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Finite element quantitative analysis and deep learning qualitative estimation in structural engineering

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Finite element method (FEM) has been widely used to study the mechanics of materials and solids, as well as fluid–structure interactions, and building construction strategies. FEM is popular all over the world with the development of computer technology. It is known for powerful computing ability, surpassing humans in computing. In this context, in addition to teaching engineers to use FEM calculation software, structural engineering education in the past nearly two decades also focuses on cultivating engineers' ability of qualitative analysis. However, the rapid development of deep learning methods in recent years means that human qualitative analysis capabilities based on rules of thumb will also be replaced by artificial intelligence. The main question of this study is: what role will deep learning methods play in the future structural analysis? In this paper, a large number of finite element analyses are carried out for three classic boundary value problems, such as the behaviour of wires under load, the problem of heat conduction, and plane strain. The deep learning model is trained with FEM simulation results. It can quickly and accurately predict the results of related similar problems, and evaluate the accuracy and efficiency. The results show that artificial intelligence can to some extent replace the work of human qualitative analysis based on rules of thumb. Predictions and expectations about the role of deep learning methods in future structural analysis processes are given.

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