Ukil, and Antonio J Jara, and Leandro Marin, "Data-driven automated cardiac health management with robust edge analytics and de-risking," Sensors, volume 19, number 12, 2019.
https://doi.org/10.3390/s19122733
https://www.mdpi.com/1424-8220/19/12/2733

2. Arijit Ukil, and Leandro Marin, Subhas Chandra Mukhopadhyay, and Antonio J Jara, "AFSense-ECG: Atrial Fibrillation Condition Sensing from Single Lead Electrocardiogram (ECG) Signals," IEEE Sensors Journal, volume 19, number 12, 2022.
10.1109/JSEN.2022.3162691

https://ieeexplore.ieee.org/abstract/document/9743469

3. Arijit Ukil, and Leandro Marin, and Jara, Antonio J Jara, "When less is more powerful: Shapley value attributed ablation with augmented learning for practical time series sensor data classification, volume 17, number 11, Plos One, 2022.
https://doi.org/10.1371/journal.pone.0277975
https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0277975

1.2 Motivation

The rapid evolution and adaption of different Internet of Things (IoT) applications along side the rising deployment of sensors in the physical world are leading to an increase in the frequency of sensor data analytics issues. One of the typical practical challenges is to solve the classification problems, particularly that deal with time series data. In fact, IoT applications are penetrating faster along with evolving techniques for deploying real world solutions for different practical problems. The availability of high-end GPU-enabled computing power [34], pervasiveness of smartphones and smart devices, such as smart bands, smart watches, and smart gears, significant advancements in sensing technologies, open access to helpful databases, and the emergence of potent artificial intelligence (AI) techniques like deep learning algorithms, present us the right opportunity to create vast pool of important applications that contain immense possibilities in human well-being-based system development [51]. As a result, interest in and expectations for AI are increasing more rapidly. The learning revolution paradigm holds that a machine or computer can learn significantly enough to be comparable to human-level abilities by being given examples or training instances. The applications stemmed out of such learned systems are ready to be deployed and consumed for diverse set of usages. Consequently, if we focus on developing different important applications, sensor signals play an important role. Sensors can be considered as a miniature depiction of our physiological and physical spaces that gather data about the respective physiological and physical worlds from its environment and supply the necessary inputs to the intelligent system so that it can sense the specified information spaces and finally make various decisions. Firstly, we need to consider the privacy preservation requirements when building computational models using physiological marker signals that contain sensitive information like health condition.

Owing to the close proximity of human being, sensor signal often carries sensitive information. In order to build effective computational learning model we further have to develop accurate models from sensor signals. The paradigm shift is from acquiring explicit expert and domain knowledge into building an intelligent system to learning from a given number of examples, called training datasets. Secondly, we intend to state that an efficient yet accurate classification model has the potential solve practical challenges For example, automated detection of atrial fibrillation, a serious cardio-vascular abnormality condition associated with long-term health issue, is one practical requirement that needs to be taken into account in order to show the effectiveness of computational learning models that perform useful tasks to solve real-world problems. Thirdly, we have observed that practical sensor datasets in supervised learning tasks often classification tasks often experience short-supply in the number of training examples upon which the model is trained. The issue is mostly due to the labeling expenses and the requirements of specialized sensor hardwares and setups. For example, classification of cardio-vascular disease detection tasks form ECG signals require 1. ECG sensors to capture the data, 2. Identification and collection from human subjects suffering from cardio-vascular, and 3. Cardiologists to annotate or label the disease class from the extracted ECG data and the expenses associated with such annotation causes scarcity in training examples in larger of instances of real-world sensor analytics problems. While, in general, deep learning algorithms expect large set of training examples for proper and sufficient learning. We consider the problem of developing solution to build computational model that can effectively provide better classification performance over diverse set of sensor datasets. Last but not the least, Thus, a holistic approach that solves the three important aspects of computational learning for sensor signal analysis are addressed to solve the practical challenges. In summary, we aim for-

(a) Privacy-preserving computational model to cater the need of minimizing the privacy breaching attacks on the sensor signal classification models that deal with sensitive information like health information to infer health condition. For example, an accurate machine learning model can determine the heart health condition using Phonocardiogram (PCG) or heart sound signals. One of the major challenges is to ensure in-built privacy protection into the computational model that automatically infers whether the patient's heart condition is normal or not from the presented PCG signals. Given that the sensor signal (PCG, for example) contains sensitive information regarding a person's health condition, the plausible action against privacy breaching attack is to be made part of the analystics system in order to ensure practical relevance and user acceptability. Further, we need to understand that privacy preservation is a critical requirements for systems that analyze sensitive information like sensor signals captured to analyze health condition.

(b) Building intelligence towards automated classification of important sensor signal like a critical physiological marker, Electrocardiogram (ECG) that carries signature of cardio-vascular activity, for example development of Atrial Fibrillation (AF) condition detection from single lead ECG data, where the ECG recordings can be obtained from off-the-shelf single lead ECG sensors without hand-crafted feature engineering. The computational model needs to be self-sufficient data-driven model that can effectively generates features from the given training datasets to construct and effective and compact model to solve practical challenges like AF condition detection from single lead ECG sensor. AF is presented as an irregular disorder of heart rhythms (arrhythmia), which is mostly accompanied by rapid heart rate and the underlying condition can be the reason of major damages to the cardiovascular systems [24], [30]. Our main focus of this particular research work is to build a reliable automated single lead ECG classification algorithm for AF detection, which is useful in ambulatory or in-home screening purpose so as part of an early-warning smart healthcare system for identifying the potentially critical cardio-vascular diseases (CVDs) of the user. Additionally, the constructed model needs to be compact in nature in order to to get deployed in edge devices including sensing platforms or smartphones so that the analysis can be performed locally.

(c) Solving the problem of training data insufficiency in the efforts of developing accurate machine learning models. Owing to the issue of expert-level annotation requirement to perform the data labeling tasks, machine learning algorithms face insufficiency in the training data space for the construction of computational models for supervised learning tasks like classification. For instance, Electrocardiogram (ECG) is a fundamental marker of heart health, which can be affordably captured from human subjects that helps us to develop important applications like automated cardio-vascular screening system as part of smart healthcare platform. However, these critical sensor signals require experts like cardiologists to get the annotation tasks done, which is an expensive process and subsequently, it results in scarcity of training examples. In fact, data scarcity is a real practical challenge [6]. In order to build such useful practical applications, we need to solve the problem of training data scarcity for building an accurate computational model by analyzing sensor signals.

Time series data are employed in a wide range of real-world applications, particularly when building intelligent systems using sensor data. As part of building intelligent systems, time series classification is an important task owing to the fact that large number of sensors capture signals which are temporal in nature. It is clearly evident that time series data analysis is crucial for creating practical applications. Time series output is provided by sensor signals that are practically crucial, such as ECG and PCG. To incorporate trustworthy decision-making into the computational model, it is important to examine the sensor measurements and run time series analysis on the collected data.

We also are witness the convergence of Internet of Things (IoT), Artificial Intelligence (AI) and advanced sensor technology is revolutionizing the consumer computing landscape and usher a new direction towards the research of developing computational models, more specifically deep learning models for performing large set of tasks including sensor signal analysis [8]. From the technical contribution point of view, we intend to bring in novel methods for the realization of diverse set of real-world applications. We particularly consider the time series sensor signal classification problems, where the task is to build multi-class classification models by training time series sensor signals. We are primarily focused on building data-centric learning models by taking the advantages of the availability of benchmark time series sensor analysis classification datasets. For instance, heart sound or PCG dataset is publicly available in [36], which contains total 2435 number of PCG recordings, where 1297 are collected from healthy subjects and rest are patients who are suffering from different conditions, including coronary artery diseases and heart valve diseases. Similarly, publicly available expert-annotated database of AF detection using single lead ECG recordings are available, where total 8,528 number of single lead ECG recordings are present with labels of normal, AF, noisy and other rhythms are labeled [11]. We further note that an outstanding effort has been made to archive different time series classification datasets [4], [3]. In fact, the time series archive database becomes one of most popular open-access benchmark database that contains large set of time series classification tasks from different types of sensors including ECG, accelerometer, energy meter etc.Large sets of real-world time series datasets, however, frequently lack labelled training examples due to a variety of factors, such as the niche and expensive requirements to setup the experiments like, "SonyAIBORobotSurface1" requires a robot to walk on various surfaces, such as cement or carpet. We also find that great amount of cost is associated

with the human-expert-in-loop annotation process ("TwoLead ECG" requires qualified medical professionals or trained cardiologists to perform the data annotation or labeling job). “SonyAIBORobotSurface1” dataset contains mere 20 number training examples, “TwoLead ECG” contains 23 number of training examples. Another import dataset "ECG 200", where two classes- normal heartbeat and a Myocardial Infarction (heart attack) are present that contains 100 training examples [4], [3]. We note that time series sensor signal classification under training datasets scarcity is a research challenge which needs to be solved to build useful applications with the help of gamut of rich sensor types [49] [27] [54]. We also like to point out that the natural temporal ordering of the attributes of a (sensor) signal in time series classification tasks makes it different from conventional classification tasks. One of the research challenges is to learning from the signal morphology to construct better representation. Such approaches are distinctly useful in ECG signals, which is quasi-periodic nature with repeated patterns.
While we are motivated by the exponential growth of AI techniques, particularly the machine learning and deep learning algorithms fueled with large number of publicly available standard datasets to develop effective computational models to solve diverse practical time series classification problems involving analysis of different sensor signals, under the user acceptability and deployment perspectives, privacy preservation of user’s data, particularly, when healthcare recordings are concerned is of utmost importance and needs critical attention. An effective computational model with data privacy protection option has immense practical significance. We further attempt to find solution for privacy preservation enabled machine learning model development. In fact, our motivation has two major components- 1. privacy preservation of sensor analytics tasks, 2. solution building towards development of practical sensor signal analysis.

1.3 Problem Formulation and Solution Sketch

We primarily focus on sensor signal classification tasks and often the sensor signals are represented as time series: $\boldsymbol{x} = [x_1, x_2, x_3, ..., x_T]$, $\boldsymbol{x} \in \mathbb{R}^T$ and $\boldsymbol{x}$ is of length T and $x_1, x_2, x_3, ..., x_T$ are the scalar measurements at time intervals $1, 2, 3, ..., T$ from a given sensor. Consider N number of seen examples which constitute the training dataset $\mathbb{X}_{Train} = [\boldsymbol{x}^{(1)}, \boldsymbol{x}^{(2)}, \ldots, \boldsymbol{x}^{(N)}]$, $\mathbb{X}_{Train}$ consists of N number of time series sensor signals each of which has T number of data samples and the training set also comprises of

labels for each of the training instances:
$\mathscr{D}_{Train} = [\mathbb{X}_{Train}, Y_{Train}] = [\{\boldsymbol{x}^{(1)}, y^{(1)}\}, \{\boldsymbol{x}^{(2)}, y^{(2)}\}, \ldots, \{\boldsymbol{x}^{(N)}, y^{(N)}\}]$
and $y^{(n)} \in [1, \mathbb{C}]$, $\forall n$, the labels correspond to one of the $\mathbb{C}$ classes, which are required to generate time series classifier model. The model gets trained with seen examples and the trained model infers or predicts the class of the given (test) sensor data set. For instance, in AF detection problem from single lead ECG sensor data [11], the primary task is to classify between normal sinus rhythm, AF or other heart rhythm. We like to point out that the traditional machine learning algorithms like Ada-boost [18] requires specific features to be extracted from the input training data or in general, the input to the Ada-boost algorithm is a set of hand-crafted features. Let us denote the the input hand-crafted or selected features be $\mathbb{F}_{train}$ and $\mathbb{F}_{test}$ be for training and testing purposes respectively. The trained model M_{train} learns from $\mathbb{F}_{train}$ and it infers $\mathbb{I}$ on the test data $\mathbb{F}_{test}$, $\mathbb{I} = M_{train}(\mathbb{F}_{test})$. Our goal is to construct a good trained model M_{train} with accurate predictability $\mathbb{I}$. The prediction accuracy $\mathbb{I}$ is computed by the trained model M_{train} over the unseen test dataset $\mathbb{F}_{test}$. While sensor signal-based applications possess considerable benefit ot human society and life, the sensor signals, primarily the physiological signals like PCG carry significant sensitive information. Hence, building of automated solutions with typical sensor signals are of little practical value if the issue of data privacy prevention is not addressed, where the de-risking of sensitive data analysis needs to be performed. In fact, the de-risking of sensitive data management is to be an integral component of different sensor signal analysis solutions including healthcare domain. However, protection data privacy has the potential side effect of minimizing the utility of the application. Data privacy in terms of obfuscation approach transforms the data into non-usable format. Under clinical management setting, such approach favorably biases privacy-utility trade-off towards the user, who can enable a user-centric privacy preservation of healthcare AI system such that the important features are privacy-protected while sharing with the non-critical stakeholders in a smart healthcare eco-sytem. $\mathbb{O} = (\mathbb{F}_{test}, \mathbb{I})$ are the clinical analytics outcomes from the machine learning model over a physiological sensor signals like PCG, where $(\mathbb{F}_{test}, \mathbb{I})$ denote the important machine learning features and the prediction or inference of the model from the test PCG signal respectively. Depending upon the user's choice of privacy protection on $\mathbb{O}$, de-risking approach is performed. When user's choice is privacy protection $\mathbb{F}_{test}, \mathbb{I} \rightarrow \mathbb{F}_{test}^{Prv}, \mathbb{I}$, the research problem is to find the transformation of $\mathbb{F}_{test}$ to $\mathbb{F}_{test}^{Prv}$ that enables the development of a method for sharing of privacy-controlled information that minimizes the privacy-breaching risk of sensitive health information. We solve this problem with controlled differential privacy approach using the statis-

tical distribution of $\mathbb{F}_{test}$ such that minimum obfuscation that is suitable to ensure the adequate privacy protection is made to warrant minimum information loss. Our novel contribution is to define the sensor data uncertainty principle which introduces controlled uncertainty to minimize the impact of privacy breaching attacks when the adversary intends for sensitive summarization, performance prediction knowledge gain. Clinical uncertainty knowledge is incorporated to appropriately introduce differential privacy for controllable obfuscation of the sensitive data. We are primarily interested in edge analytics-based applications with deployment architecture as per Figure 3.1. The machine learning model and controlled privacy protection are performed at the edge devices, where the data owner receives the analytics outcome and related information. Our architecture controls the amount of required data privacy protection such that the user or the data owner has the complete command on his/her data privacy and such mechanism brings transparency of the private data flow as depicted in Figure 3.2. Privacy preservation transforms in general, the clinical analytics outcome $\mathbb{O} = (\mathbb{F}, \mathbb{I})$. $\mathbb{S}$ is a conservative user and she does not intend to disclose her clinical outcome $\mathbb{O} = (\mathbb{F}, \mathbb{I})$ to clinical researcher in anonymized but raw form. Privacy preservation module obfuscates $\mathbb{F}, \mathbb{I}$ to $\mathbb{F}^{Prv}$ and shares $\mathbb{F}^{Prv}$ for the user $\mathbb{S}$. Hence, a controlled, user-driven, proactive privacy preservation takes place in the event of positive triggering for privacy implementation. When user $\mathbb{S}'$ does not express or intend privacy risk, then $\mathbb{F}, \mathbb{I}$ corresponding to the user $\mathbb{S}'$ is shared to the prospective clinical researchers.

Related publication:
Arijit Ukil, Antonio J Jara and Leandro Marin, "Data-Driven Automated Cardiac Health Management with Robust Edge Analytics and De-Risking", MDPI Sensors, 19:12(2733), 2019.

While privacy preservation issue is tackled in our previous research publication [50], the expert-dependent hand-crafting of feature generation to construct the train model is a practical constraint. For example, Atrial Fibrillation (AF) condition from ECG sensor signal requires cardiologists' intervention to identify the relevant features, which is significantly expensive and limits the process of computational model development. However, AF condition detection through automated analysis of ECG signal is one of critical components of a smart cardio-vascular screening systems. AF condition is a kind of highly prevalent CVD and a major healthcare burden. AF is presented as an irregular heart rhythms and it is likely to cause severe long-term critical damages

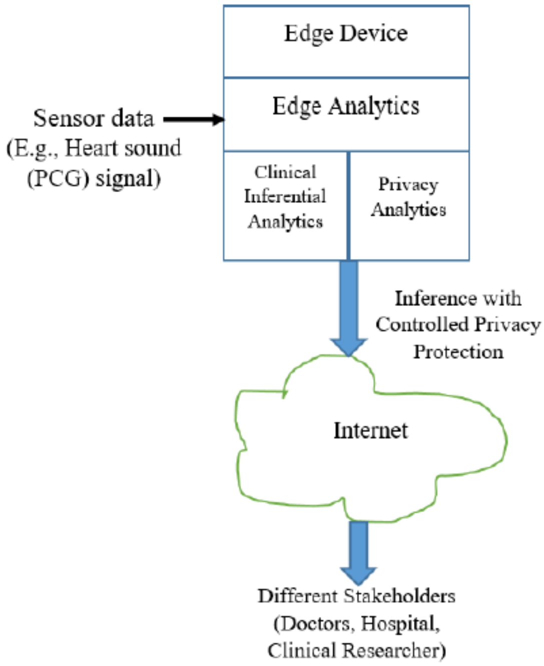

Fig. 1.1 Smart edge sensor analytics for inference and controlled privacy protection: Deployment architecture [50].

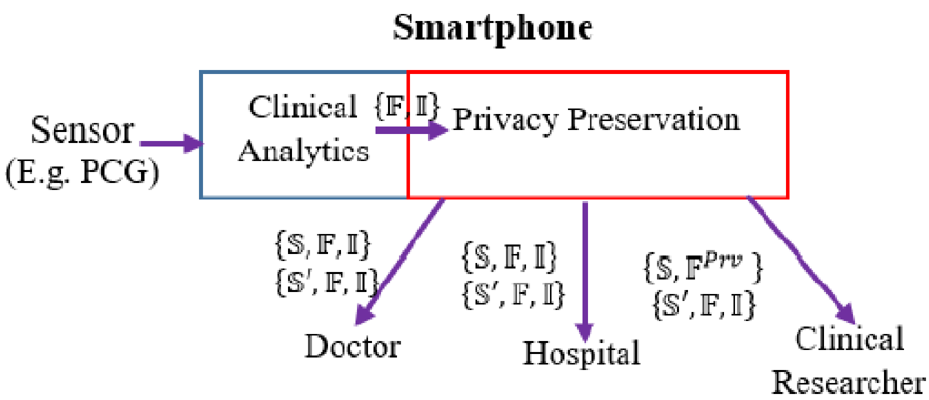

Fig. 1.2 Data-driven on-demand privacy preserved analytics: functional architecture [50].

to the cardiovascular systems [30] [39]. It is known that cardio-vascular diseases (CVDs) are the leading cause of deaths worldwide [1]. ECG signal has the capability of capturing the AF condition and when AF is detected early, prognosis is very positive and promising. Hence, Automated detection of AF condition from off-the-shelf single ECG sensors is of immense practical importance to build automated early warning system for AF diagnosis.

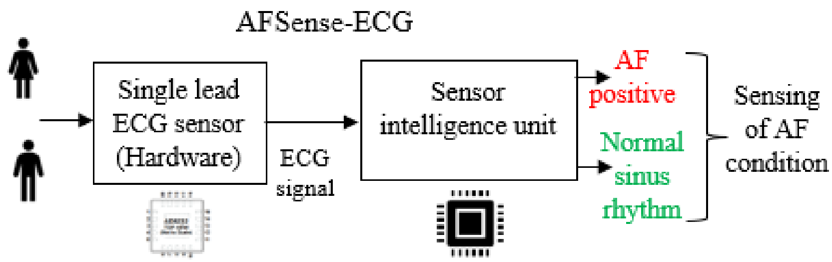

Fig. 1.3 Block diagram of AFSense-ECG [53].

The given problem is to build tailored or specialized computational model, preferably using deep learning technique to classify AF condition from single lead ECG recordings. While state-of-the-art algorithms for AF detection from ECG signals [22] [9] [57] demonstrate excellent classification performance, the models are computationally expensive and require substantial memory budget. Such models are not suitable to develop intelligent sensing platform with off-the-shelf single lead ECG sensors like Alivecore (kardia.com) or AD8232 (https://www.analog.com/media/en/technical-documentation/data-sheets/ad8232.pdf) and typical inexpensive microcontroller like ESP32WROVERE (https://www.espressif.com/sites/default/files/documentation/esp32-wrover-e_esp32-wrover-ie_datasheet_en.pdf).
We solve the problem of modeling without expert-intervened feature generation with the objective of building compact yet effective model construction for problem of AF condition detection from single lead ECG signals as depicted in 3.3. We have realized equivalent classification performance of state-of-the-art methods while being lean with reduced model parameter size to enable edge device deployment for off-the-shelf single lead ECG classification that detects AF condition. We intend to introduce inferential sensing capability to the single lead ECG sensor devices.The typical morphological characteristics of ECG signals with of repeating P-wave, QRS complex, and T-wave patterns [2] is captured by AFSense-ECG during feature extraction, representation learning, which results in learning rate optimization and accurate modeling with convolutional neural network (CNN) construction. We are motivated by the observation that ECG analysis using deep learning-based methods perform better than traditional machine learning approaches with feature engineering [26]. Further, CNN is a well-accepted and widely-used deep learning architecture, which has successfully achieved benchmark results on diverse classification tasks including ECG classification [31] [22] [59]. Hence, CNN turns out to be our apt choice as our deep learning model architecture. There are total five convolution blocks in AFSense-ECG deep neural

architecture. Each of the convolutional layers are followed by one Rectified Liner Unit (ReLU) activation function as well as one batch normalization function. After the final convolution block, Global Average Pooling is used as the last layer before softmax activation output layer. The AFSense-ECG model architecture is shown in Figure 1.4.

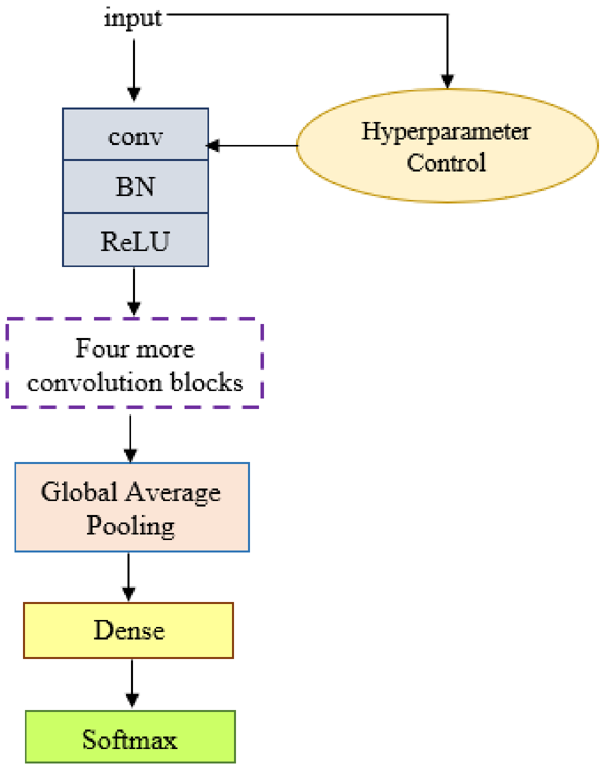

Fig. 1.4 Deep neural network architecture of AFSense-ECG [53].

Our novel contribution is enforcing the CNN feature maps to capture the ECG signal characteristics such that signal morphology plays an important role in the generation of the receptive fields. In this work, we put paramount importance to leverage the ECG signal morphology and temporal information while modeling the deep neural network and corresponding representation learning. Hence, the learning process gets higher chance of capturing the required details of ECG signal by properly adjusting the receptive field that constructs the CNN feature maps. In order to capture ECG morphology in the CNN feature extraction process, we adjust the receptive field to induce the domain characteristics into the feature maps. The first convolution layer is suitable to capture the morphological features in terms of QRS-complexes from an ECG signal.Therefore, we make an estimation of the value for the first convolution layer stride length hyperparameter ψ_1 to ensure that the clinical morphology of ECG

in terms of QRS-complexes gets captured in the generated feature maps. We propose our hypothesis that for a clinical morphology-induced representative feature map construction from ECG signals, the following relationship needs to hold:
$\psi_1 \propto sample\ density(s_d), \quad s_d = \frac{z_p}{s_p}$
where, z_p denotes the sampling frequency of an arbitrary p^{th} ECG sensor. From that ECG sensor, s_p length of sample points are captured and the complete training instance matrix $s_p \times N$ is fed to the CNN model for total N number of training instances, where N is the total number of instances each with time steps of s_p. We compute the sample density $s_d = \frac{z_p}{s_p}$. If there exists only single ECG sensor, $p = 1$. Let M^* be the model of a state-of-the-art AF classification with $\alpha*$ number of parameters with classification performance merit (e.g., in terms of F1-score, etc.) of $\gamma*$ over a given dataset $\mathscr{D}$. Our problem is to develop M^{ours} with α number of parameters with classification performance merit (e.g., in terms of accuracy, F1-score, etc.) of γ over $\mathscr{D}$, such that $\alpha \ll \alpha*$ and $\gamma \sim \gamma*$. We attempt to find such compact model h^{ours} which eventually enables us to realize AF detection from single lead ECG signals deployed at low-cost microcontrollers with off-the-shelf inexpensive ECG sensors for accomplishing local analysis of ECG signals.

Related Publication:
Arijit Ukil, Leandro Marin, Subhas Chandra Mukhopadhyay, and Antonio J. Jara, "AFSense-ECG: Atrial Fibrillation Condition Sensing from Single Lead Electrocardiogram (ECG) Signals," IEEE Sensors Journal, March, 2022.

Currently, we are witnessing gamut of requirements and demands to use time series signals for the development of number of useful sensor analytics applications like identification of normal and abnormal cardiac condition from the time series sensor signal (e.g., ECG) from smart wristband or smart watch. While such kind of applications have tremendous potential for enabling predictive analytics in remote healthcare system, these are niche in nature and require specialized (sometimes expensive) hardware to acquire the training set, and importantly, the annotation or labeling of training datasets require specialized training, expert human intervention and are very much costly. Such practical challenges demand some novel representation space enrichment principles for the betterment of computational modeling through sophisticated deep neural network construction. Deep neural networks often need a huge collection of training datasets for dependable and stronger learning [27]. For instance, ImageNet 2012 classification

dataset includes 1.28 million training datasets and the CIFAR-10 dataset contains 50,000 training photos [32], [15], [33].
Let, N be the number of seen examples, refereed to as the given training dataset $\mathbb{X}_{Train} = [\boldsymbol{x}^{(1)}, \boldsymbol{x}^{(2)}, \ldots, \boldsymbol{x}^{(N)}]$, and the labelled training data
$\mathscr{D}_{Train} = [\mathbb{X}_{Train}, Y_{Train}] = [\{\boldsymbol{x}^{(1)}, y^{(1)}\}, \{\boldsymbol{x}^{(2)}, y^{(2)}\}, \ldots, \{\boldsymbol{x}^{(N)}, y^{(N)}\}]$
and $y^{(n)} \in [1, \mathbb{C}]$, $\forall n$, the labels correspond to one of the $\mathbb{C}$ classes. Our focus is on supervised classification problem solving, where the task is to generate a reliable deep learning model without feature engineering effort from the given training dataset $\mathscr{D}_{Train}$. For instance, in AF detection problem from single lead ECG sensor data [11], the primary task is to classify between normal sinus rhythm, AF or other heart rhythm. In supervised learning setting, we attempt to find a model or function $h_\theta(.)$ parameterized by θ with joint distribution $p_{data}(\mathbf{x},\mathbf{y})$.
In machine learning, the foremost important objective is to minimize the mistake of the model function $h_\theta(.)$. The corresponding objective function is called the loss function as $L(h_\theta(x), y)$. [1] Consequently, the expected risk is defined as
$R(h) = \mathbb{E}_{(\mathbf{x},\mathbf{y}) \sim p_{data}}[L(h_\theta(\mathbf{x}), \mathbf{y})]$

However, it is to be noted that we seldom or practically never have the full knowledge about $p_{data}(\mathbf{x},\mathbf{y})$ and we only have the given training dataset $\mathscr{D}_{Train} = (x^{(n)}, y^{(n)})$ and the corresponding empirical risk minimization (ERM) is defined as:
$\hat{R}emp(h) = \frac{1}{N} \sum_{n=1}^{N} L(h_\theta(x^{(n)}), y^{(n)}))$.
The maximum likelihood estimation (MLE) cost function is defined as:
$J(\theta) = \mathbb{E}_{(\mathbf{x},\mathbf{y}) \sim \hat{p}_{data}} - log\ p_\theta(\mathbf{y}|\boldsymbol{x})$
Hence, the goal of a "good" machine learning algorithm is to successfully attempt for the minimization of the cost function $J(\theta)$ for the purpose of reliable estimation of the model parameter θ from the empirical distribution $\hat{p}_{data}$. The optimization problem is defined as follows:
$\theta^* = \arg\min_{\theta} J(\theta)$

In time series classification tasks, particularly that involve sensor signals do not enjoy large N and T unlike the regular computer vision classification tasks [6]. Often the number of training instances (N) in classification tasks that involve sensor data is less than 100, while conventional computer vision classification tasks, for instance in ImageNet 2012 there are about 1.28 million training examples [32], [15]. Thus,

[1] Acknowledging https://blog.christianperone.com/2020/11/optimization-deep-learning/

we cannot reliably assume that $\hat{p}_{data}$ and p_{data} are close. Therefore, the estimation of the model parameters from $J(\theta)$ is bad or incomplete, which may result in learning degradation issue. Given that limitation on number of training data is a generic problem in time series sensor data classification tasks [54], our research problem is to ensure better learnability under training data scarcity problem for diverse and heterogeneous varieties of time series sensor data.

The regular solution to tackle the training data limitation challenge is to introduce adversarial training [40], [56], [21] for augmented learning, where adversarial training examples as perturbed input forms attempt to construct a generalized model [28], [29]. However, we are unsure about the positive impact of the adversarial examples into the training process. Hence, finer control of creation of adversarial training plays an important role. We solve the finer control of adversarial training by suitable feature space or in current context, apt input space selection to enable better generalizability capability to the trained model by identifying a subset of inputs that are important and relevant towards model's predictability. We consider game theoretic set up of Shapley value [42, 44, 19]-based feature or input importance estimation to discard the negatively contributing samples, if exist. We propose a novel deep learning method Shapley Attributed Ablation with Augmented Learning (ShapAAL), which is a residual network with augmented learning capability along with Shapley value-estimated input sample ablation as depicted in Figure 1.5 and Figure 1.6.

Related Publication:
Arijit Ukil, Leandro Marin, Antonio J. Jara, "When less is more powerful: Shapley value attributed ablation with augmented learning for practical time series sensor data classification," PLOS One, Vol. 17, Issue. 11, Published: November 23, 2022. https://doi.org/10.1371/journal.pone.0277975.

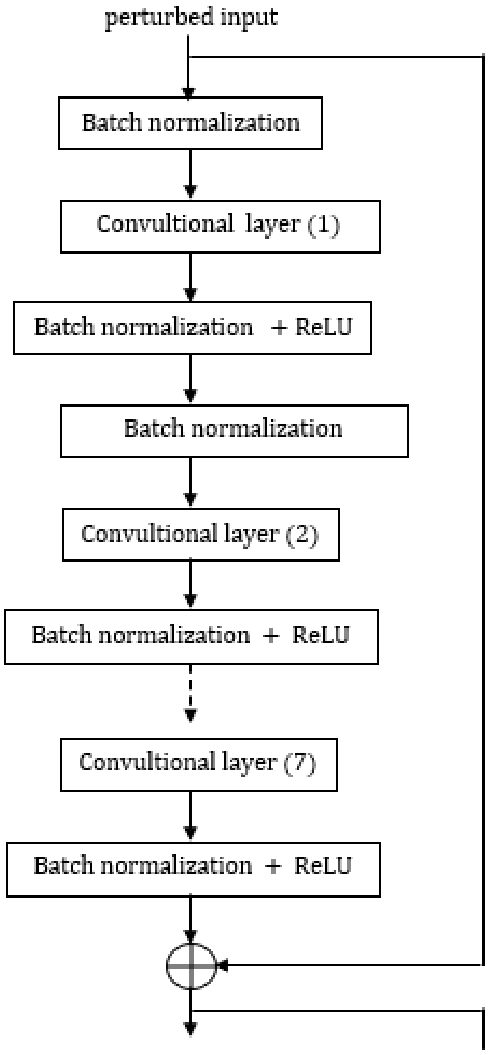

Fig. 1.5 ShapAAL network architecture with residual blocks and perturbed input [52].

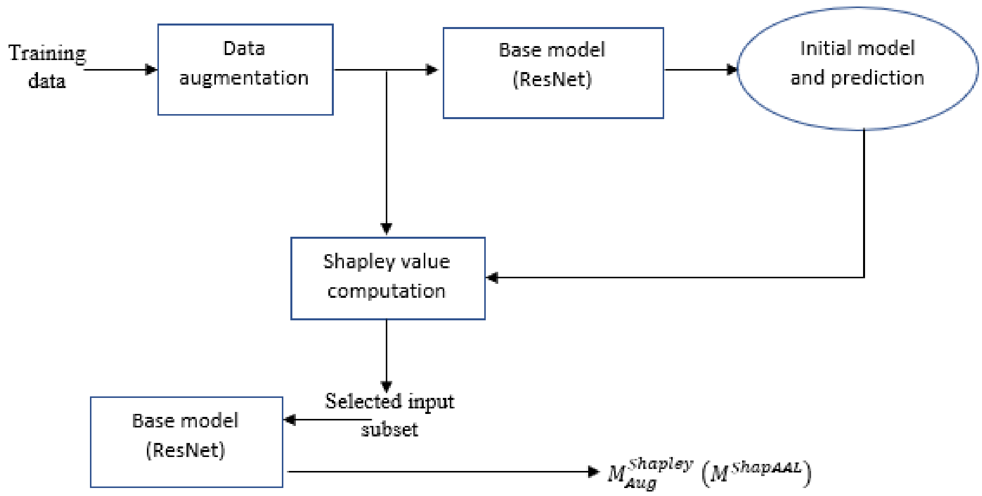

Fig. 1.6 Constructing the proposed ShapAAL model Mwith additive perturbation and Shapley-value based feature (input) attribution [52].

Chapter 2

Publication

This research work consists of three publications.

2.1 Study 1- "Data-driven automated cardiac health management with robust edge analytics and de-risking [50]"

Publication details
Arijit Ukil, and Antonio J Jara, and Leandro Marin, "Data-driven automated cardiac health management with robust edge analytics and de-risking," Sensors, volume 19, number 12, 2019.
https://doi.org/10.3390/s19122733
https://www.mdpi.com/1424-8220/19/12/2733
Author details
Arijit Ukil, TCS Research, Tata Consultancy Services, Kolkata, India
Antonio J. Jara, Libelium, Ceutí, Murcia, Spain
Leandro Marin, University of Murcia, Spain
Summary
Remote and automated healthcare management is a high impact application to deliver better and on-demand monitoring as well as medical service provision which has the potential to enhance the prognosis rate of different disease conditions, including cardio-vascular diseases. It is to be noted that cardio-vascular diseases are the cause of highest number of human deaths worldwide. It is understood that Internet of

Things (IoT) can enable the development and implementation ecosystem of such automated smart healthcare systems to attain the requirement of large number of stakeholders. In this paper, we particularly focus on cardiac health management system that performs clinical decision making through data-driven algorithms. We show that the proposed method is capable of ensuring significant merit of clinical decision making performance by employing robust machine learning methods, where the machine learning algorithms are fed with relevant and selected signal processing features. We consider Phonocardiogram (PCG) or heart sound, which is a fundamental marker to capture the heart health abnormalities as the exemplary physiological or biomedical signal. We know that PCG signal carries basic cardiac health condition signature. Our aim is to establish data-centric clinical utility through supervised learning to classify normal and abnormal heart conditions. Such analytics would be performed at edge gateway. However, it is a well-known fact that analysis of healthcare data poses with privacy breaching risk owing to the presence of different sensitive information contained in the extracted physiological signals. Hence, privacy protection is of clear importance for practical acceptability of such computational models. In this paper, we additionally solve the problem of healthcare data privacy prevention issue by de-risking of sensitive data using differential privacy, such that the controlled privacy protection on sensitive healthcare data can be enabled to develop privacy preserved data management. When a user sets or wishes for privacy protection, appropriate privacy preservation is guaranteed to defend against privacy-breaching knowledge mining attacks with differential privacy technique by estimating the distribution of the sensitivity content of the PCG signal. Given the proliferation of IoT application using machine intelligence techniques, we sincerely hope that the research work is of substantial real-world importance as it enables on-demand automated screening of cardiac health that minimizes the privacy breaching risk. We propose an integrated method of computational analysis of cardiac health state detection along with data privacy preservation. We conduct empirical investigation with publicly accessible, expert-annotated MIT Physionet Challenge 2016 PCG database. The empirical study shows substantial clinical efficacy of the proposed method and it also sufficiently protects the sensitive data privacy when privacy preservation demand is set.

2.2 Study 2- "AFSense-ECG: Atrial fibrillation condition sensing from single lead electrocardiogram (ECG) signals [53]"

Publication details

Arijit Ukil, and Leandro Marin, Subhas Chandra Mukhopadhyay, and Antonio J Jara, "AFSense-ECG: Atrial Fibrillation Condition Sensing from Single Lead Electrocardiogram (ECG) Signals," IEEE Sensors Journal, volume 19, number 12, 2022.
https://doi.org/10.1109/JSEN.2022.3162691
https://ieeexplore.ieee.org/abstract/document/9743469

Author details

Arijit Ukil, TCS Research, Tata Consultancy Services, Kolkata, India
Leandro Marin, University of Murcia, Spain
Subhas Chandra Mukhopadhyay, Macquarie University, Australia
Antonio J. Jara, Libelium, Ceutí, Murcia, Spain

Summary

In order to develop practical applications like disease detection using wearable technology, local generation of sensing knowledge, or remote monitoring of health condition, it is well understood that the augmentation of sensing capability of hardware sensors that capture physiological signals like Electrocardiogram (ECG) with intelligence is of the utmost importance. In this study, we present AFSense-ECG, a single lead ECG sensor with integrated intelligence that is capable of reliable detection of the atrial fibrillation (AF) condition, the most prevalent continuous cardiac arrhythmia and it is known to be associated with a greater risk of stroke in sub-clinical AF patients. For the purpose of detecting AF conditions, AFSense-ECG serves as an early-warning sensor. A single lead ECG sensor from the market, such as the Alivecor or AD8232, is combined with a processing unit (such as the ESP32WROVERE microcontroller) that embeds intelligence. We proposed convolutional neural network (CNN)-based deep learning (DL) method for supervised learning of single lead ECG signals. The hyperparameter-tuned CNN based deep neural network model of AFSense-ECG consists of an adjustable configuration for learning optimization through learning rate regulation. The feature extraction approach and the representation learning process of model development in AFSense-ECG takes into account the quasi-periodic character of typical ECG data with repeating P-wave, QRS complex, and T-wave patterns. The effectiveness of the suggested ECG signal characteristics-based hyperparameter-tuned

ECG classification model development is supported by our empirical investigation. In comparison to the publicly accessible single lead ECG datasets of the Physionet 2017 Challenge, AFSense-ECG reports an F1-measure of 86.13%, whereas the state-of-the-art techniques show F1-measures of 83.70%, 83.10%, 82.90%, 82.60%, 82.50%, and 81.00%. Also, the suggested learning model for inferential sensing is compact (about 25 times simpler in terms of total number of trainable parameters than the relevant state-of-the-art methods that uses more than 30 number of convolutional neural network layers, where total 10474607 number of trainable parameters is present, and in our proposed model, there are 433675 trainable parameters). We arrive at the conclusion that intelligent ECG sensing is a potentially useful method for deriving practically meaningful knowledge from physiological marker signals like the ECG, and AFSense-ECG converts the raw ECG sensor into a medical condition monitoring system through intelligence embedding. The single lead ECG sensors that are available off-the-shelf can now have in-built intelligence thanks to the suggested sensing-based CNN algorithm. The proposed deep neural network model requires a small memory footprint that is quite effective at detecting AF condition on the analytics side from single lead ECG signals. Although we have now tested for AF condition sensing and detection, the methodology of the proposed data-driven computational learning for ECG signal categorization is a generic one. While the suggested AFSense-ECG model size is substantially smaller than the state-of-the-art, it performs better. The overparameterization of common DL models for capturing fine features in the representation space is another point we want to make emphasis. The way input signal is presented to the model, however, also affects the representation space. For ECG signals, we have shown that a better result can be obtained through an efficient hyperparameter estimation by computing the sample density of the input ECG recordings while taking into account the distinct quasi-periodic property and related morphology of ECG signals. Thus, the proposed model is not overparameterized. As a result, the AFSEnse-ECG model is not only efficient but also compact with a significantly less number of model parameters than the most recent model and we feel that compact, yet effective models are crucially important for the realization of real-world applications. From the standpoint of clinical utility, AFSense-ECG opens the natural path towards the creation of an intelligent healthcare system and has the potential to greatly reduce the need for frequent clinician intervention for on-demand assessment of the heart condition. It in fact aids in the rapid identification of the currently present non-diagnosed or sub-clinical AF disease from off-the-shelf single lead ECG signals.

2.3 Study 3- "When less is more powerful: Shapley value attributed ablation with augmented learning for practical time series sensor data classification [52]"

Publication details

Arijit Ukil, and Leandro Marin, and Jara, Antonio J Jara, "When less is more powerful: Shapley value attributed ablation with augmented learning for practical time series sensor data classification," volume 17, number 11, Plos One, 2022.

https://doi.org/10.1371/journal.pone.0277975

https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0277975

Author details

Arijit Ukil, TCS Research, Tata Consultancy Services, Kolkata, India

Leandro Marin, University of Murcia, Spain

Antonio J. Jara, Libelium, Ceutí, Murcia, Spain

Summary

Due to the costs involved with the expert-intervened annotation efforts, tasks involving time series sensor data classification frequently experience a problem with a lack of training data. As an instance, the classification problem of Electrocardiogram (ECG) data for the identification of Cardio-Vascular Disease (CVD) necessitates the use of pricey labeling techniques with direct assistance of the cardiologists. Deep learning (DL) models, one of the most cutting-edge algorithms currently available that accurately perform different classification tasks, have demonstrated exceptional performance when compared to other algorithms when a high sample size of training data or seen examples is available. In this study, we propose Shapley Attributed Ablation with Augmented Learning (ShapAAL), which shows how deep learning algorithms with carefully chosen subsets of observed examples or by ablating the unimportant ones from the provided small training dataset can consistently guarantee better classification performance under augmented training principle. We choose the crucial inputs from the given training dataset that have a beneficial influence on the predictability of the provided model with the help of the "efficiency" and "null player" axioms of transferable utility games, upon which Shapley value computation game is built on. Subsequently, we perform additive perturbed training in ShapAAL to enhance the input space that compensates the scarcity in the training examples. We use Residual Network (ResNet) architecture. Shapley attribution first seeks the subset from the given input training examples and then, it augments training space for improved

learnability such that we can achieve higher accuracy in general predictive performance. In ShapAAL, the subset of training instances that favorably affect a supervised learning setup is created via coalition games utilizing Shapley values related to each input's contribution to the model prediction. In ShapAAL, a revolutionary push-pull deep architecture, subset selection by Shapley value attribution pushes the model to a lower dimension while enhanced training increases the model's capacity for learning from previously unexplored material. Our conducted ablation study provides the necessary empirical support to substantiate our claim, and we demonstrate that the proposed ShapAAL method consistently outperforms the current benchmarks and cutting-edge algorithms for time series sensor data classification tasks from publicly available UCR time series archives that include various practically important classification problems including the detection of CVDs from ECG. Our goal is to create a solution for the significant practical issue of training data scarcity in time series sensor data classification tasks when implementing various types of real-world applications, such as smart cardio-vascular disease detection using ECG data to create an efficient early-warning, on-demand heart health monitoring eco-system. Across a variety of time series sensor data analysis tasks, our suggested augmented learning with input subset selection strategy using Shapley value-based attribution has exhibited considerably correct performance. We have proposed a novel learning mechanism that first unlearns the non-important samples by identifying their contributions to the model predictability through Shapley value computation from coalition game setup with transferable utility, then it re-learns with those important subset samples to make up for the inadequacy of the training data. Our innovative, three-stage time series classification model, which involves finding non-contributing inputs with Shapley value attribution, unlearning those non-contributing inputs, and finally, relearning through augmentation of chosen input features with adversarial training mechanism, has shown classification efficacy. We demonstrate the performance of the proposed method not only through ablation study but also through comparative state-of-the-art research. The empirical study clearly shows that the suggested three-stage approach has a considerable favourable influence on the model's learnability. We experiment with diverse set of time series classification tasks and we show that the proposed model consistently outperforms the relevant state-of-the-art approaches, and the amount of training samples required to develop our model is noticeably low. As a result, we claim the effectiveness of the suggested model and identify it as the model of preference for effectively building trained models when the amount of training data is limited.

Chapter 3

Conclusion

We focus on building a holistic framework for effective computational model construction for diverse set of real world sensor signal classification tasks, especially for sensor analysis problems which often relate to human life and society. We have identified that the impetus of the research community (more precise the machine learning and deep learning models for supervised training). We solve the most important problem of privacy preserving sensor signal analytics. It is understood that data privacy is of utmost importance in building platforms or eco-system that handle sensitive data like smart health-care management. However, privacy is an individual option. We propose an user-controlled privacy preservation technique for heart sound-based computational model generation. Secondly, we demonstrate that deep learning model like CNN with appropriate hyperparameter selection can effectively create a compact model for practical sensor signal classification tasks like AF condition detection from single lead ECG signals without expert-intervened feature extraction and selection process. Thirdly, we observe the generic problem of scarcity of training examples in the process of computational model construction for sensor signal classification task. As the classification model does not get sufficiently labeled training data, the training of the model over such dataset may invariably rise to over-fitting issue. Hence, our endeavor is to solve the problem owing to the incomplete learnability of classification models due to training data insufficiency by proposing novel generic methods and models with Shapley-value attributed adversarial training.

3.1 Results Outline

3.1.1 Result Sketch- "Data-driven automated cardiac health management with robust edge analytics and de-risking [50]"

We conduct our empirical evaluation using publicly available, expert-annotated MIT-Physionet Challenge 2016 PCG or heart sound database [36]. MIT-Physionet Challenge 2016 PCG contains 'Normal' and 'Abnormal' labels correspond to clinical normal heart condition and clinical abnormal heart condition respectively. We demonstrate accuracy, sensitivity and specificity scores >0.8 through our domain feature engineered Adaboost [18]-based ensemble learning algorithm. In order to enable data privacy protection, differential privacy [16]-based obfuscation technique is applied. The obfuscation method distorts the features in a measured way such that the the obfuscated outcome is equivalently to random outcome with accuracy, sensitivity and specificity measures are ~ 0.5. We depict in Figure 3.1 to demonstrate shows that while the machine learning algorithm produces significant clinical efficacy in terms of Accuracy, Sensitivity, Specificity values (all more than 0.8) but the obfuscation with proposed differential privacy based method drops the clinical efficacy factors close to 0.5, which in fact renders no knowledge gain for the privacy attacker.

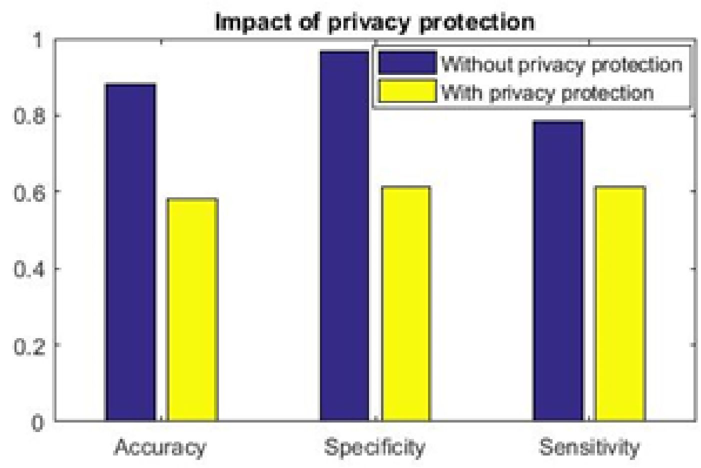

Fig. 3.1 Demonstrating the impact of proposed privacy preservation algorithm to nullify the intention of clinical knowledge gain of the privacy breaching attacks.

Further, we show in Figure 3.2 that our proposed differential privacy protection obfuscates the distribution of the machine learning features (f_1, f_2, f_3) (we have demonstrated

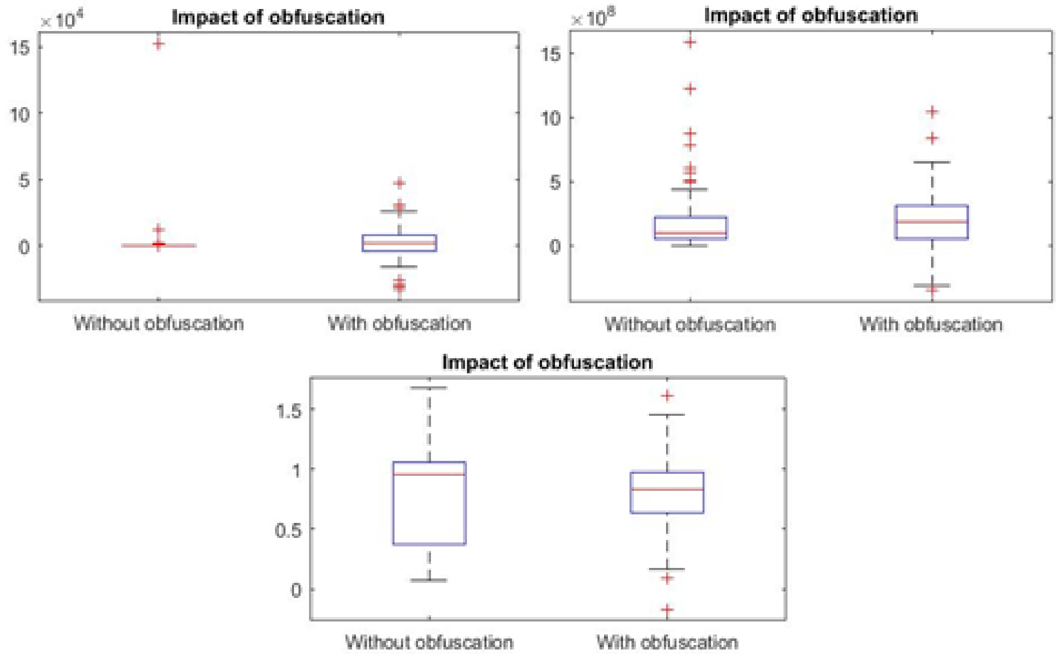

Fig. 3.2 Demonstrating the impact of proposed privacy preservation algorithm on the statically significance of the obfuscated features (f_1, f_2, f_3).

using Box-Whisker plot) to confuse the attacker to derive any effective inference. We conclude that user-controlled data-distribution aware privacy preservation can effectively solve the privacy breaching attacks to safeguard the privacy of the sensitive data. The proposed scheme ensures controlled privacy protection of user's sensitive information which enables practical deployment and acceptability of important sensor signal analytics applications.

3.1.2 Result Sketch- "AFSense-ECG: Atrial fibrillation condition sensing from single lead Electrocardiogram (ECG) signals [53]"

PhysioNet-Computing in Cardiology (CinC) Challenge 2017 is one of the most popular benchmark ECG databases, which is the largest known publicly available single lead ECG dataset for cardio-vascular disease lables (Atrial Fibrillation) with total 8,528 number of expert-labeled single lead ECG signals are available and this dataset consists of 60.4% normal sinus rhythm diagnosis (total 5154 cases), 9.0% AF diagnosis (total 771 cases), 30.0% other cardiovascular diseases (total 2557 cases) and 0.6% noisy data (total 46 cases) [11].

AFSense-ECG demonstrates effective classification performance to infer from sensor signal like ECG without hand-crafted, expert-intervened feature generation and selection processes. The considered classification performance metric is F1-score (F1-score is harmonic mean of recall and precision). The F1-measure of AF condition detection from our method is86.13%, where as the relevant state-of-the-art methods report F1-measures of 83.70% [22], 83.10% [48], 82.90% [12] [41], 82.60% [58], 82.50% [25], 82.00% [59], 81.00% [10] over publicly available single lead ECG datasets for AF condition detection from Physionet 2017 Challenge [11] as described in table 3.1. Further, our proposed learning model is lean with the proposed AFSense-ECG model consists of about 25 times less number of model parameters than the corresponding state-of-the-art model [22]. In order to deploy in edge devices, where the computation tasks are performed by micro-controller units (MCUs), the model memory size is an important design criterion. For example, typical representative MCU like ESP32WROVER consists of 8MB PSRAM and 8MB flash memory. State-of-the-art [22] algorithm model memory size is 115.6 MB, which is non-deployable in MCUs, where as the model size of AFSense-ECG is less than 4.4 MB. In fact, using lossless compressed file storage in .zip format, the model size becomes 3.8 MB. We have developed TensorFlow Lite model [13] by converting the TensorFlow model of 4.4 MB size into a compressed flat buffer model of 1.43 MB size with the TensorFlow Lite Converter for embedded micro-controller deployment.

We conclude that AFSense-ECG is an elegantly designed CNN-based deep learning model and it is efficiently parameterized. It is much leaner model than the relevant state-of-the-art [22] and the compactness in the design does not compromise on the classification performance. Our proposed model not only shows better classification performance, but also it is an efficient one to deploy in practical edge applications. We have demonstrated that better classification results can be obtained by using novel hyperparameter estimation to capture the morphology of ECG signals.

3.1.3 Result Sketch- "When less is more powerful: Shapley value attributed ablation with augmented learning for practical time series sensor data classification [52]"

We consider a generic problem in time series classification, where the model does not have the opportunity to get trained with adequate number of training data. The training

Table 3.1 Experimental validation of the proposed AFSense-ECG algorithm with respect to state-of-the-art methods.

State-of-the-art method	F1-measure (%)
AFSense-ECG (our method)	86.13
Hannun et al. [22]	83.70
Teijeiro et al. [48]	83.10
Datta et al. [12], [41]	82.90
Zabihi et al. [58]	82.60
Hong et al. [25]	82.50
Christov et al. [10]	81.00
Chandra et al. [9]	71.00
Zihlmann et al. [59]	82.00
Stępien [47]	75.00
Rubin et al. [43]	80.00
Baydoun et al. [11]	82.20
Bin et al. [11]	82.10
Zilhlmann et al. [11]	82.10
Xiong et al. [11]	81.80
Sodmann et al. [46]	82.00

data limitation issue is not only a practical problem, but also a research challenge given the typical machine learning and deep learning algorithms expect sufficient number of seen examples or training instances for better learning on the data distribution.

We have proposed ShapAAL: Shapley Attributed Ablation with Augmented Learning, a novel residual network architecture-based deep learning model [23] with both adversarial training as augmented learning process and input sample compaction with Shapley value-based input importance estimation, where the augmented training of on the model learning converts $R(h)$ into adversarial risk $R_{aug}(h) = \mathbb{E}_{(\mathbf{x},\mathbf{y})\sim p_{data}}[\max_{\delta\in\Delta} L(h_\theta(\boldsymbol{x}+\delta), y)]$, where Δ represents the set of adversarial perturbations in δ. The inclusion of Δ is the deliberation towards inducing mis-classification of the model and eventually, the model learns to minimize such mistakes.

It is well-accepted to consider time series classification archive- UCR [4] as the benchmark archives [20]. We experiment with number of diverse set of sensor datasets that fulfill the criteria of being limited in number of training instances (≤ 200). Firstly, we conduct ablation study involving the four components of ShapAAL- M is the base model, which is a ResNet architecture that directly gets trained only and all the training data; $M^{Shapley}$ is the Shapley value-based feature or input selection model that gets trained only by the non-negative Shapley value-attributed inputs; M_{aug} is the adversarially trained model; and $M_{aug}^{Shapley}$ is the proposed ShapAAL model with supposedly constructed with the best of $M^{Shapley}$ and M_{aug} algorithms. $M_{aug}^{Shapley}$ is in fact the proposed $M^{ShapAAL}$ model. The ablation investigation results that demonstrate the performances of each of the models- M, $M^{Shapley}$, M_{aug}, $M^{ShapAAL}$ are depicted in Table 3.2, which shows that $M^{ShapAAL}$ is consistently performing better than the rest.

Table 3.2 Ablation study depicting the performance superiority of the proposed ShapAAL model ($M^{ShapAAL}$) with respect to M, $M^{Shapley}$, M_{aug}.

ALGORITHM	M	$M^{Shapley}$	M_{aug}	$M^{ShapAAL}$
CHINATOWN	0.890	0.901	0.9211	0.9722
COFFEE	0.976	1.00	0.998	1.00
ECG200	0.83	0.86	0.87	0.92
ECGFIVEDAYS	0.989	1.00	1.00	1.00
FREEZERREGULARTRAIN	0.9865	0.9901	0.9933	0.9984
FREEZERSMALLTRAIN	0.8640	0.8640	0.8613	0.9309
ITALYPOWERDEMAND	0.8910	0.8901	0.9356	0.9704
MOTESTRAIN	0.8101	0.8233	0.9087	0.9084
POWERCONS	0.8576	0.8571	0.9083	0.9633
SONYAIBO1	0.8121	0.8439	0.8907	0.9682
SONYAIBO2	0.9355	0.9451	0.9406	0.9461
TWOLEADECG	0.8860	0.9006	0.9304	0.9994

We have further performed empirical study to compare the performance of proposed model $M^{ShapAAL}$ over the baseline algorithms like 1NN-DTW-based model [35] and relevant state-of-the-art algorithms like RISE [17], COTE [5], TS-Chief [45], Time Series Forest (TSF) [14], Proximity Forest (PF) [38], Catch22 [37], and time series ResNet [55]. The empirical study is shown in Figure 3.3 using differential test accuracy gain, which is defined as $\frac{test\ accuracy\ of\ the\ algorithm - benchmark\ test\ accuracy}{benchmark\ test\ accuracy}$. When the differential test accuracy gain is positive, we understand that $M^{ShapAAL}$ is empirically better performing. The results in Figure 3.3 clearly indicate the superiority of ShapAAL over the baselines and current state-of-the-art models.

The significance of proposed ShapAAL as a sensor data classification model is established through ablation investigation and study with respect to state-of-the-art algorithms. We conclude that ShapAAL creates new benchmark in sensor signal classification tasks. ShapAAL demonstrates consistent performance on diverse set of time series sensor data and the approach itself is a generic one. We claim and establish

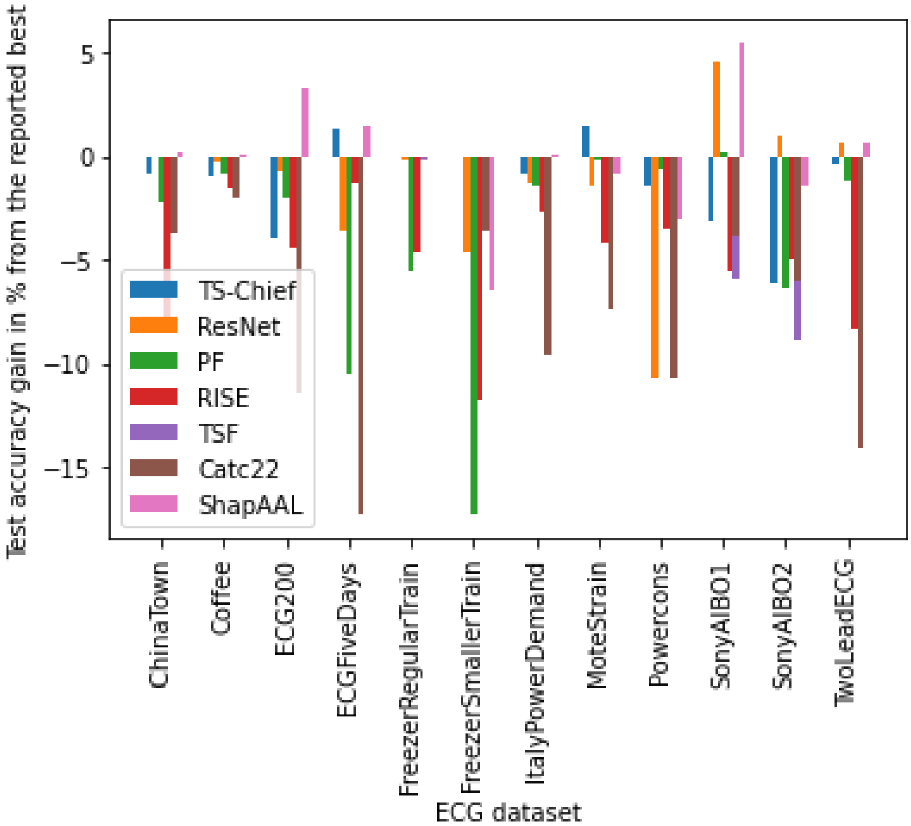

Fig. 3.3 Differential test accuracy gain of our proposed ShapAAL with respect to baselines and current state-of-the-art models over diverse set of time series sensor data.

that the proposed model is a general deep learning benchmark model for time series sensor signal classification tasks particularly in the event of training examples scarcity.

Briefly, we can state that the three research works usher a new direction towards solving the practical challenges of sensor signal classification and constructs a holistic approach towards the development and deployment of different sensor-centric applications which are of immense importance. Our research outcomes are of practical relevance and will surely enable newer and novel applications to get developed and used for the benefit of human life and society.

References

[1] Abrams, L. R., Myrskylä, M., and Mehta, N. K. (2021). The growing rural–urban divide in us life expectancy: contribution of cardiovascular disease and other major causes of death. *International journal of epidemiology*, 50(6):1970–1978.

[2] Andreao, R. V., Dorizzi, B., and Boudy, J. (2006). Ecg signal analysis through hidden markov models. *IEEE Transactions on Biomedical engineering*, 53(8):1541–1549.

[3] Bagnall, A., Dau, H. A., Lines, J., Flynn, M., Large, J., Bostrom, A., Southam, P., and Keogh, E. (2018). The uea multivariate time series classification archive, 2018. *arXiv preprint arXiv:1811.00075*.

[4] Bagnall, A., Lines, J., Bostrom, A., Large, J., and Keogh, E. (2017). The great time series classification bake off: a review and experimental evaluation of recent algorithmic advances. *Data Mining and Knowledge Discovery*, 31:606–660.

[5] Bagnall, A., Lines, J., Hills, J., and Bostrom, A. (2015). Time-series classification with cote: the collective of transformation-based ensembles. *IEEE Transactions on Knowledge and Data Engineering*, 27(9):2522–2535.

[6] Bansal, M. A., Sharma, D. R., and Kathuria, D. M. (2020). A systematic review on data scarcity problem in deep learning: Solution and applications. *ACM Computing Surveys (CSUR)*.

[7] Bengio, Y., Lecun, Y., and Hinton, G. (2021a). Deep learning for ai. *Commun. ACM*, 64(7):58–65.

[8] Bengio, Y., Lecun, Y., and Hinton, G. (2021b). Deep learning for ai. *Communications of the ACM*, 64(7):58–65.

[9] Chandra, B., Sastry, C. S., Jana, S., and Patidar, S. (2017). Atrial fibrillation detection using convolutional neural networks. In *2017 Computing in Cardiology (CinC)*, pages 1–4. IEEE.

[10] Christov, I., Krasteva, V., Simova, I., Neycheva, T., and Schmid, R. (2018). Ranking of the most reliable beat morphology and heart rate variability features for the

detection of atrial fibrillation in short single-lead ecg. *Physiological measurement*, 39(9):094005.

[11] Clifford, G. D., Liu, C., Moody, B., Li-wei, H. L., Silva, I., Li, Q., Johnson, A., and Mark, R. G. (2017). Af classification from a short single lead ecg recording: the physionet/computing in cardiology challenge 2017. in 2017 computing in cardiology (cinc).

[12] Datta, S., Puri, C., Mukherjee, A., Banerjee, R., Choudhury, A. D., Singh, R., Ukil, A., Bandyopadhyay, S., Pal, A., and Khandelwal, S. (2017). Identifying normal, af and other abnormal ecg rhythms using a cascaded binary classifier. In *2017 Computing in cardiology (cinc)*, pages 1–4. IEEE.

[13] David, R., Duke, J., Jain, A., Janapa Reddi, V., Jeffries, N., Li, J., Kreeger, N., Nappier, I., Natraj, M., Wang, T., et al. (2021). Tensorflow lite micro: Embedded machine learning for tinyml systems. *Proceedings of Machine Learning and Systems*, 3:800–811.

[14] Deng, H., Runger, G., Tuv, E., and Vladimir, M. (2013). A time series forest for classification and feature extraction. *Information Sciences*, 239:142–153.

[15] Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., and Fei-Fei, L. (2009). ImageNet: A Large-Scale Hierarchical Image Database. In *CVPR09*.

[16] Dwork, C. (2009). The differential privacy frontier. In *Theory of Cryptography Conference*, pages 496–502. Springer.

[17] Flynn, M., Large, J., and Bagnall, T. (2019). The contract random interval spectral ensemble (c-rise): the effect of contracting a classifier on accuracy. In *International Conference on Hybrid Artificial Intelligence Systems*, pages 381–392. Springer.

[18] Freund, Y. and Schapire, R. E. (1997). A decision-theoretic generalization of on-line learning and an application to boosting. *Journal of computer and system sciences*, 55(1):119–139.

[19] Fryer, D., Strümke, I., and Nguyen, H. (2021). Shapley values for feature selection: the good, the bad, and the axioms. *IEEE Access*, 9:144352–144360.

[20] Gay, D. and Lemaire, V. (2019). Should we reload time series classification performance evaluation?(a position paper). *arXiv preprint arXiv:1903.03300*.

[21] Goodfellow, I. J., Shlens, J., and Szegedy, C. (2014). Explaining and harnessing adversarial examples. *arXiv preprint arXiv:1412.6572*.

[22] Hannun, A. Y., Rajpurkar, P., Haghpanahi, M., Tison, G. H., Bourn, C., Turakhia, M. P., and Ng, A. Y. (2019). Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. *Nature medicine*, 25(1):65–69.

[23] He, K., Zhang, X., Ren, S., and Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778.

[24] Helms, T. M., Duong, G., Zippel-Schultz, B., Tilz, R. R., Kuck, K.-H., and Karle, C. A. (2014). Prediction and personalised treatment of atrial fibrillation—stroke prevention: consolidated position paper of cvd professionals. *EPMA Journal*, 5(1):1–7.

[25] Hong, S., Wu, M., Zhou, Y., Wang, Q., Shang, J., Li, H., and Xie, J. (2017). Encase: An ensemble classifier for ecg classification using expert features and deep neural networks. In *2017 Computing in cardiology (cinc)*, pages 1–4. IEEE.

[26] Hong, S., Zhou, Y., Shang, J., Xiao, C., and Sun, J. (2020). Opportunities and challenges of deep learning methods for electrocardiogram data: A systematic review. *Computers in Biology and Medicine*, 122:103801.

[27] Huang, C., Wu, X., Zhang, X., Lin, S., and Chawla, N. V. (2019). Deep prototypical networks for imbalanced time series classification under data scarcity. In *Proceedings of the 28th ACM International Conference on Information and Knowledge Management*, pages 2141–2144.

[28] Ilyas, A., Santurkar, S., Tsipras, D., Engstrom, L., Tran, B., and Madry, A. (2019). Adversarial examples are not bugs, they are features. *Advances in neural information processing systems*, 32.

[29] Iwana, B. K. and Uchida, S. (2021). An empirical survey of data augmentation for time series classification with neural networks. *Plos one*, 16(7):e0254841.

[30] Kalantarian, S., Stern, T. A., Mansour, M., and Ruskin, J. N. (2013). Cognitive impairment associated with atrial fibrillation: a meta-analysis. *Annals of internal medicine*, 158(5_Part_1):338–346.

[31] Krasteva, V., Ménétré, S., Didon, J.-P., and Jekova, I. (2020). Fully convolutional deep neural networks with optimized hyperparameters for detection of shockable and non-shockable rhythms. *Sensors*, 20(10):2875.

[32] Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. In Pereira, F., Burges, C. J. C., Bottou, L., and Weinberger, K. Q., editors, *Advances in Neural Information Processing Systems 25*, pages 1097–1105. Curran Associates, Inc.

[33] Krizhvesky, A. (2009). The need for biases in learning generalizations. Technical report, University of Toronto.

[34] LeCun, Y. (2018). The power and limits of deep learning: In his iri medal address, yann lecun maps the development of machine learning techniques and suggests what the future may hold. *Research-Technology Management*, 61(6):22–27.

[35] Lines, J. and Bagnall, A. (2015). Time series classification with ensembles of elastic distance measures. *Data Mining and Knowledge Discovery*, 29(3):565–592.

[36] Liu, C., Springer, D., Li, Q., Moody, B., Juan, R. A., Chorro, F. J., Castells, F., Roig, J. M., Silva, I., Johnson, A. E., et al. (2016). An open access database for the evaluation of heart sound algorithms. *Physiological Measurement*, 37(12):2181.

[37] Lubba, C. H., Sethi, S. S., Knaute, P., Schultz, S. R., Fulcher, B. D., and Jones, N. S. (2019). catch22: Canonical time-series characteristics. *Data Mining and Knowledge Discovery*, 33(6):1821–1852.

[38] Lucas, B., Shifaz, A., Pelletier, C., O'Neill, L., Zaidi, N., Goethals, B., Petitjean, F., and Webb, G. I. (2019). Proximity forest: an effective and scalable distance-based classifier for time series. *Data Mining and Knowledge Discovery*, 33(3):607–635.

[39] Morillo, C. A., Banerjee, A., Perel, P., Wood, D., and Jouven, X. (2017). Atrial fibrillation: the current epidemic. *Journal of geriatric cardiology: JGC*, 14(3):195.

[40] Mounsaveng, S., Vazquez, D., Ayed, I. B., and Pedersoli, M. (2019). Adversarial learning of general transformations for data augmentation. *arXiv preprint arXiv:1909.09801*.

[41] Mukherjee, A., Choudhury, A. D., Datta, S., Puri, C., Banerjee, R., Singh, R., Ukil, A., Bandyopadhyay, S., Pal, A., and Khandelwal, S. (2019). Detection of atrial fibrillation and other abnormal rhythms from ecg using a multi-layer classifier architecture. *Physiological measurement*, 40(5):054006.

[42] Roth, A. E. (2005). The shapley value.

[43] Rubin, J., Parvaneh, S., Rahman, A., Conroy, B., and Babaeizadeh, S. (2017). Densely connected convolutional networks and signal quality analysis to detect atrial fibrillation using short single-lead ecg recordings. In *2017 Computing in cardiology (cinc)*, pages 1–4. IEEE.

[44] Shapley, L. S. (1951). Notes on the n-person game—ii: The value of an n-person game.(1951). *Lloyd S Shapley*.

[45] Shifaz, A., Pelletier, C., Petitjean, F., and Webb, G. I. (2020). Ts-chief: a scalable and accurate forest algorithm for time series classification. *Data Mining and Knowledge Discovery*, 34(3):742–775.

[46] Sodmann, P., Vollmer, M., Nath, N., and Kaderali, L. (2018). A convolutional neural network for ecg annotation as the basis for classification of cardiac rhythms. *Physiological measurement*, 39(10):104005.

[47] Stepien, K. and Grzegorczyk, I. (2017). Classification of ecg recordings with neural networks based on specific morphological features and regularity of the signal. In *2017 Computing in Cardiology (CinC)*, pages 1–4. IEEE.

[48] Teijeiro, T., Garcıa, C. A., Castro, D., and Félix, P. (2017). Arrhythmia classification from the abductive interpretation of short single-lead ecg records. in 2017 computing in cardiology (cinc).

[49] Ukil, A., Bandyopadhyay, S., and Pal, A. (2019a). Dyreg-fresnet: Unsupervised feature space amplified dynamic regularized residual network for time series classification. In *2019 International Joint Conference on Neural Networks (IJCNN)*, pages 1–8. IEEE.

[50] Ukil, A., Jara, A. J., and Marin, L. (2019b). Data-driven automated cardiac health management with robust edge analytics and de-risking. *Sensors*, 19(12):2733.

[51] Ukil, A., Marin, L., Jara, A., and Farserotu, J. (2019c). Knowledge-driven analytics and systems impacting human quality of life. In *Proceedings of the 28th ACM International Conference on Information and Knowledge Management*, pages 2989–2990.

[52] Ukil, A., Marin, L., and Jara, A. J. (2022a). When less is more powerful: Shapley value attributed ablation with augmented learning for practical time series sensor data classification. *PloS one*, 17(11):e0277975.

[53] Ukil, A., Marin, L., Mukhopadhyay, S. C., and Jara, A. J. (2022b). Afsense-ecg: Atrial fibrillation condition sensing from single lead electrocardiogram (ecg) signals. *IEEE Sensors Journal*.

[54] Wang, Q., Farahat, A., Gupta, C., and Zheng, S. (2021). Deep time series models for scarce data. *Neurocomputing*, 456:504–518.

[55] Wang, Z., Yan, W., and Oates, T. (2017). Time series classification from scratch with deep neural networks: A strong baseline. In *2017 International joint conference on neural networks (IJCNN)*, pages 1578–1585. IEEE.

[56] Worzyk, N. and Yu, S. (2021). Broad adversarial training with data augmentation in the output space. In *The AAAI-22 Workshop on Adversarial Machine Learning and Beyond*.

[57] Wu, M., Lu, Y., Yang, W., and Wong, S. Y. (2021). A study on arrhythmia via ecg signal classification using the convolutional neural network. *Frontiers in computational neuroscience*, page 106.

[58] Zabihi, M., Rad, A. B., Katsaggelos, A. K., Kiranyaz, S., Narkilahti, S., and Gabbouj, M. (2017). Detection of atrial fibrillation in ecg hand-held devices using a random forest classifier. In *2017 Computing in Cardiology (CinC)*, pages 1–4. IEEE.

[59] Zihlmann, M., Perekrestenko, D., and Tschannen, M. (2017). Convolutional recurrent neural networks for electrocardiogram classification. In *2017 Computing in Cardiology (CinC)*, pages 1–4. IEEE.