

## **Impact learning: A learning method from feature's impact and competition**

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### **ABSTRACT**

Machine learning is the study of computer algorithms that can automatically improve based on data and experience. Machine learning algorithms build a model from sample data, called training data, to make predictions or judgments without being explicitly programmed to do so. A variety of well-known machine learning algorithms have been developed for use in the field of computer science to analyze data. This paper introduced a new machine learning algorithm called impact learning. Impact learning is a supervised learning algorithm that can be consolidated in both classification and regression problems. It can furthermore manifest its superiority in analyzing competitive data. This algorithm is remarkable for learning from the competitive situation and the competition comes from the effects of autonomous features. It is prepared by the impacts of the highlights from the intrinsic rate of natural increase (RNI). We, moreover, manifest the prevalence of impact learning over the conventional machine learning algorithm.

### **KEYWORDS**

Asthma prediction; Classification; Diabetes prediction; Heart disease identification; Impact learning; Machine learning; Regression

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