Tiako P.F. (ed) *Intelligent Computing and Consumer Support Applications*. Chronicle of Computing. OkIP

https://doi.org/10.55432/978-1-6692-0003-1_1

Autonomous Systems Functional Safety Overview with Multimodality and Explainability Perspectives

Pierre F. Tiako[a]*, Bernard Kamsu-Foguem[b]

[a]*Tiako University in Oklahoma, USA*

[b]*University of Toulouse, France*

ABSTRACT

Functional safety is crucial in automation systems, particularly for autonomous vehicles. It is important because it protects humans, systems or vehicles, and operating environments from harm. Automated systems can expose operators to severe safety risks. Functional safety aims to minimize safety risks associated with autonomous systems to protect operators, the environment with nearby infrastructure and people, and the systems themselves. This paper overviews multiple facets of Artificial Intelligence (AI) techniques that reduce functional safety risks. As AI and Machine Learning (ML) progress theoretically and in their application, we face new technical challenges in dealing with Multimodality and Explainability. We will discuss these concepts before briefly providing their perspectives on minimizing safety risks in autonomous systems.

Keywords: Functional Safety, Machine Learning, Autonomous Vehicle, Soft Error, Explainability, Multimodality, Deep Learning, Neural Network.

I. INTRODUCTION

Functional safety is crucial in automation systems, particularly for autonomous vehicles. It is important because it protects humans, systems or vehicles, and operating environments from harm. Automated systems can expose operators to severe safety risks. Functional safety aims to minimize safety risks associated with autonomous systems to protect operators, the environment with nearby infrastructure and people, and the systems themselves. No matter the level of autonomy and the application domain, including safety risks, automation requires a lot of AI, data integration, and functional coordination capability. Everything that moves will be autonomous at some point in time and all will rely on AI. Functional safety allows autonomous systems to function safely if there is an electrical or electronic malfunction. Autonomous system products incorporate complex microelectronics and software into their design, making assessing and implementing functional safety in such systems a real challenge.

Functional safety standards ensure that autonomous systems are equipped with automatic protection incorporating predictable and intelligent responses to failures from humans, hardware, or the environment. AI is vital in designing and implementing autonomous systems' safety functions. When implementing such intelligent systems, we must deal with a lot of data and information integration, making multimodality crucial for any safety risk implementation. Multimodal machine learning aims to create models capable of processing and linking information from multiple modalities (data from textual elements, voice, or visual signals).

Explainable Artificial Intelligence (XAI) is an emerging field that can explain how AI obtained a particular result or has answered a specific question (Gohel et al., 2016). Explainability is crucial for applications requiring trust, transparency, compliance, confidentiality, safety, fairness, accountability, and ethics. Explainability is then very important in functional safety. This paper overviews multiple facets of Artificial Intelligence techniques that reduce functional safety risks based on Machine Learning with Multimodality and Explainability perspectives for minimizing safety risks in autonomous systems.

Related work referenced in this paper differs from our contribution. Work dealing with safety and some AI explainability, such as Abella et al., 2023 has not proposed any support for multimodality. Proposals addressing safety such as Biswas et al., 2005, Mariani et al., 2021, and Mukherjee et al. 2004 have no ML consideration. Contributions dealing with some safety, particularly hardware failures such as Dubrawski & Sondheimer, 2011, Ignat et al., 2006, Furst 2019, Rajaram, 2020, Sridharan & Kaeli 2010, and Vankeirsbilck et al, 2015 have no AI or ML consideration. Papers with some AI support particularly multimodaly, such as Junchi et al., 2016, Kounta et al., 2022, Nie et al., 2021 and Poria et al., 2016 are implemented without any functional safety component. Work proposed by Arrieta et al., 2020, Coulibaly et al., 2022, Gohel et al., 2016, and Khan & Vice, 2022 deals with some AI and Explainability without any functional safety consideration. Contributions dealing with some safety, incorporating AI, particularly multimodality such as Paraskevopoulos et al., 2022 have no hardware failure consideration.

This paper is organized as follows. Section I introduces this paper before presenting related work. Section II overviews functional safety concepts with ML foundation, including presenting a process for dealing with hardware failures. Section III describes the concepts and importance of multimodality and explainability in AI for autonomous and industrial systems. Section IV discusses the challenges and perspectives of functional safety, multimodality, and explainability for functional safety. Section V concludes this paper.

II. FUNCTIONAL SAFETY IN AUTONOMOUS SYSTEMS

An autonomous system, particularly an Autonomous Vehicle (AV) senses its surroundings and operates itself to perform all driving functions without any human physical intervention. Such a vehicle utilizes a fully automated driving system to deal with the vehicle's internal and external situations, usually managed by a human. There are two primary levels of vehicle driving automation. The lower levels of autonomy, where a human driving a vehicle monitors its environment, can be assisted in performing a few specific tasks. The car can

* Corresponding author E-mail: tiako@ieee.org

Presented at the 2022 OkIP International Conference on Automated and Intelligent Systems (CAIS) in Oklahoma City, OK, USA, and Online, on October 3-6, 2022

perform tasks such as helping with parking, braking, steering, and speed monitoring. The driver monitors all the automated functions and can take control when needed. This case is illustrated by Fig 1 where a human interacts and deals with all the parameters and components of its environment e*1*, e*2*, …, e*n* when handling all the functions f*1*, f*2*, …, f*n* of an AV.

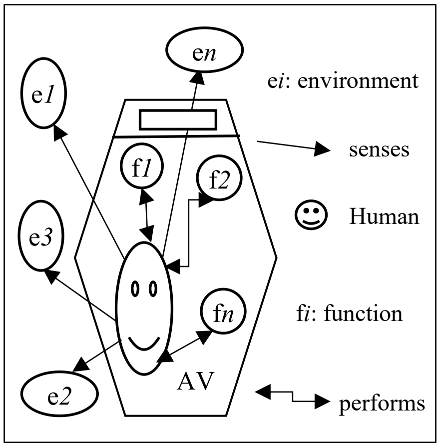

Fig 1. No Automation

The higher levels of autonomy range from dependent or conditional automation to complete or full automation. The dependent automation mode allows the vehicle to perform most of the driving functions, including all environmental detection capabilities, with an option for the human driver to override some of them. This case is illustrated by Fig 2 where a human interacts and deals only with some parameters and components of its environment e*1*, e*2*, …, e*k* when handling some of the functions f*1*, f*2*, …, f*m* of an AV. The AV takes care of the remaining parameters and components of the environment e*k+1*, …, e*n* when handling functions f*m+1*, …, f*n*.

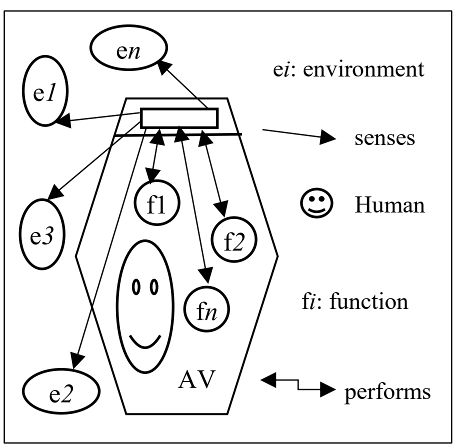

Fig 2. Dependent Automation

The complete automation option allows the vehicle to perform all the driving functions under all conditions and circumstances without human intervention. This case is illustrated by Fig 3 where a human in the AV is passive, letting an AV deal with all the parameters and components of its environment e*1*, e*2*, …, e*n* when handling all its functions f*1*, f*2*, …, f*n*.

No matter the level of autonomy and the application domain, dependent or conditional automation requires a lot of Artificial Intelligence (AI), data integration, and functional coordination capability. Modern function safety and soft error modeling are usually overlooked regarding functional coordination capability.

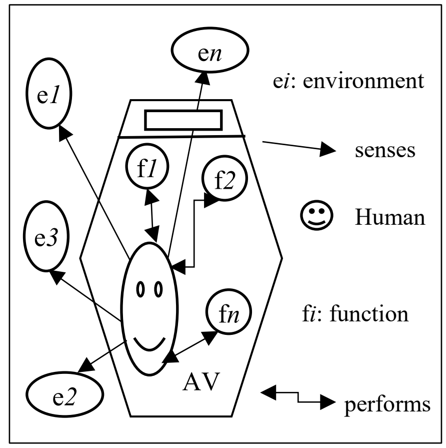

Fig 3. Complete Automation

A. Development Process, Validation, and Dependability

Deep Learning (DL) is a new computing model supported by Artificial Neural Networks (ANN) (Choi et al, 2020). ANN is a collection of simple, trainable mathematical units that collectively learn complex functions. Contrary to a traditional learning approach requiring domain experts and prone to errors, the DL approach uses several layers of ANN to learn from data (LeCun et al., 2015) ". DL learning is easy to extend and can be speeded up with GPUs. Given sufficient training data, an ANN can approximate complex functions, mapping raw data to output decisions. The training process is repetitive and involves forward and backward propagation. Using hidden layers, ANN is converted to Deep Artificial Neural Networks (DANN) (Annarumma et al., 2019). AV requires an end-to-end development Process. Including (1) Data collection Ops, (2) Data Labeling/Processing, (3) Mapping, (4) AI Model Development, (5) Autopilot, (6) NCAP, (7) Drive Valet, (8) Drive Concierge, and (9) Validation. AV also requires a very comprehensive validation approach, including end-to-end system-level tests, large scale with millions of miles, diverse vehicles, and world conditions, environment and situations, data-driven and different use case scenarios, validation needs to be repeatable and reproducible. Dependability (Athavale et al., 2020) should deal with not only the conflicts among these technologies but also the synergies among them. We should consider how to define a holistic technology architecture that considers the requirements of technologies dealing with security, safety, time determinism, and reliability separately and when put all together.

B. Functional Safety in AI and ML

Functional safety allows AVs to function safely if there is an electrical or electronic malfunction. AV products incorporate complex microelectronics and software into their design, making assessing and implementing functional safety in such systems a real challenge. We define functional safety as the absence of unreasonable risk due to hazards caused by the malfunctioning behavior of electric or electronic systems. Two types of failures must be considered regarding AV functional safety: systematic and random hardware failures. Systematic failures deal with bugs in software, hardware design, and tools (Rajaram, 2020). Per ISO 26262, systematic failures are "failures related in a deterministic way to a certain cause that can only be eliminated by a change of the design or of the manufacturing process, operational procedures, documentation or other relevant factors." Some interesting techniques for early warning of systematic failures in the aerospace sector, partly applicable to the AV industry are proposed by Dubrawski & Sondheimer (2011).

We distinguish systematic failures from random hardware failures, which can be permanent and transient faults when the parts are inoperable in the field. Per ISO 26262, random hardware failures are "failures that can occur unpredictably during the lifetime of a hardware element, and that follow a probability distribution." In random hardware failures, permanent fault models include stuck-at fault, open circuit fault, bridging fault, and single event hard error fault. Permanent faults can be caused by reliable prediction models (IEC62380), stress tests, wear out, field data, etc. Transient fault models include single event transient, single event upset, single bit upset, multiple cell upset, and multiple bits upset. Soft errors can cause these faults due to high-energy neutrons, alpha particles, etc. Transient failure rates remain dominant in functional safety applications compared to permanent failures. Mitigating transient failures is one of the key focuses of any architecture design for safety applications. A model to evaluate random hardware failures based on fault tree analysis and Markov chain and applicable to the AV industry is proposed by Wang et al. (2019).

C. *Soft Error and Classification*

Generally, a soft error in an AV hardware (computing, electrical, and electronics) architectural component, is a type of error where a signal or datum is wrong and has changed from 0 to 1 or 1 to 0. A soft error may go unnoticed without an error mitigation, detection, and correction system built into such an AV hardware component. The mitigation phase helps minimize the rate of soft errors at the AV hardware architectural design level. A Graphics Processing Unit (GPU) is a chip architecture designed to manipulate and alter memory to support self-driving technology and particularly advanced driver-assistance systems (ADAS) in the AV sector.

D. *Soft Error Detection and Correction*

The detection phase of soft errors uses both hardware and software techniques at the CPU (Central Processing Unit), register, and internal RAM level to deal with issues. IEC 61508 with contents related to Soft Errors provides some standards for this phase. For instance, the IEC 61508 Soft Errors standard of the CPU requires the register and the internal RAM to be diagnosed at several requirement levels.

Low requirement levels, or a minimum of 60%, are considered when dealing with some stuck-at faults with data and addresses. Medium requirement levels or a minimum of 90% are considered when dealing with some moderate soft errors changing information in the system. High requirement levels or a minimum of 99% are considered when dealing with more severe soft errors, and also changing information in the system.

Anyway, the soft error and its detection techniques are linked to requirements imposed by the functional safety standards (Vankeirsbilck et al, 2015). The soft error detection and classification of the possible outcomes of a faulty bit are determined by the algorithm in Fig 4. The algorithm is adopted from several pieces of literature (Biswas et al., 2005; Ignat et al., 2006, Junchi et al., 2016).

```
If no faulty bit is read
then
benign fault; no error
else
 -- If detection and correction can be made
 -- then
 -- fault corrected/benign fault; no error
 -- else
 -- ---If detection can be made when Bit has
 -- ---error protection
    ---then
 -- ---        If bit does matter
 -- ---        then
 _  ---        true detected unrecoverable error
 -- ---        else
 -- ---        false detected unrecoverable error
 -- ---        end if
 -- ---else
 -- ---        If bit does matter
 -- ---        then
 -- ---        silent data corruption
 -- ---        else
 -- ---        benign fault; no error
 -- ---        end if
 -- ---end if
 -- end if
end if
```

Fig 4. Soft Error Classification Algorithm adopted from flowcharts [Biswas et al., 2005]

E. *Functional Safety Vulnerability Factors and Mitigation Mechanisms*

1) Functional Safety Vulnerability Factors: The vulnerability factors detailed in Mukherjee et al. (2004) depend on several parameters and variables, including the Architectural Vulnerability Factor (AVF), Timing Vulnerability Factor (TVF), and Program Vulnerability Factor (PVF). Sridharan and Kaeli (2010) have introduced and analyzed the Hardware Vulnerability Factor (HVF) to quantify the vulnerability of hardware. All these variables must be considered when designing and implementing AV systems and components.

2) Functional Safety Mitigation Mechanisms: A functional safety standard relative to mitigation mechanisms includes ISO 26262 2nd edition (ISO 26262 2018). It covers different ranges of diagnostic from Low, Medium to High. The low range includes (1) one-bit hardware redundancy and (2) stack over/underflow detection. The medium range includes (1) multi-bit hardware redundancy, (2) read back of the sent event, (3) transmission redundancy, (4) information redundancy (5) frame counter, (6) time-out monitoring, (7) self-test by software, and (8) self-test supported by hardware. The high range includes (1) complete hardware redundancy, (2) inspection using test patterns, (3) combination of information redundancy, (4) software diversified redundancy, (5) reciprocal comparison by software, (6) hardware redundancy, (7) configuration register test, and (8) integrated hardware consistency monitoring.

III. Multimodality and Explainability in AI and ML

Machine learning continues to make progress both theoretically and in application. However, it must face certain challenges, including multimodality and explainability, which we are interested in. The first part of this section focuses on multimodality with a learning approach based on developing a multi-branch deep neural network (DNN), each branch designed to process a certain type of data. The second part of this section focuses on the explainability of learning by proposing an approach combining several existing methods. The idea is to use their complementarities to enrich the explanations provided. The two concepts are important for functional safety.

A. Multimodality in AI and ML

Multimodal machine learning aims to create models capable of processing and linking information from multiple modalities (data from textual elements, voice, or visual signals). It is a dynamic multidisciplinary field of growing importance, with great potential and many challenges. It includes representation, translation, alignment, fusion, and co-learning (Baltrusaitis et al., 2019).

1) Representation: Multimodal representation represents data using information from multiple entities (Paraskevopoulos et al., 2022). Joint representations combine the unimodal signals into the same representation space, while coordinated representations process unimodal signals distinctly, but enforce some similarity constraints on them to bring them to a coordinated space. For safety, using image captioning (You et al., 2016) for ambient awareness on a sidewalk is critical for safe navigation, especially for the blind or visually impaired (Ahmed et al., 2018).

2) Translation: Given an entity in one modality, the task is to generate the same entity in a different modality via a mapping. On the one hand, example-based models employ a dictionary when translating between the modalities. On the other hand, generative models, build a model that can produce a translation. In safety, translation (Sulubacak et al., 2020) plays a crucial role in preventing accidents and injuries by ensuring that all humans and autonomous systems clearly understand safety instructions and procedures, warning signs, and other safety-related communications.

3) Alignment: Multimodal alignment finds relationships and correspondences between sub-components of instances from two or more modalities. Explicit alignment is performed if the main modeling objective concerns alignment between subcomponents of instances from two or more modalities. Implicit alignment is used as an intermediate (often latent) step for another task and the model can learn how to latently align the data during training. Aligning images and texts can help humans or autonomous systems walk or navigate more safely. For instance, an image of a supposed dry sidewalk or road and the text “Ice” when aligned can alert of a dangerous icy road situation.

4) Fusion: Multimodal fusion (Nie et al., 2021) is the concept of integrating information from multiple modalities to predict an outcome measure: a class (e.g., normal vs. abnormal) through classification, or a continuous value (e.g., the superiority of a particular measure) through regression. Model-agnostic approaches are not directly dependent on a specific machine learning method whereas model-based approaches explicitly address fusion in their construction. Fusioning an image from a camera, the speed from GPS, and the angles of a wheel from a sensor could help an autonomous vehicle take appropriate safety actions to prevent an accident.

5) Co-learning: Multimodal machine learning (Rahate et al., 2022) applications can be found in several areas including, but not limited to, speech recognition and synthesis, event detection, emotion (Fig. 5) and affect, media description, and multimedia retrieval. To operate safely, Autonomous vehicles use information remotely sensed from Synthetic Aperture Radar (SAR) images and optical images. If optical images are unavailable due to poor weather conditions, co-learning can help compensate for missing optical image fragments (Zheng et al.,2021).

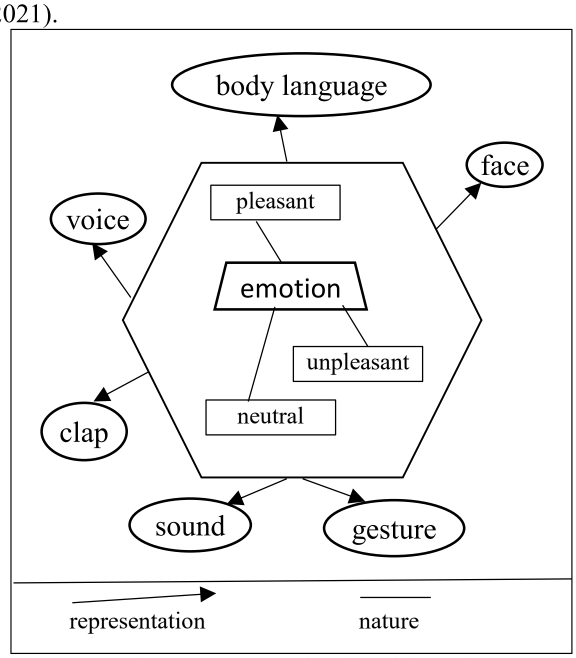

Fig 5. Some Facets of Multimodal Emotions

The applications of multimodal learning can relate to the contexts of information sciences (speech recognition and synthesis, event detection, emotion and affect, media description and Multimedia retrieval) or industrial contexts such as the verification of the quality of the surfaces of parts obtained after machining processes (Kounta et al., 2022).

B. Explainability in AI and ML

Explainable Artificial Intelligence (XAI) is an emerging field of Artificial Intelligence (AI) that can explain how AI obtained a particular result or has answered a specific question (Gohel et al., 2016). Explainability is crucial for applications requiring trust, transparency, compliance, confidentiality, safety, fairness, accountability, and ethics.

The development of AI relative to ML methods provides powerful tools to analyze difficult problems while taking explainability needs (Arrieta et al., 2020). This opens the way to a better understanding of the predictions induced, particularly on a global or local scale, but facilitates the implementation of actions promoting the development of justification through symbolic and numerical reasoning (Bennetot et al., 2022). To increase user trust in AI and ML, XAI provides ways to easily understand the algorithms and results used in each AI process when making decisions, predictions, and insights.

1) Explainability Levels: We can differentiate several levels of explainability in AI. The data, process, prediction, and complexity levels.

2) Explainability Deployment: It deals with the deployment of explainability techniques in the processing of data acquired by connected objects. For example, it helps implement innovative safety services in agriculture (harmful insects, plant diseases) (Coulibaly et al., 2022).

3) Explainability Cases: Various sectors in our daily lives are involved with risky decision processes and must heavily deal with XAI. Some of such areas involving XAI can be found in AVs, healthcare, agriculture, industry, business, and finance, just to name a few. The AI used in such sectors and systems should be explainable and support some or most of the features described in Fig 6.

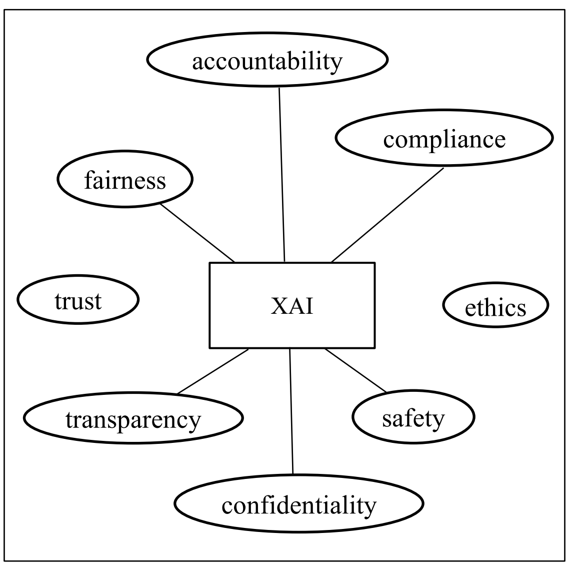

Fig 6. Some important XAI features

IV. Functional Safety, Multimodality, and Explainability: Challenges and Perspectives

This section describes some challenges and perspectives of functional safety in autonomous systems before presenting how explainability of algorithm results is important in AI and the role of multimodal machine learning in predicting outcomes.

A. Functional Safety Challenges and Perspectives

Functional safety and soft error rate requirements pose challenges in markets such as autonomous vehicles. The transient failure rates continue to reduce the functional safety of applications. Methodology to analyze and strengthen functional safety components should consider its safety goal, soft error testing and modeling methodologies, error classification, and innovative mitigation strategies in hardware and software. We must explore innovations in all layers, including technology, hardware, software, and firmware mitigation. The combinations of on-chip and off-chip features and techniques are critical to meet safety requirements.

B. Explainability of AI Algorithm Results

As AI acceptance and automatic decisions impact people, some minimum elements of transparency are required, explaining how the algorithmic decisions were made. We say that an algorithmic decision is interpretable if it is possible to account for it explicitly from known data and characteristics of the situation. In other words, if it is possible to relate the values taken by certain variables (characteristics) and their consequences on the forecast, such as a score, and thus on the decision. On the other hand, an algorithmic decision is said to be explainable if it is only possible to identify the characteristics or variables that contribute the most to the decision, or even to quantify their importance. Each actor, public or private, and each field, health, justice, employment, banking, insurance, and police requires a specific reading of what algorithmic transparency can be concerning the right to explanation. In any case, it seems essential to be able to make a social choice on what is preferable in a balance of detailed interests between the quality of the explanation and the quality of the forecast, at least in the hypotheses where the characteristics of the algorithms are reducible to these two main qualities.

C. Multimodal Machine Learning for Enhancing Predictions

Multimodal machine learning aims to create models capable of processing and linking information from multiple modalities (data from textual elements, voice, or visual signals). It is a dynamic multidisciplinary field of growing importance and with great potential, but with many challenges. Multimodal machine learning includes representation, translation, alignment, fusion, and co-learning. Multimodal fusion is one of the original themes of multimodal machine learning, with works in the literature favoring early, late, and hybrid fusion approaches. Technically, multimodal fusion is the concept of integrating information from multiple modalities to predict an outcome of a measurement: a category by classification, or a continuous value by regression. Interest in multimodal fusion stems from three main advantages it can provide. First, having access to several modalities that observe the same phenomenon can lead to more robust predictions. Secondarily, having access to multiple modalities might allow us to capture complementary information not independently discernible in individual modalities. Third, a multimodal system can still work when one of the modalities is missing, for example, recognizing the characteristics of a phenomenon with the visual signal in the absence of an audio signal.

V. Conclusion

This paper overviewed multiple facets of AI techniques that reduce functional safety risks. As AI, Machine Learning, and Deep Learning progress theoretically and in their application, we face new technical challenges in dealing with Multimodality and Explainability. We have presented these concepts before briefly providing their perspectives on minimizing safety risks in autonomous systems. Future work will discuss in more detail how Multimodality and Explainability can be used to support Functional Safety.

Acknowledgment

We gratefully acknowledge the inputs of Jyotika Athavale, Synopsys, Inc., in preparing the functional safety section of this manuscript when she was at Nvidia.

References

Abella, J et al. (2023), SAFEXPLAIN: Safe and Explainable Critical Embedded Systems Based on AI. 2023 Design, Automation & Test in Europe Conference & Exhibition, Antwerp, Belgium, 2023, pp. 1-6, doi: 10.23919/DATE56975.2023.10137128.

Ahmed, F., Mahmud, M. S., Al-Fahad, R., Alam, S., and Yeasin M. (2018) Image Captioning for Ambient Awareness on a Sidewalk. 2018 1st International Conference on Data Intelligence and Security (ICDIS), South Padre Island, TX, USA, 2018, pp. 85-91, doi: 10.1109/ICDIS.2018.00020.

Annarumma, M., Withey, S.J., Bakewell, R.J., Pesce. E., Goh, V., & Montana, G. (2019). Automated Triaging of Adult Chest Radiographs with Deep Artificial Neural Networks. Radiology, 291(1):196-202. Doi: 10.1148/radiol.2018180921.

Arrieta, A. B., Diaz-Rodriguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020) Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges toward Responsible AI. Information Fusion, Volume 58, Pages 82-115. Doi: 10.1016/j.inffus.2019.12.012.

Athavale, J., Baldovin, A., Mo S., & Paulitsch, M. (2020). Chip-Level Considerations to Enable Dependability for eVTOL and Urban Air Mobility Systems. In 2020 AIAA/IEEE 39th Digital Avionics Systems Conference (DASC), pp. 1-6. Doi: 10.1109/DASC50938.2020.9256436.

Baltrusaitis, T., Ahuja, C., & Morency, L.-P. (2019). Multimodal Machine Learning: A Survey and Taxonomy. IEEE Transactions on Pattern Analysis and Machine Intelligence, 41(2), pp. 423-443. Doi: 10.1109/TPAMI.2018.2798607.

Bennetot, A., Franchi, G., Del Ser, J., Chatila, R., & Diaz-Rodriguez, N. (2022). Greybox XAI: A Neural-Symbolic Learning Framework to Produce Interpretable Predictions for Image Classification. Knowledge-Based Systems, Volume 258, 109947. Doi:10.1016/j.knosys.2022.109947.

Biswas, A., Racunas, P., Cheveresan R., Emer, J., Mukherjee S. S., & Rangan, R. (2005). Computing Architectural Vulnerability Factors for Address-based Structures. In 32nd International Symposium on Computer Architecture (ISCA'05), pp. 532-543. Doi: 10.1109/ISCA.2005.18.

Choi, R. Y., Coyner, A. S., Kalpathy-Cramer, J., Chiang, M. F., & Campbell, J.P. (2020). Introduction to Machine Learning, Neural Networks, and Deep Learning. Translational Vision Science & Technology, 9(14). Doi: 10.1167/tvst.9.2.14

Coulibaly, S., Kamsu-Foguem, B., Kamissoko, D., & Traore D. (2022). Explainable Deep Convolutional Neural Networks for Insect Pest Recognition. Journal of Cleaner Production, Volume 371, 133638. Doi: 10.1016/j.jclepro.2022.133638.

Dubrawski, A., & Sondheimer, N. (2021). Techniques for Early Warning of Systematic Failures of Aerospace Components. In 2011 Aerospace Conference, pp. 1-9. Doi: 10.1109/AERO.2011.5747589.

Furst, S. (2019). System/ Software Architecture for Autonomous Driving Systems. In 2019 IEEE International Conference on Software Architecture Companion (ICSA-C), pp. 31-32. Doi: 10.1109/ICSA-C.2019.00013.

Gohel, P.,Singh, P., & Mohanty, M. (2016). Explainable AI: Current Status and Future Directions. IEEE Access, Vol. 4. Doi: 10.1109/ACCESS.2017.DOI

Ignat, N., Nicolescu, B., Savaria Y., & Nicolescu, G. (2006). Soft-error Classification and Impact Analysis on Real-time Operating Systems. Proceedings of the Design Automation & Test in Europe Conference. Doi: 10.1109/DATE.2006.244063.

ISO, 26262., (2018). ISO, 26262 Road vehicles — Functional safety. https://www.iso.org/standard/68383.html

Junchi, M., Yu, D., Wang, Y., Cai, Z., Zhang, Q., & Hu, C. (2016). Detecting Silent Data Corruptions in Aerospace-Based Computing Using Program Invariants. International Journal of Aerospace Engineering, 1(10). Doi: 10.1155/2016/8213638.

Khan, M. M., & Vice, J. (2022). Toward Accountable and Explainable Artificial Intelligence Part One: Theory and Examples. IEEE Access, Vol. 10, pp. 99686-99701. Doi: 10.1109/ACCESS.2022.3207812.

Kounta, C. A. K. A., Kamsu-Foguem, B., Noureddine, & F., Tangara, F. (2022). Multimodal Deep Learning for Predicting the Choice of Cut Parameters in the Milling Process. Intelligent Systems with Applications. Volume 16, 200112. Doi: 10.1016/j.iswa.2022.200112.

LeCun, Y., Bengio, Y. & Hinton, G. Deep Learning. Nature 521, 436–444 (2015). https://doi.org/10.1038/nature14539

Mariani, R., Maor, N., Athavale, J., & Gay K. (2021). The Importance of Interoperability in Functional Safety Standards. Computer 54(3), pp. 80-84. Doi: 10.1109/MC.2021.3050453.

Mukherjee, S. S., Weaver, C., Emer, J., Reinhardt, S.K., & Austin, T. (2003). A Systematic Methodology to Compute the Architectural Vulnerability Factors for a High-performance Microprocessor. In Proceedings. 36th Annual IEEE/ACM International Symposium on Microarchitecture (MICRO-36), pp. 29-40. Doi: 10.1109/MICRO.2003.1253181.

Nie, J., Yan, J., Yin, H., Ren L., and Meng, Q. (2021). A Multimodality Fusion Deep Neural Network and Safety Test Strategy for Intelligent Vehicles. IEEE Transactions on Intelligent Vehicles, Vol. 6, No. 2, pp. 310-322, Doi: 10.1109/TIV.2020.3027319

Paraskevopoulos, G., Pistofidis, P., Banoutsos, G., Georgiou,E, Katsouros, V (2022) Multimodal Classification of Safety-Report Observations. Applied Science, 12,5781. https://doi.org/10.3390/app12125781

Poria, S., Cambria, E., Howard, N., Huang, G.-B., & Hussain, A. (2016). Fusing Audio, Visual, and Textual Clues for Sentiment Analysis from Multimodal Content. Neurocomputing, Volume 174, Part A. Doi: 10.1016/j.neucom.2015.01.095

Rahate, A., Walambe, R., Ramanna, S., Kotecha, K. (2022). Multimodal Co-learning: Challenges, Applications with Datasets, Recent Advances and Future Directions. Information Fusion, Volume 81, Pages 203-239, ISSN 1566-2535, https://doi.org/10.1016/j.inffus.2021.12.003

Rajaram, B. (2020). Understanding Functional Safety FIT Base Failure Rate Estimates per IEC 62380 and SN 2950. Texas Instruments Incorporated SLOA294. https://www.ti.com/lit/wp/sloa294/sloa294.pdf

Sridharan, V., Kaeli, D. R. (2010). Using Hardware Vulnerability Factors to Enhance AVF Analysis. SIGARCH Comput. Archit. News 38(3), 461–472. Doi: 10.1145/1816038.1816023

Sulubacak, U., Caglayan, O., Grönroos, SA. et al. (2020). Multimodal Machine Translation through Visuals and Speech. Machine Translation 34, 97–147. https://doi.org/10.1007/s10590-020-09250-0

Vankeirsbilck, J., Hallez, H., & Boydens, J. (2015). Integration of Soft Errors in Functional Safety: a conceptual study. Proceeding of the 2015 International Scientific Conference Electronics, Volume: 9, Sozopol, Bulgaria.

You, Q., Jin, H., Wang, Z., Fang, C., Luo, J. (2016) Image Captioning with Semantic Attention. arXiv 2016, arXiv:1603.03925

Wang, T., Chen, X., Cai, Z., Mi, J., & Lian, X. (2019). A mixed Model to Evaluate Random Hardware Failures of Whole-redundancy System in ISO 26262 based on Fault Tree Analysis and Markov Chain. Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering. 233(4):890-904. Doi:10.1177/0954407018755613

Zheng, Z., Ma, A., Zhang, L., Zhong, Y. (2021). Deep Multisensor Learning for Missing-modality all-Weather Mapping, ISPRS J. Photogramm. Remote Sens. 174 (2021) 254–264. https://doi.org/10.1016/j.isprsjprs.2020.12.009.