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EXPLAINABLE AI IN CLINICAL DECISION SUPPORT: INTERPRETABLE NEURAL MODELS FOR TRUSTWORTHY HEALTHCARE AUTOMATION

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Abstract—Clinical decision support (CDS) involves the use of AI-based systems that synthesize patient information and suggest recommendations for diagnosis or treatment. These systems help clinicians manage the growing amount of patient data while ensuring safety and performance. However, interpretability is crucial, as patients have a right to know the reasons be- hind important clinical decisions, and doctors must trust the outputs before acting on them. Recent regulatory statements have underscored the increasing focus on AI interpretability in healthcare. An interpretable model is one for which users can easily comprehend the rationale for its predictions. Empirical evidence shows that trust in a prediction is determined by its explanation. Explanations should therefore be tailored to the audience's knowledge and expectations—supporting clinical decision-making processes—and authoritative in guiding action. Achieving trustworthy healthcare automation requires converg- ing interpretability and safety. Interpretable models complement risk assessment, governance, and continuous evaluation, and integrate with safety measures such as monitoring, fail-safe design, and auditing.
Index Terms—Explainable AI, healthcare, clinical decision support, neural networks, interpretability, safety ,Explainable AI (XAI) ,Clinical Decision Support Systems (CDSS),Interpretable Neural Networks,Trustworthy AI,Model Transparency, Medical Explainability ,Healthcare Automation, I- driven Diagnostics, Interpretability Methods ,Human–AI Collaboration in Medicine.

I. INTRODUCTION

The goal of this work is to advance Trustworthy Healthcare Automation through Explainable AI in Clinical Decision Sup- port. Clinical Decision Support (CDS) systems help automate a subset of human reasoning during clinical tasks, placing them in a unique position to assist clinicians with both special- ized knowledge and availability. However, current automated decision-making systems are largely black boxes, leading to increased caution or outright rejection of recommendations, especially in high-risk domains such as healthcare. In these settings, interpretability is generally recognized as a prereq- uisite towards the broader concepts of trust or reliability. The potential impact of increased trust in automated model outputs is particularly relevant for spaces with high human availability and specialized knowledge, such as clinical decision support, where decision augmentation is viable (the model serves merely as a guide) rather than decision replacement. A limited inspection of the literature makes it clear that consider the model's decisions as proposals or addition of hypothesis rather

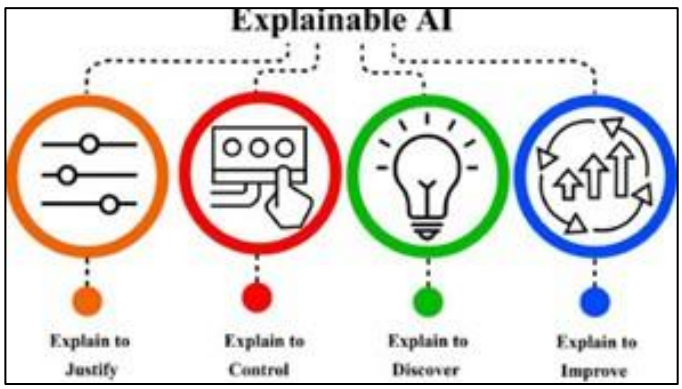

Fig. 1. Explainable Artificial Intelligence in healthcare

than full replacement model might help alleviate some of these concerns, since it agrees with the way humans work. Therefore, models in this setting could benefit from intrinsic interpretability by: favoring classes of models that

provide trustable explanations about its outputs; using attention mech- anism and rational sub-models when possible; or being able to produce other types of interpretations such as counterfactual or rule-based explanations in a reliable and robust way; All of this without sacrificing prediction performance, as those models need evaluate multiple hypothesis in a small amount of time.

A. Background and Significance

Clinical decision support (CDS) enhances clinical decisions by combining medical knowledge with patient data. The effec- tiveness of CDS systems has fallen short of expectations, partly because many approaches do not provide interpretable results when combined with machine learning algorithms, especially deep learning. Interpretability is desirable because physicians are unlikely to accept patient-critical decisions made by an opaque clinical AI. Consequently, the popularity of explainable AI has risen within the deep learning community, with the ambition of making black-box deep models transparent and trustworthy. Interpretability is a precondition for trustworthy healthcare automation. The right to explanation, enshrined in data protection legislation, requires patients to comprehend how their data are used by automated decision-making systems and to grant or deny consent accordingly. Clear, meaningful results that explain the model's reasoning are necessary for an interpretable AI. Furthermore, the absence of interpretability can also render a system biased and unsafe, reducing public confidence in healthcare AI and hindering adoption. In light of these factors, developing interpretable CDS models is a pressing concern for researchers in trustworthy healthcare automation.

II. Foundations of Explainable AI in Healthcare

A concise overview of crucial concepts in explainable AI for healthcare and the special requirements for clinical applications. 2.1. Definitions and Desiderata of Interpretability The interpretability of machine learning models is critical in domains such as medicine, finance, and law that require explanations to be accountable for decisions. In contrast to other areas, however, a predictive black box model may be sufficient, provided that it has been thoroughly tested, including an assessment of the consequences of the decisions that it makes. In medicine, the ideal situation is one in which the neural model is interpretable. Here the following concepts are distinguished: interpretability, intelligibility, transparency, and the related notion of operator support. Interpretability is the highest level of model understanding, enabling the user to grasp the principles governing a model's behaviour. An interpretable model reveals its innards expressed in the same domain as the inputs, such as decision trees or sets of rules. A post-hoc interpretation provides a local approximation of the model as perceived by a specific decision-maker. Intelligibility is the next level of model understanding, which simply eases prediction. An intelligible model is equipped with a simple, easily digestible decision rule, such as a short, human-written natural-language statement, albeit in different languages. Transparency implies that the model operates according to principles perceivable by its user. A transparent model is a black box but one for which its inputs and outputs evoke a mental image of its inner workings. The ideal operator-support feature provides an AI-supported model built to assist a specific type of operator in his or her decision-making process at a given stage. Recent work in clinical decision support has underscored the need for appropriate neural model interpretability by explicitly integrating clinicians' requirements for decision support directly into the explanation process. An effective XAI process involves four key components: XAI desiderata, the main interpretability requirements, model-inherent capabilities, and the demands of model consumers. Adopting a consumer-based perspective ensures that the diagnostic, prognostic, risk ostensive, and therapy advice functions of clinical decision support are suitably fulfilled. The oral and visual nature of clinical interactions points to the need for decision support that supplies natural-language explanations and/or pictorial visualizations suitable for reading and viewing, respectively. Differentiating explanatory information according to the stage of the clinical decision-making process aligns with the need for different types of explanation.

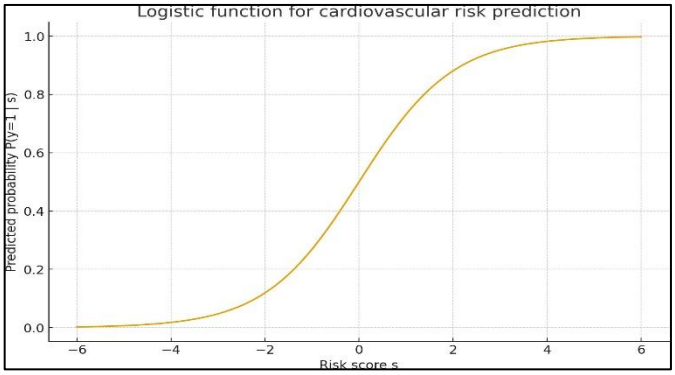

Fig. 2. Logistic function for cardiovascular risk prediction

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Equation 01: Logistic risk model for clinical decision support
From linear risk score to probability Let

$$s = w^{\top}x + b \quad (1)$$

$x \in R^d$ = feature vector
(age, systolic BP, cholesterol, diabetes flag, etc.)
$w \in R^d$, $b \in R$ = learnable parameters
$y \in \{0, 1\}$ = outcome (0 = no event, 1 = event) This is just a weighted sum of risk factors.

A. Definitions and desiderata of interpretability

Interpretability characterizes the comprehensibility of a model's decision process. Interpretability occurs both through inherent model design and through additional means that provide after-the-fact insight. Intelligibility, on the other hand, speaks to users' understanding of an interpretation, and thus its usability in their tasks. Transparency describes a model's inherent lack of complexity and, hence, the reduced need for external clarification. An ideal interpretable model should be self-understandable and intelligible, affording both an in- trinsic understanding of its decision-making and additional formulations that satisfy the needs of the intended audience. For a model to be interpretable, it must satisfy established criteria of interpretability or possess properties that naturally lead to successful interpretation. These properties, as described in the literature on interpretable machine learning, include explanation by design, attention mechanisms, a modular archi- tecture that mirrors the decision-making process, and sparse representations that highlight salient features of the decision task. A model that offers a decision rule, expresses different decision paths for different classes, or tasks several feature sets with specialized roles is better interpretable for clinical use. Nonetheless, users seek support for their clinical reasoning, not just a breakdown of the model's computation. Consequently, the most effective interpretations are human-friendly and fulfill the specific needs of the target audience.

B. Regulatory and ethical considerations

Patients possess the right to attentive, individualized care, underpinned by in-depth medical knowledge, clear commu- nication, and informed consent. These expectations extend to the use of AI systems, which—when deployed in health- care—must prioritize safeguarding patients from unreasonable risks, comprehensively addressing concerns related to account- ability, bias, data governance, privacy, and maintaining clin- ician trust. The developer's responsibility can be discharged only if the model outputs are reliable and the system is properly monitored, checked, and governed. Concrete failure scenarios, along with the associated negative consequences, should be considered early in the design process. Available techniques for risk assessment, such as Healthcare Failure Mode and Effect Analysis (HFMEA) for qualitative analysis and Fault Tree Analysis (FTA) or Failure Mode and Effect Analysis (FMEA) for quantitative approaches, can then be applied. Steps to reduce risk should include not only best practices for the chosen task but also auxiliary strategies cover- ing governance, continuous evaluation, stakeholder education and harmonization, and combination with established clinical knowledge.

III. Neural Models for Clinical Decision Support

Deep learning, a powerful data-driven approach, has become increasingly popular for clinical decision-support tasks. Nev- ertheless, the perception of neural networks as black boxes has fueled concerns over their reliability and suitability for safety- critical applications. Addressing these shortcomings is crucial in order to leverage their full potential for trustworthy health- care automation. A growing body of work aims to explain the decisions of deep learning models post-hoc, but surro- gates and explanations must be trusted themselves. Moreover, intrinsic methods providing high fidelity explanations remain under-explored. Proposals for transparent and interpretable architectures, leveraging clinical data, and tailored to clinical decision-support tasks are now urgently needed. Models based on convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks, transformers, and graph neural networks offer varying ad- vantages for specific clinical tasks. Architectures facilitat- ing the extraction of explanations that align with clinical reasoning—such as attention mechanisms, modular designs, and sparse feature representations—are well-suited for tasks demanding high interpretability. In addition, challenges related to the privacy of the clinical data, possible biases present in the population cohort and data sources, and differences across the patient cohorts must be carefully addressed during any integrated execution of the model development and evaluation life cycle. Meeting those requirements will build user confi- dence and trust, while also avoiding the propagation of errors to subpopulations of users or patients that are different from

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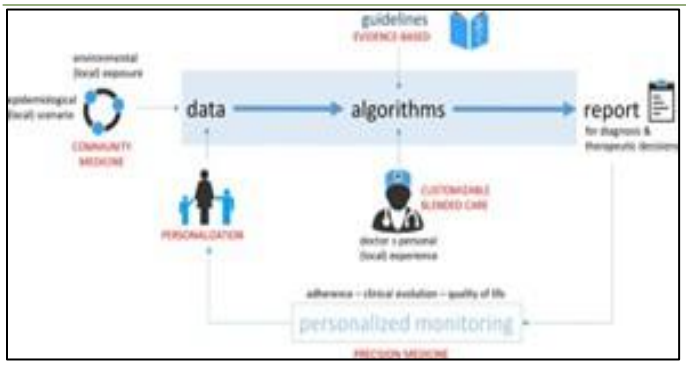

Fig. 3. Neural Networks in Decision Support

those present in the population over which the model has been originally validated.

A. Architectures suitable for clinical tasks

Convolutional neural networks (CNNs) dominate image- based clinical tasks, particularly medical imaging. Regional image annotations ease training with a direct pixel-to- prediction mapping. Robustness and generalization typically improve with larger models, although interpretability and com- putational cost may decline. Long short-term memory (LSTM) units and recurrent neural networks (RNNs) are standards for sequential data. For text and time-series data, transformer architectures outperform LSTMs in most applications, accel- erating speed and supporting word-attention. Self-supervised learning with large pretrained models may eliminate label- processing bottlenecks in NLP tasks. Closer to interpretability, modular graph-based models may facilitate causality analysis and transfer learning within and across health domains. While CNNs, RNNs, and transformer architectures lend themselves to a broad spectrum of clinical applications, these neural network classes generally perform poorly in either sample efficiency or interpretability. In safety-critical environments such as medicine, fewer labeled data are preferred. Representa- tion power along with intelligibility enhance transfer learning across both tasks and domains—features not easily offered by the leading neural architectures. Hybrid models enabling trans- parent reasoning may nevertheless expedite clinical workflows.

B. Data considerations: privacy, bias, and generalization

De-identification and federated learning protect sensitive information, while dataset shift and fairness require careful testing across different groups. Clinical applications of AI are entrusted with precious patient information—their data must remain confidential and protected. When handling sensitive patient information, compliance with data protection law such as HIPAA in the U.S., GDPR in Europe, and other national regulations must be ensured. Federated learning is an approach that mitigates privacy concerns by distributing the training pro- cess across various organizations without sharing the patient data itself. Each participating hospital trains the model on its own patient data, then shares only the model gradients with a central server that aggregates these updates into a global model. Although federated learning is a promising solution,

it remains in the experimental stage. Some deep learning methods have been shown to produce biased models that can

The likelihood of observing $y^{(i)}$ is

$$L(i) = \begin{cases} p^{(i)} \text{ if } y(i) = 1 \end{cases}$$

for diabetic retinopathy based on non-mydratic retinal pho- tographs failed to generalize to non-white populations because the training dataset included only images of patients with similar ancestry. Because model performance can vary greatly across different population groups, bias mitigation and testing on demographic subgroups should be routine practices for clinical decision support systems. Risk assessment and quality evaluation should consider the impact of dataset shift, includ- ing changes in data distribution across time, location, and other factors. Model validation should therefore be conducted on datatypes and subpopulations that differ from those in the training datasets, and these tests should be repeated regularly for models deployed in real settings.

IV. METHODS FOR INTERPRETABILITY IN NEURAL

MODELS

Interpretability can be pursued through intrinsic design choices or post-hoc analysis of black-box models. 4.1. Intrinsic Interpretability Approaches Favorable model classes include fully convolutional networks, recurrent neural networks and other architectures that follow the spatiotemporal flow of information, attention-based models focusing on high- importance inputs, neural concepts that connect activations with human-dictated attributes, and modular neural networks with interpretable subcomponents. Sparse representations, through dropout or engineered priors, may also be useful, especially if combined with a reconstruction objective. For tasks benefiting from a

physician's reasoning process, representations closely paralleling such reasoning are especially desirable. Predictive qualities of the underlying phenomena or high-dimensional inputs further motivate these emulation-focused approaches. 4.2. Post-hoc Explanation Techniques Saliency maps identify relevant input regions or samples for individual predictions, whether through derivatives, perturbation, gradient–input correlation, noise sensitivity or other means. They include occlusion, class activation maps, integrated gradients and others. Extractions of rules or exemplars administer guidelines to clinicians; rule-extraction derives piecewise-linear functions, and neural-symbolic integration merges symbolic descriptions with neural representations. Surrogate models provide intelligible approximations, either global or local. Counterfactual explanations inform users how predictions would change with slight input modifications. Effective explanations must satisfy clinicians' requirements regarding fidelity, robustness, form and content, and ease of use.

Equation 02: Cross-entropy loss for training

We want parameters w, b that fit the data Given one patient $(\phi(x^{(i)}), \psi(y^{(i)}))(x^{(i)}, y^{(i)})$

$$p^{(i)} = P(y^{(i)} = 1 \mid x^{(i)}) = \sigma(w^{\top}x^{(i)} + b) \qquad (2) \qquad 1 - p^{(i)} \quad \text{if } y(i) = 0$$

This can be written compactly as

$$L(i) = (p^{(i)})^{y(i)}(1 - p^{(i)})^{1-y(i)}$$

To make optimization easier, we minimize

$$\ell(i) = -\log L(i) \quad -\log L(i) = -[y(i) \log p^{(i)} + (1 - y(i)) \log(1 - p^{(i)})]$$

So

$$\ell(i) = -[y(i) \log p^{(i)} + (1 - y(i)) \log(1 - p^{(i)})]$$

For a dataset of N patients

$$L(w, b) = \sum_{i=1}^{N} \ell(i)$$

This is the binary cross-entropy loss, standard for CDS classifiers.

A. Intrinsic interpretability approaches

Some architectures outperform others regarding inter- pretability, clinical relevance, and support for regulatory re-quirements. Convolutional neural networks (CNNs) enable interpretable low-level text processing, while recurrent neu- ral networks (RNNs) and long short-term memory networks (LSTM) provide natural encoding for sequential relationships and temporal dependencies. Their bidirectional versions utilize information flow in both directions. Non-sequential trans- formers enhance efficiency by processing all input in paral- lel, and attention heads capture salient associations. Graph- based models represent data with minimal prior assumptions, improving risk for assessment and bias mitigation. These advantages come with a cost: less transparency and more reliance on data for decisions compared to explicit model classes such as logic rules or decision trees. Nevertheless, concealed knowledge can be inferred through dedicated ex- planation techniques, thus supporting the user requirement of transparency in addition to intelligibility when deploying transparent-AI solutions. Relying exclusively on scalability- enhancing architectures, however, poses a different challenge: where is the reasoning? Textual, temporal, and relational data are often inherently structured, and exploring specific knowl- edge patterns can substantially improve AI-aided reasoning. Intrinsically interpretable modules such as symptom checkers or hospital discharge models can thus complement attention heads, and stepwise prediction in recurrent architectures can follow intuitive human reasoning instead of brute-forcing large text corpus predictions. Evaluating a model with multilabel text classification as a symptom checker, for instance, reveals that the main reason for altering the care plan is aggravation of one or more conditions. Exploring such reasoning pathways with dedicated models delivers valuable clinical knowledge while also supporting monitoring and accountability. Lastly, learning sparse representations is highly desirable to decrease reliance on holistic associations that can grow untrustworthy in high-dimension/non-Euclidean spaces.

B. Post-hoc explanation techniques

Post-hoc explanation techniques radicate on the concept of constructing an alternative explanation for an existing predic- tion model. Here, saliency maps become prominent as simple, gradient-based approaches adapted from computer vision can seamlessly apply on various domains. However, optimizing for explanation directly using only saliency supervision is known to suffer from instability while generalizing poorly across distribution shift. Thus, utilizing saliency map super- vision along with original label to balance the trade-off would ensure both common sense-guided insight yet generalization to unseen distribution shift. The rule-extraction process de- termines how to simulate the original black-box model using simpler logic rules, revealing the decision rationale. Proxy or surrogate models facilitate using simpler interpretable mod- els to mimic more complex models, producing explanations from the simpler models while ensuring hidden complexity contained in the complex model class. Again, caution should be taken as the degree to which a proxy model can reveal the underlying informative decision rationale often becomes a central concern. Techniques that induce perturbation or intervention through counterfactual generation

then become an effective avenue to provide descriptive insights, by adopting such an approach for medical data generation. These post- hoc techniques only yield an explanation by itself, essentially they transfer the understanding to the end-users. Therefore, the confidence of the generated explanation can only be as- sessed by comparing against clinicians' knowledge, essentially assessing their fidelity. Since health-care is a domain that explicitly requires the cooperation among clinician and ML models to improve patients' health but not for stand-alone prediction, measuring the robustness of the explanation against perturbation along the axes defined by clinicians' perception hence becomes particularly valuable. Most importantly, be- cause those explainability techniques are designed to explain any deep-model prediction, without keeping track of how well it simulates clinicians' reasoning process which is another important aspect that clinicans care about.

V. Trustworthy Healthcare Automation

Interpretability is essential for safe AI-driven clinical de- cision support, yet it is only one of several requirements. By complementing interpretability with additional desiderata, such as safety and regulatory compliance, it becomes possible to develop trustworthy healthcare automation systems that truly promote patient welfare. Safety, reliability, and account- ability are crucial for healthcare systems. Clear definitions for which aspects of the system require monitoring, for what failures safety mechanisms exist, how auditing is performed, and who is responsible for which parts of the system can foster accountability among all parties involved. Habli et al. propose the following criteria to guide implementation in autonomous systems, describing the design considerations, responsibilities, and procedures relevant for monitoring robust AI-based systems in practice: 1. A failure hazard analysis able to identify hazardous events requiring safety validation.

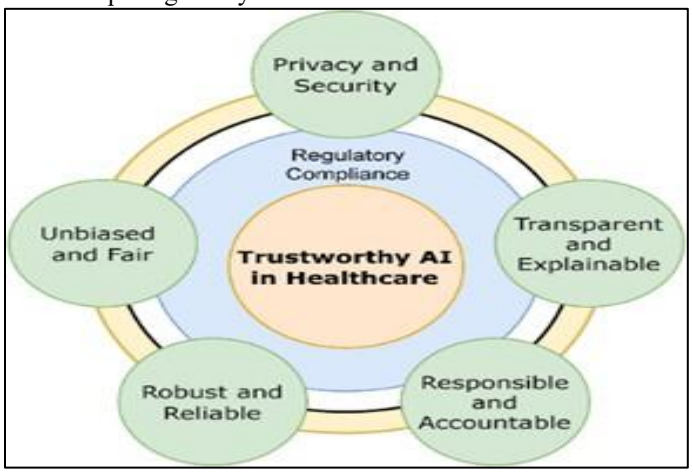

Fig. 4. Trustworthy AI in Healthcare

2. A fail-safe design that identifies events where conventional data may not be available, and provides safety guarantees in these circumstances. 3. An audit plan for evaluating whether the system is performing correctly within specified limits.
4. An explicit allocation of responsibility for all aspects of the system, including training, verification, maintenance, and operation.

A. Safety, reliability, and accountability

Automated clinical decision support systems are deployed in high-stakes domains and thus need to be not merely accurate but also safe. Just like safety is paramount for autonomous vehicles, hospitals may not be ready for admitting self-driving AI that makes clinical decisions. Instead of an 'AI take all' scenario, a combination of human and machine intelligence is preferred. Such a means of human-collaborative system will need to be closely monitored. Therefore, extensive safety considerations need to be in place to make sure that automated systems assist doctors rather than become an unwanted and uncertain second opinion. An automated system that does not undergo continuous monitoring/auditing or cannot be explained, is not trustworthy. Further, researchers behind the model also share responsibility for any adverse effects that arise. Already, advanced starting point questions for risk anal- ysis can be found in the existing literature. Monitoring involves constantly discovering errors from the model and taking action against that. The system can be monitored by scrutinizing the input data before it is served to the model. Data filtering techniques and outlier detection techniques can be employed to constantly keep monitoring the model's input data. Fail- safe measures require the incorporation of another module that predicts the level of uncertainty in the model to mitigate the risk of decision failure. Such an uncertainty module can also help in holding back the predictions of the automated system and alarm the human clinicians when detection accuracy is low. Such monitoring and fail-safe systems require continuous auditing. The core part of the automated model along with the monitoring and

modulating system need to be audited regularly in order to achieve accurate results. In case of biased results, re-evaluation of the model development pipeline is required and also the privacy policy of the service organization behind the automated model.

B. Risk assessment and mitigation strategies

Risk assessment determines safeguards necessary for com- pliance with safety and user requirements; failure to analyze risks leads to inadequate safety measures. Risk mitigation strategies spell out the steps needed to minimize the risk of harm. At a high level, the strategy includes appointing an external AI application expert to identify a list of hazards, conducting a formal qualitative safety analysis to recommend necessary fail-safe mechanisms, and documenting how the design and software transparently record the decisions and actions of the AI application during implementation. The mitigation plan is ongoing and will evolve with further deploy- ment toward more challenging situations. Bias-risk mitigation actions are covered in Section 4.2. Hazard identification is highly context-dependent, relying on knowledge of the ap- plication domain. For cardiology, specifically the assessment of cardiovascular risk, a review of published real-life cases as well as discussions with clinicians yielded a preliminary list of plausible hazards. Each was summarized in natural language, with reference to external literature. A qualitative risk analysis was completed by a small group of cardiological specialists from university hospitals. For ongoing risk assessment, a Google Doc shared with the clinicians allowed new hazards to be added quickly, with a free description of the risk. At every stage of development, further questions about potential hazards

Accurate risk stratification is crucial in guiding clinical decisions and deploying preventive measures, especially since the disease often presents silently. The Framingham Heart Study introduced a widely used risk score based on age, sex, smoking status, diabetes presence, hypertension, dyslipidemia, and cardiovascular disease history. Despite its popularity, the risk score makes aunt predictive use of other common parameters, such as values for high-sensitivity C-reactive protein, ankle-brachial index, and electrocardiography data, to inform decisions about drug therapy or lifestyle changes. Hence, the Framingham score is currently nonoptimal for many patients because clinical decisions are typically based on more parameters than those included in this classical test. A transparent deep neural network model of cardiovascular risk stratification has been developed to address this limitation by making use of LED indicator representation, which should additionally increase clinico-naturel interpretability and could lead to new discoveries of risk factor interactions and coefficients. The model is interpretable due to an additional layer consisting of decision-indicating LED indicator simulators that represent pairs of opposing colors in a natural way. Each of these pairs can be set to positive or negative values, thus indicating presence or absence of the corresponding indicator. Full transparency and interpretability of the model are ensured through the transparency of all network parameters and functions. The application of visio-temporal representation darkens and enhances natural guiding structure in the CNN-routed network, simultaneously boosting performance. Interpretation results demonstrate the consistent use of risk factors and their interactions by the model, which can be used to unveil the nature of diseased data over time through the indication of risk factor phases.

Equation 03: Integrated Gradients (IG)

IG is an attribution method often used in healthcare models Given

were raised and answered by the cardiologists, generating the complete collection of external and internal checks listed.

$$IGi(x) = (xi - xi') \int_{\alpha=0}^{1} \frac{\partial F(x' + \alpha(x - x'))}{\partial x_i} d\alpha$$

The winning submission in the Defake Detection Challenge provided a compelling example of a system containing an effective layer of external checks.

VI. Case Studies

Demonstrating practical applications and benefits of interpretability, two case studies illustrate the integration of explainable AI in trustworthy healthcare automation. In the first study, an interpretable neural model for cardiovascular risk stratification is described, detailing the data, model choices, interpretability outputs, and clinical implications. The second study focuses on transparency-enhanced neural networks for sepsis prediction. Relevant data sources, model design, explanation mechanisms, and impacts on clinical decisions are presented. 6.1. Cardiovascular risk stratification with interpretable models. Cardiovascular disease remains the leading cause of mortality globally.

black-box model F (x) (e.g., probability of sepsis), baseline input x' (e.g., “average patient” or all-zeros), actual patient input x,

IG defines the attribution for feature i as:

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A. Cardiovascular risk stratification with interpretable models

Predicting the risk of cardiovascular disease and related events over a specific interval can guide the allocation of limited healthcare resources. Traditional risk calculators incor- porate readily available clinical indicators to improve decision- making, yet they generally lack transparency. How would the clinical application of a risk model change if the results could be trusted? Cardiovascular risk stratification is an established but often-underused method to guide clinical management and preventive measures. Implementing such screening in routine care can be resource-intensive even for a well-resourced

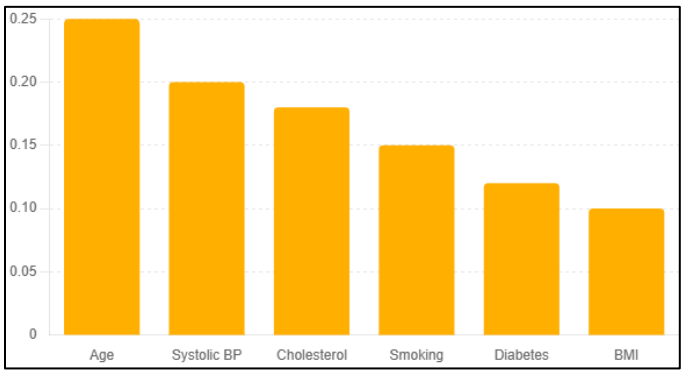

Fig. 5. Synthetic feature importance for CVD risk model

healthcare system, and stratification based on elevated pre- dicted risk can justify more aggressive interventions, yet it is not universally beneficial. Recent developments in deep learning have yielded rich internal representations that capture high-dimensional relationships, but due to their complexity, such neural networks are commonly seen as black-box models, and as such, their predictions are assigned little weight in clinical practice. These models leverage additional predictors not contained in standard risk calculators, support more flex- ible severity categorization than the three-tiered classification of traditional calculators, and output epoch-averaged saliency maps alongside risk estimates. Supervised risk stratification with interpretable models can therefore detect the same pa- tients who would be given additional treatment for primary prevention owing to elevated 10-year risk as a traditional risk calculator; clarify the risk factors that are driving the predictions for these patients; and potentially enhance clinical management by identifying individuals at risk of a major cardiovascular event within a shorter follow-up interval.

B. Sepsis prediction with transparency-enhanced neural net- works

A study on sepsis demonstrated how transparency adds value both in clinical decision-making and as a mechanism for efficient validation. The training set was derived from pub- licly available data corresponding to 65,000 EHRs obtained between 2010 and 2012 from a large cohort of hospital admis- sions, and the validation set comprised an independent batch of 8,000 records corresponding to later admissions. In this context, an experimental comparison was performed between a traditional LSTM architecture and a second set-up in which the hidden states of the LSTM were projected on the input space of a Transformer decoder. Instead of using attention weights to capture dependencies between the input streams, the approach computed two recurrent connections from the embedding and encoder layers to the decoder; these connections were trained together with the other model parameters. The introduction of explicit password paths towards a properly tuned Transformer decoder proved beneficial, as the attention weights in the original LSTM revealed known artifacts and depended heavily on noisy features. The model could thus be validated withoutreverting to the extrapolated logic of a black box, and rules and thresholds could therefore be extracted based on the attention mechanism. This was particularly valuable information for medical personnel, as it provided a succinct justification for the model prediction in a clinical setting characterized by an aggressive control and decision making process. It was finally reported that the adoption of a clinical perspective in the model development did not hinder the overall predictive power of the model family, as the clinically less-appealing architecture delivered on par performance with respect to the original LSTM.

VII. CONCLUSION

Research into trustworthy healthcare automation seeks to enhance clinical decision support systems with transparent algorithms that can be understood by healthcare professionals. The interpreter's perspective places emphasis on the inter- pretability of KDD pipelines, model behavior across training, validation, and deployment, and the governance and contin- uous evaluation of deployed models. Actual mathematical behaviour may diverge from clinical expectations and affect decisions made by both model users and stakeholders at later stages within the KDD pipeline,

before and after deployment. Patient safety relies on appropriate monitoring before and after deployment, and sufficient model justification is vital for auditing and accountability. Emerging approaches are beginning to address the clinical need for model-informed and clinically valid risk assessment. These evolving risk as- sessment capabilities, coupled with established strategies for hazard identification and qualitative risk analysis, offer the foundation for a holistic risk assessment framework. Recent work has shown how transparency-enhanced sepsis prediction models can inform clinician decision-making and potentially mitigate risks associated with inappropriate antibacterial ther- apy, thereby addressing a key clinical objective in a concretely defined manner. Despite the intrinsic gap between clinical reasoning and pure mathematics, strides are being made to bridge the distance between the two cognitive worlds—without requiring formal expertise in mathematics and AI.

A. Emerging Trends

The increasing availability of electronic health records (EHR) enables the construction of ever-larger healthcare datasets. Exploiting this wealth of data for clinical risk strat- ification is a major challenge of its own, requiring special attention for the assessment of safety and interpretability. Recent years have seen growing interest in the development of AI systems, coupled with advances in computing capabilities, that perform satisfactorily in real-world clinical scenarios and could potentially support medical professionals. Nevertheless, research on interpretable models or on care pathways that incorporate considerations of safety and risk assessment — indeed, the very desiderata identified for trustworthy health- care automation — is still limited. Going beyond the mere design of explainable AIs, the generation of trustworthy healthcare automation requires a more complete consideration
of safety, reliability, and accountability principles, including risk assessment and mitigation strategies. Progress in these areas provides a roadmap for the real-world implementation of AI-based CDSS. In particular, combining interpretability with safety/guidance features greatly enhances the potential of AI systems to support clinical decision-making in a reliable way. Several innovative solutions adopt explainable AI methods as suitable safety monitoring mechanisms, highlighted by the definition of trustworthy healthcare automation that considers the relationship with the medical expert system and integrates recommendations in AIs' use.

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