# Assured Machine Learning

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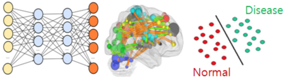
# Machine Learning Applications in Safety-Critical Environments

- Decision making in life-threatening conditions (Machine-Learning (ML) based medical decision support systems)

Figure: ML Based Brain Disease Diagnosis[1]



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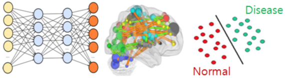


Figure: Surgical Robots[2]

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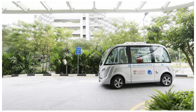
- Decision making in life-threatening conditions (Machine-Learning (ML) based medical decision support systems)
- Robots (surgical robots, industrial robots, etc.)
- Autonomous vehicles

Figure: Autonomous Shuttle



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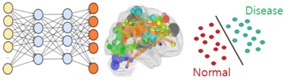


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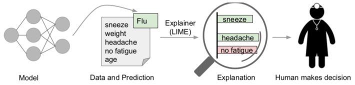
- Error Rate:The estimate of error rate of a ML model with respect to the test data is not reliable
- Instability: A small change in the training process may produce a different result, and hence it is difficult to debug models or reuse parts of previous safety assessments.
- Difficulty in verification: Formal verification of ML components is a difficult, and somewhat ill-posed, problem due to the complexity of the underlying ML algorithms and large feature spaces

# Potential Strategies for Safety Assurance

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

Figure: Explanations improve trust in prediction [?]



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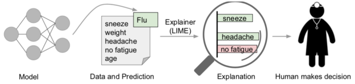


Figure: Explanations improve trust in prediction [**?**]

Technique used in ML when predictions cannot be given confidently is the reject option [**?**]

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- Interpretability & Transparency: Improve the interpretability & transparency of the ML component
- Fail-Safe: The model reports that it cannot reliably give a prediction and does not attempt to do so, thereby failing safely
- Abstract: Abstract the ML component and input feature space, and identify scenarios that could cause violation of safety specifications

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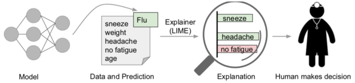


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