SOUTENANCE DE THÈSE

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Soutiendra sa thèse de **doctorat** sur le sujet :

Evidential deep neural network in the framework of Dempster-Shafer theory

Unité de recherche : ***Heudiasyc***

Le lundi 14 mars 2022 à 10h
à l'université de technologie de Compiègne
Salle GI-42

Devant le jury composé de :

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Deep neural networks (DNNs) have achieved remarkable success on many real-world applications (e.g., pattern recognition and semantic segmentation) but still face the problem of managing uncertainty. Dempster-Shafer theory (DST) provides a well-founded and elegant framework to represent and reason with uncertain information. In this thesis, we have proposed a new framework using DST and DNNs to solve the problems of uncertainty.

In the proposed framework, we first hybridize DST and DNNs by plugging a DST-based neural-network layer followed by a utility layer at the output of a convolutional neural network for set-valued classification. We also extend the idea to semantic segmentation by combining fully convolutional networks and DST. The proposed approach enhances the performance of DNN models by assigning ambiguous patterns with high uncertainty, as well as outliers, to multi-class sets. The learning strategy using soft labels further improves the performance of the DNNs by converting imprecise and unreliable label data into belief functions.

We have also proposed a modular fusion strategy using this proposed framework, in which a fusion module aggregates the belief-function outputs of evidential DNNs by Dempster's rule. We use this strategy to combine DNNs trained from heterogeneous datasets with different sets of classes while keeping at least as good performance as those of the individual networks on their respective datasets. Further, we apply the strategy to combine several shallow networks and achieve a similar performance of an advanced DNN for a complicated task.