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Enhanced Method to Predict Machine Life Using Deep Learning

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Abstract*:* *The amount of time a device can perform the same task while being competitive is referred to as its remaining useful life. Manufacturers can reduce development costs by deciding when to replace parts and utilities by calculating the remaining usable life. The amount of time that the machine's original parts are expected to maintain working perfectly before being upgraded is known as the machine's remaining useful life. The amount of time, or the number of cycles or cycles, that a machine can still technically be used in regular service is known as its remaining useful life. The amount of years (often) that a component of equipment or machinery is anticipated to last before becoming outdated is known as its remaining usable life. A decision tree classifier is employed in this model to determine whether or not you demand service guess it depends on the machine's monthly earnings. Using a decision tree classifier, the machine learning method is used to determine whether a service is needed or not. Data classification can be done in many different ways. Decision tree learning, which is a strategy for determining the best decision tree from a collection of input values to achieve the maximum of each of its leaf nodes, is one of the most well-liked classification strategies. Decision tree learning is an algorithm in use by data scientists to label objects in a dataset. In our model, we will compute the remaining useful life (RUL).We will use lasso regression to determine the age of a machine's investment spending. This machine's average service is added toward its life expectancy, and the estimation is found, from which we are able to evaluate the machine's remaining useful life*.

Keywords: Cycle-consistent learning, deep learning, degradation alignment, prognostics, remaining useful life (RUL) prediction.

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