Machine Learning in Safety-Critical Domain

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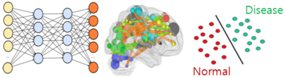
Machine Learning Application in Safety Critical Environments

- Decision making in life-threatening conditions (diagnosis, prognosis,machine learning-based medical decision support systems).



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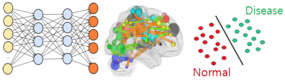
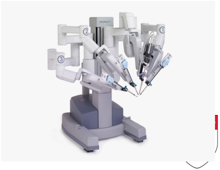


Figure: Surgical Robots[2]



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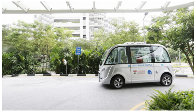
- Decision making in life-threatening conditions (diagnosis, prognosis,machine learning-based medical decision support systems).
- Robots (surgical robots, industrial robots, etc)
- Autonomous vehicles.

Figure: Autonomous Bus



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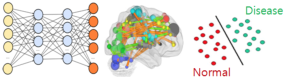

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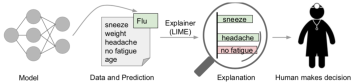
- Instability A small change in the training process may produce a different result, and hence it is difficult to debug models or reuse parts of previous safety assessments.
- Difficulty in verification: Formal verification of machine learning components is a difficult, and somewhat ill-posed problem due to the complexity of the underlying machine learning algorithms, large feature spaces.

Potential Strategies for Achieving Safety

- Interpretability & Transparency: Improve the interpretability & transparency of the ML component.

Figure: Explanations make the user to trust the prediction [3]



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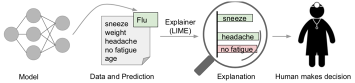

A technique used in machine learning when predictions cannot be given confidently is the reject option [4].

$$\hat{y}(x) = \begin{cases} -1 & \text{if } \phi(x) \le t \\ \text{reject, if } \phi(x) \in (-t, t) \\ 1 & \text{if } \phi(x) \ge t \end{cases}$$

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- Interpretability & Transparency: Improve the interpretability & transparency of the ML component.
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- Abstract. Abstract the ML component and input feature space and identify scenarios that could cause violation of safety specification.

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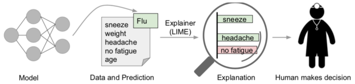

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