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EXPLAINABLE ARTIFICIAL INTELLIGENCE THEORY IN DECISION MAKING TREATMENT OF ARITHMIA PATIENTS WITH USING DEEP LEARNING MODELS

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ABSTRACT

In the context of Explainable Artificial Intelligence, there are two important keywords: interpretability and "explainability". Interpretability is the extent to which humans can understand the causes of decisions. The better the interpretability of an AI/ML model, the easier it is for someone to understand why certain decisions or predictions have been made. Some cases of AI/ML implementation may not require explanation, because they are used in a low-risk environment, meaning mistakes will not have serious consequences. The need for interpretability and explainability arises when an AI system is used for certain high-risk problems or tasks, so it is not enough just to get predictive/classification decision outputs, but also needs explanations to convince users that AI (1: Model Explainability) is working the right way and (2: Decision Explainability) has made the right decision (Hotma, 2022). This research provides benefits for the development of knowledge regarding the implementation model of Explainable AI Theory in assisting Doctors' Decision Making for patients with cardiac arrhythmias with the Deep Learning Model in assisting Doctors' Decision Making for patients with cardiac arrhythmias. Knowing the Deep Learning Algorithm can be used in Machine Learning to read EKG Results. Knowing how to improve the results of the accuracy of the Explainable AI Application in Decision Making by Doctors for patients with cardiac arrhythmias. The use of Explanable Artificial Intelligence in the management of arrhythmia patients can provide an interpretation for doctors to be more optimal in treating patients. The results of this AI machine decision can increase doctors' confidence in treating arrhythmia patients optimally, effectively and efficiently. And also treatment will be faster because it is assisted by tools, so that patients can be treated more quickly. Thus it will reduce the mortality rate in arrhythmia patients.

Key Word : AI, DSS, DEEP LEARNING

INTRODUCTION

The term Artificial Intelligence (AI) was first coined by John McCarthy in 1956 when he held the First Academic Conference on the Subject. It is defined as the Science and Engineering of making Intelligent Machines (The History of Artificial Intelligence-University of Washington December 2006). Artificial Intelligence is related to the development of computers that are capable of engaging in human-like thinking processes such as learning, reasoning, and selfcorrection (Artificial Intelligence-ISSN2249054X-V2I4M4-072012). Decision-making as the main human task in general can be approached both normatively and descriptively. Normative referred to here is an ideal approach in decision making, meaning that the decision maker is seen as one of the elements in a process that runs with logic and standard rules (Fachmi Basyaib). Recent Explainable Artificial Intelligence (XAI) techniques have been introduced to explain the decisions made by Machine Learning models . (Laios et al. 2022)

Through this theory much can be facilitated in decision making, both in terms of prediction and in helping to classify diseases to the management stage. Likewise for arrhythmia patients, this theory can be applied in making decisions on their management by a doctor. Arrhythmia is a disorder of the electrical impulses that regulate the heartbeat. This disorder causes the heart to beat too fast, too slow or you could say it's irregular. The condition of a stable rhythm of the heart beats about 60-100 times per minute. This means that every day the heart can beat as much as 100 thousand times. Meanwhile, in people with arrhythmias, the rhythm of the heartbeat is abnormal and irregular.

In line with the research that will be carried out regarding the decision-making process in Arrhythmia patients, there are other studies designed to support global and local explanations of predictions. problem h and evaluation of interpretation with analyzed feature interactions using prospective enrolled data from EOC patients received surgical treatment. The main results are construction and performance Machine Learning (ML) models to predict surgical attempts resulting in incomplete cytoreduction, and the development of the XAI methodology to explain ML predictions by setting and investigate data- driven relationships between features . (Laios et al. 2022) .

Literature reviews method

A four-step sample selection process, consisting of database selection, preliminary searching, selecting the sample, and refining the sample, was used after identifying the most linked articles. when the database was first searched using the keywords: asphalt, rubber, and pavement which, related results were discovered. Reading the title and abstract eliminated all extraneous studies from the first search for the sample .

Random Forest Method

Random Forest, Decision Stump, J48 and Random Tree with 10-fold cross-validation. Other than analyzing individual algorithms, hybrid algorithms are also selected for experimentation. This includes Adaboost M1+Decision Stump and Bagging + Random Tree algorithms. Additionally, the prediction model was also tested using the Bayes algorithm which too lies in eager learning class and performs better on larger datasets consisting of millions of records. It could be used for real-time prediction, multi-class prediction, text classification, spam filtering, sentiment analysis, and recommendation system. The classification algorithms Random Forest (RF), Artificial Neural Networks (ANN), decision tree, C5, Multilayer Perceptron (MLP) and Logistic Regression (LR)are also used in the simulation experiment. The classification process is performed using the WEKA 3.8 toolkit. (Wu et al. 2020)

LSTM method

The traditional neural network model is fully connected from the input layer to the hidden layer and then to the output layer, which means there is no connection between nodes in the same layer, and the propagation of the network is sequential. (is kind of network structure often appears powerless to deal with sequence or time-series problems because of its lack of memory. (erefore , a new kind of network—recurrent neural network (RNN)—is required. LSTM is a type of RNN that is especially good at processing sequence data. The efficiency of LSTM is that, by increasing the input, forgetting, and output thresholds, the weight of the self-loop is changed. In the case of fixed model parameters, the integration scale at different times can be dynamically changed, thereby avoiding the problem of gradient disappearance or expansion (Karn et al. 2021)

Cardiac Arrhythmia

Arrhythmia is a disorder of the electrical impulses that regulate the heartbeat. This disorder causes the heart to beat too fast, too slow or you could say it's irregular. The condition of a stable rhythm of the heart beats about 60-100 times per minute. This means that every day the heart can beat as much as 100 thousand times. Meanwhile, in people with arrhythmias, the rhythm of the heartbeat is abnormal and irregular. Atrial flutter is a form of arrhythmia where the atrium beats around 240-400 beats/minute. Atrial flutter is the second most common type of supraventricular tachycardia after atrial fibrillation. Atrial flutter has a distinctive re-entrant rhythm, in which the re-entry circuit occupies a large area of the atrium. (Andrianto. 2020)

EXPLAINABLE ARTIFICIAL INTELLIGENT

Used to make important decisions concerning human life. Not every domain needs the ability to be described, for example: weather forecasts don't need explanation if a black box can provide highly accurate results. Likewise, ads displayed on social media based on browsing habits do not require an explanation of how these ads were selected. Explainable AI has become a prerequisite for building trust.

In order to detect analysis patterns in arrhythmic patients, or to perform investigative tasks using link analysis or graph mining, many machine learning methods are found in the literature, with reasonable accuracy. Based on 43 previous studies describing ML methods, and excluding studies describing approaches, system architecture, or papers from other domains. These methods are classified using the categories of supervised, semi-supervised, unsupervised, and reinforcement learning. The *issues* column shows the main issue addressed by *the method* using the *data* in the paper mentioned in the *Ref column.*

The meaning of *interpretability* in the 'Is Method Interpretable' column is ability method to present indicators that can help humans to understand the functioning of the method to know how decisions are made by the method. Advances in computing and storage infrastructure, the creation of large volumes of data and the need to leverage this data to derive actionable insights have increased research in machine learning methodologies over the past decade. Accurate prediction remained the main goal during model development and eventually resulted in many complex models or black box models, such as high accuracy DL models. These complex models are opaque, whose actions are hard for humans to understand.

Table 1.
Interpretability of the methods used for AML

No.	Category	Problem	Method	Is Method Interpretable	Data	Year	Ref
1	Supervised learning	Watch-list filtering automation to prevent false positives	SVM, Naïve Bayes, Decision Tree - individually	Yes	Synthetic	2021	[46]
2		Identification of illicit Bitcoin transactions	Ensemble Method using RF, Extra Trees, and Bagging Classifier.	No	Elliptic	2020	[47]
3		Predict illicit transactions in bitcoin transaction graph	Graph Convolutional Network and Multi-Layer Perceptron together.	No	Elliptic	2020	[47]
4		Detecting potentially illicit behavior	Logistic Regression, *Extreme gradient boosting trees Catboost methods*	No*	Real	2020	[48]
5		Detect illicit accounts involved in money laundering over ethereum blockchain	Extreme Gradient Boosting (XGBoost)	No	Public Dataset	2020	[49]
6		Examine AI methodologies against money laundering crimes	Logistic regression, decision tree, *Random Forest, XGBoost, and AutoEncoder, DNN*	No*	Real	2020	[50]
7		Detect suspicious money laundering transactions	XGBoost algorithm	No	Real	2020	[32]
8		Detect suspicious money laundering transactions	Naïve Bayes Classifier	Yes	Synthetic	2020	[51]
9		Identification of suspicious transactions and categorizing the type of finance crime	SVM, Liner Regression, *Multi-layer Perceptron*	No*	Synthetic	2019	[41]
10		Suspicious money laundering transaction detection	Bayes Logistic Regression, Decision Tree, Random Forest, SVM, and *ANN*	No*	Real	2019	[52]
11		Suspicious money laundering transaction detection	Random Forest; MinMaxScaler method	Yes	Synthetic	2018	[53]
12		Proposes a technique for generating variants of typologies	Graph Learning, BigData	No	Unclear	2018	[54]
13		Detect money laundering criminals – actual court case	Logistic Regression, Decision Tree, Random Forest and *Neural Networks*	No*	Real	2018	[55]
14		Detect money launders laundering groups	Support Vector Machine and *Random Forests*	No*	Real	2017	[56]
15		Improve the suspicious transaction signaling process by client profiling	PART algorithm that implements Decision tree, best leaf technique	Yes	Real	2016	[57]
16		Suspicious money laundering transaction detection	Affiliation Mapping Calculation and Sequential Mining (AMC-SM)	Unclear	Unclear	2016	[58]
17		Identification of suspicious money laundering accounts	Probabilistic Relational Model using the Audit Sequential Pattern (PRM-ASP) Mining	Unclear	Real	2015	[59]
18		Detection of fraud chains in Mobile Money Transfer systems.	Predictive Security Analysis at Runtime (PSA@R)	Unclear	Synthetic	2014	[60]
19		Identification of suspicious money laundering transaction	DBSCAN Clustering algorithm, Link analysis	Yes	Real	2014	[61]
20		Identification of suspicious financial transactions	Clustering, Dynamic Bayesian Networks, Anomaly Detection	Yes	Real	2011	[62]
21		Suspicious money laundering transaction detection	Graph learning method	No	Synthetic	2011	[63]
22		Identify suspicious money laundering activities	Decision Tree (BIRCH and k-means)	Yes	Unclear	2011	[64]
23		Suspicious money laundering transaction detection	Clustering (K-means), *Neural Network (back-propagation)*	No*	Real	2010	[65]
24		Identify the most critical classifiers for decision tree used in investigation of money laundering	Decision Tree	Yes	Real	2010	[66]
25		Identify money laundering cases within investment activities	Clustering, *Neural Network*, Genetics Algorithm	No*	Real	2010	[67]
26		Identification of suspicious money laundering transaction	Decision Tree	Yes	Real	2008	[68]

No.	Category	Problem	Method	Is Method Interpretable	Data	Year	Ref
27		Detection of hidden money laundering behavior	*Multi-agent Neural Network*, *Text Mining*, Genetic Algorithms, Velocity Analysis and Case-based reasoning	No*	Real	2007	[69]
28		Facilitate investigation of money laundering crime	Link discovery based on correlation analysis	Yes	Real	2003	[70]
29	Unsupervised learning	Suspicious money laundering transaction detection	Core Decision Tree and Clustering Algorithm	No*	Real	2021	[71]
30		Identify fraudulent financial transactions	Outlier Detection Methods, Visual Analytics Method	Yes	Real	2020	[72]
31		Identify anomalies in a set of transactions of a non-banking correspondent	Isolation Forest, One Class SVM	Yes	Real	2020	[73]
32		Detect hidden networks of money launderers	Isolation Forest One Class SVM	Yes	Synthetic	2020	[74]
33		Identify suspicious transaction in crypto currency	Expectancy Maximization (for clustering datasets), Random Forest (for anomaly detection)	No	Elliptic	2019	[75]
34		Detect anomalies considering the regular transaction patterns	AutoEncoder and PCA examined separately	No	Real	2017	[76]
35		Identify suspicious money laundering transactions	*Ensemble* of algorithms (Isolation Forests, One Class SVM, *Gaussian Mixture Models*, EM)	No*	Real and Synthetic	2017	[77]
36		Detection of money launderers gangs	Community detection using temporal-directed Louvain algorithm	No	Real	2017	[78]
37		Detection of money laundering transactions. Visualization and analysis system for Police Analysts.	Apriori, PrefixSpan, FP-growth and Eclat algorithms	Yes	Real	2016	[79]
38		Suspicious money laundering transaction detection	Clustering CLOPE algorithm	Yes	Real	2012	[80]
39		Identify suspicious sequences of transaction level for financial institutions	Scan Statistics	Yes	Real	2010	[81]
40		Detect suspicious money laundering transactions	Semantic Core Tree	Yes	Synthetic	2006	[82]
41	Semi-supervised learning	Investigation Support System for AML	Multi-channel Convolutional Network based on NLP	No	Synthetic	2015	[83]
42	Reinforcement learning	Incremental graph pattern matching algorithm to deal with time-evolving graph data for detecting money laundering	Incremental graph pattern matching (IGPM) algorithm and partial execution manager (PEM) to re-compute the updated subgraphs	No	Temporal graph data	2019	[84]
43	Supervised and unsupervised learning	Detect trade-based money laundering	Supervised – Bayesian network, Cost sensitive learning Unsupervised – clustering, regression	Yes	Real	2019	[85]

* It indicates that the methods used by authors of respective paper includes interpretable and non-interpretable methods.

Based on an analysis of 43 articles from research conducted by Dattatray Wishnu Kute screened that provide solutions using machine learning models for money laundering pattern detection, suspicious transaction detection, money laundering group detection and aid investigation using link analysis. The data shows that the highest number of articles published in 2020 was in the AML domain, indicating increased subject attention to leveraging machine learning technologies to help solve one of the industry's most complex problems.

The data shows that 51% of researchers have used methods that cannot be interpreted. The data also shows that 65% of the methods are based on supervised learning while only 2% are using reinforcement learning models, 58% of methods were trained or evaluated on a small set of real data older than 2 years. 21% of the research is based on synthetic data. It was observed that the actual data was obtained from the following organizations – financial institutions, financial intelligence units, police departments and involved organizations in export.

In view of the steps involved in anti laundering money, an effort involving several organizations together, it becomes more important to identify suspicious money laundering transactions, patterns, groups as accurately as possible along with adequate explanations for decisions made by ML models. As model accuracy increases, interpretability decreases, and in order to know how the model makes decisions, it needs to be interpreted. So far, the research focus has been on improving model accuracy and rather than ensuring model interpretation. This has sparked another research area namely Explainable AI.

XAI is a class of systems that provide visibility into how AI systems make decisions, predict and carry out their actions. A cross-disciplinary research field, XAI has attracted great attention from researchers worldwide. XAI techniques are applied in other related domains.

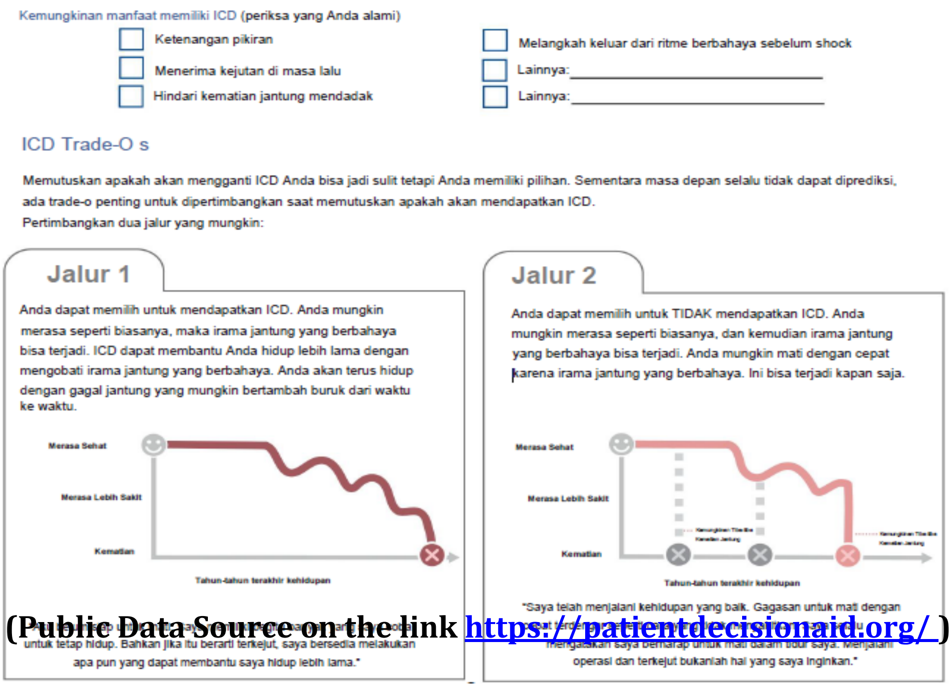
In the DL and XAI technology that will be carried out, it is possible that the direction of this research will be jointly conducted between academics and health agencies that focus on identifying types of arrhythmias and decision support systems. The application of the XAI technique to visualize and understand the results obtained from unsupervised learning, provides an anomaly detection technique that can be explained for the detection of arrhythmias, but there is no research in the literature that describes the application of the XAI technique to explain the results of the treatment of arrhythmic patients who have been defined.

The management of arrhythmia patients is based on the theory of Shared Decision Making or SDM. The goal of this decision-making approach is to co-produce and decide with each patient a plan of care that makes sense for each patient in response to the situation they are facing. The plan must make sense intellectually (consistent with evidence, responsive to their situation), emotionally or balance the tolerability of the plan for the patient), and practical (feasible in the patient's life, so that it can be implemented in a way that maintains the plan's intended safety and effectiveness). In aggregate, HR can increase the absorption of reasonable interventions that are underused and can reduce the absorption of unreasonable and overused interventions.

HR is a process that can be performed with or without decision aids , but trials of HR results often test the usefulness of decision aids. In the trial, there were no between-group differences in general health outcomes. Outcomes related to patient values (i.e., how patients judge outcomes arising from various choices)1 include preferred value clarification methods, knowledge, decision-making processes, decision conflicts, uncertainty, satisfaction, decision preferences, treatment goals, actual health behaviors, regret and, in some cases, health outcomes or costs. 15 A recent systematic review reported HR as having a significant association with affective-cognitive outcomes in 54% of studies and behavioral outcomes in 37% of studies. 16 The strength of the evidence is weakest for outcomes health, where the HR impact was significant in 25% of studies, all of which used patient-reported outcome measures (eg, symptom reduction) rather than clinically assessed outcomes. (Chung et al, 2021)

Decision theory in HR will be implemented in the Explanable Artificial Intelligence model. Examples of management decision-making in the application of HR decision-making theory to arrhythmic patients are as follows:

For patients who already have an ICD and are considering replacement.


Kemungkinan manfaat memiliki ICD (periksa yang Anda alami)

- Ketenangan pikiran
- Menerima kejutan di masa lalu
- Hindari kematian jantung mendadak
- Melangkah keluar dari ritme berbahaya sebelum shock
- Lainnya:
- Lainnya:

ICD Trade-O s

Memutuskan apakah akan mengganti ICD Anda bisa jadi sulit tetapi Anda memiliki pilihan. Sementara masa depan selalu tidak dapat diprediksi, ada trade-o penting untuk dipertimbangkan saat memutuskan apakah akan mendapatkan ICD.
Pertimbangkan dua jalur yang mungkin:

Jalur 1

Anda dapat memilih untuk mendapatkan ICD. Anda mungkin merasa seperti biasanya, maka irama jantung yang berbahaya bisa terjadi. ICD dapat membantu Anda hidup lebih lama dengan mengobati irama jantung yang berbahaya. Anda akan terus hidup dengan gagal jantung yang mungkin bertambah buruk dari waktu ke waktu.

untuk tetap hidup. Bahkan jika itu berarti terkejut, saya bersedia melakukan apa pun yang dapat membantu saya hidup lebih lama."

Jalur 2

Anda dapat memilih untuk TIDAK mendapatkan ICD. Anda mungkin merasa seperti biasanya, dan kemudian irama jantung yang berbahaya bisa terjadi. Anda mungkin mati dengan cepat karena irama jantung yang berbahaya. Ini bisa terjadi kapan saja.

"Saya telah menjalani kehidupan yang baik. Gagasan untuk mati dengan
mengatakan saya berharap untuk mati dalam tidur saya. Menjalani operasi dan terkejut bukanlah hal yang saya inginkan."

(Public Data Source on the link https://patientdecisionaid.org/)

Proposed further Research

The use of Explanable Artificial Intelligence in the management of arrhythmia patients can provide an interpretation for doctors to be more optimal in treating patients. The results of this AI machine decision can increase doctors' confidence in treating arrhythmia patients optimally, effectively and efficiently. And also treatment will be faster because it is assisted by tools, so that patients can be treated more quickly. Thus it will reduce the mortality rate in arrhythmia patients.

This model uses the SHAP framework to provide per-sample (local per cohort (global)) feature descriptions for decisions made by the high-performance XgBoost Ensemble tool that outperforms DNN assessments. And also implements Deep learning methods as well as random forest and LSTM algorithms. Thanks to the innovative Explanable Artificial Intelligence approach , it is possible to learn how to augment machine explanations with self-interpretable data on the decision-making process in the management of arrhythmia patients.

CONCLUSION

The use of Explanable Artificial Intelligence in the management of arrhythmia patients can provide an interpretation for doctors to be more optimal in treating patients. The results of this AI machine decision can increase doctors' confidence in treating arrhythmia patients optimally, effectively and efficiently. And also treatment will be faster because it is assisted by tools, so that patients can be treated more quickly. Thus it will reduce the mortality rate in arrhythmia patients.

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