Comparing Tsetlin Machines to DNNs in model performance and efficiency

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Introduction

The research compared a novel and uprising Tsetlin Machines paradigm to Deep Neural Networks in terms of model performance as understood by the Accuracy and F1 metrics, and model efficiency as understood by energy and time consumption of training and running the models.
Experiments for 9 datasets have been performed, so that the functional relationship between dataset characteristics and the comparative model performance and efficiency could be investigated.
For obtaining results of statistical significance bootstrap procedure has been used. The efficiency differences proved TMs to be better than the DNNs, with comparable results for the model performance measures. Main findings of the prior work have been replicated and built upon this work.
The differences in both performance and efficiency correlated with class imbalance while number of features and number of instances had influence on the prediction time and energy, which grants support for future work.

Sensitivity to Hyperparameters

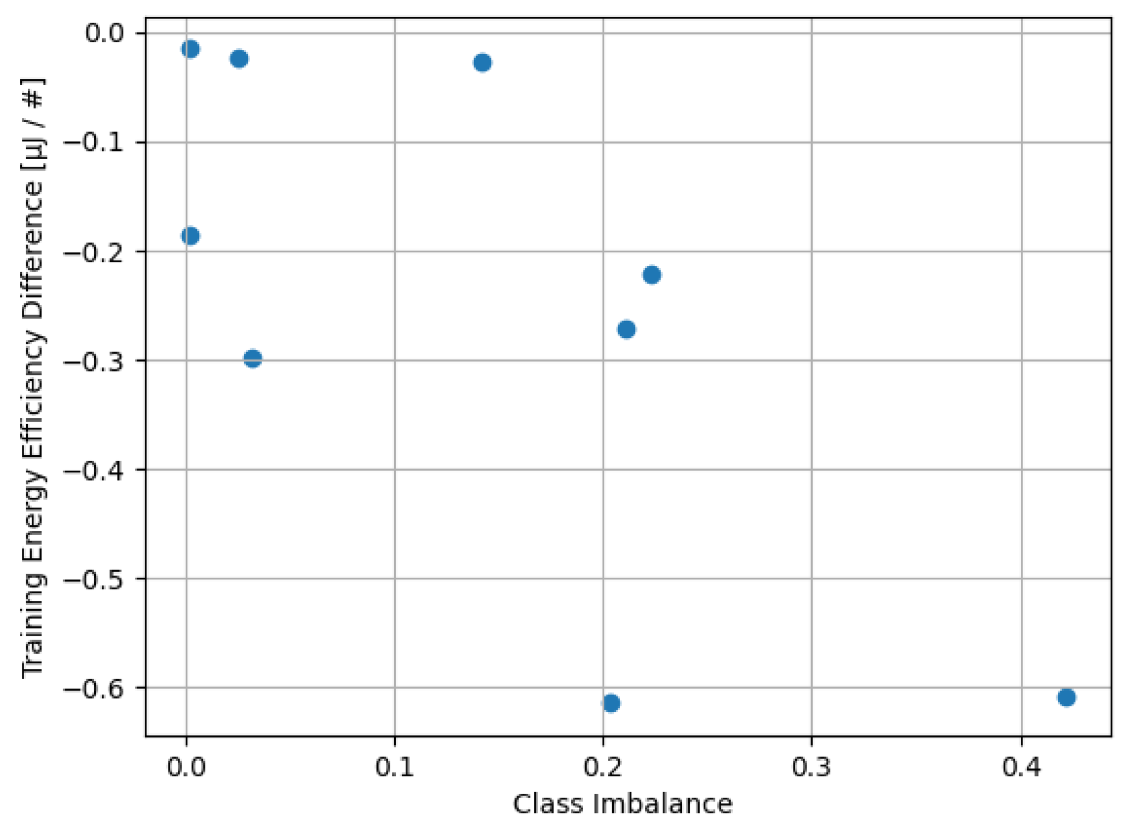
Tsetlin Machines scored much better in the energy efficiency, where the results did not depend as heavily as the Deep Neural Networks. This is perhaps because multiple parameters of the DNNs are expected to influence this metric, which are the number of hidden neurons, number of examples in the learning batch or the number of epochs, where there are only two parameters expected to have significant impact on the efficiency, which are the number of clauses and the number of epochs.

Performance and Efficiency

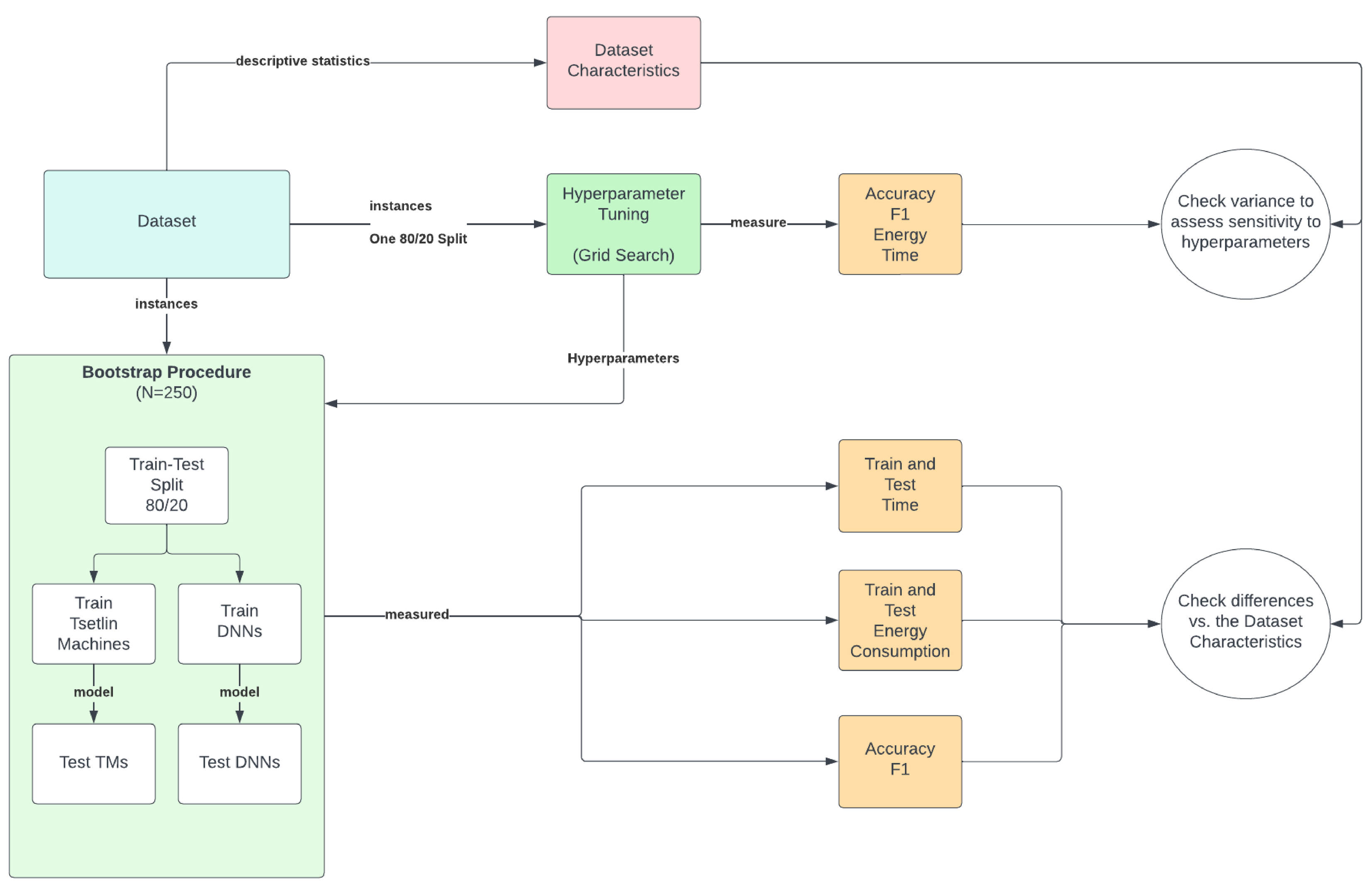
The differences in every measured metric is almost entirely statistically significant.
Findings from [?] are replicated entirely for the energy efficiency benefit of Tsetlin Machines over the Deep Neural Networks.
The model performance metrics are comparable: in some of the datasets such as ANNEALING, BC and FLAGS Tsetling Machines are outperforming the DNNs.
It is worth mentioning that the datasets where DNNs thrive are the purely numeric datasets such as HVR, MNIST or SONAR, the latter also replicating findings of the literature.
What is also worth mentioning is that both time and energy efficiency differences are very high.

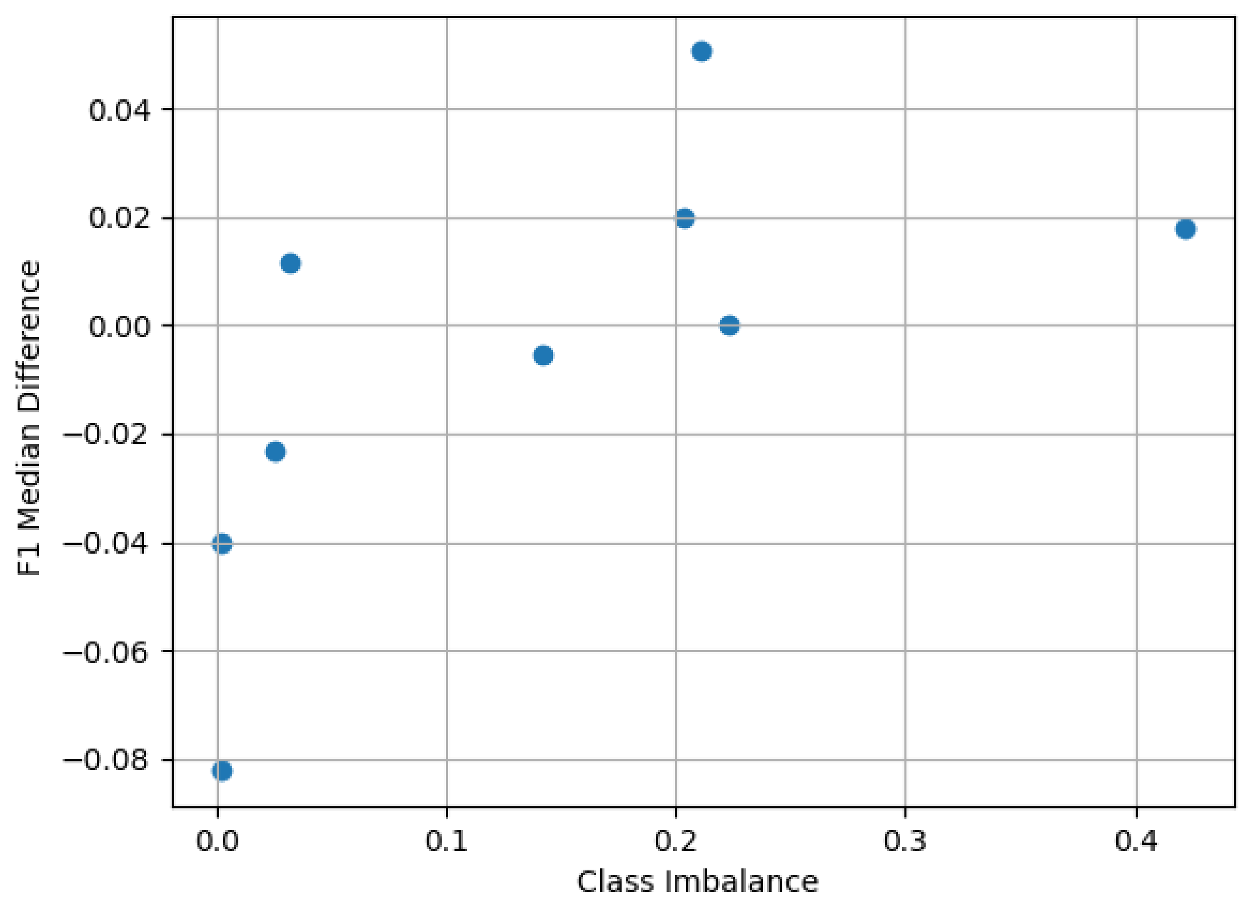
Differences as a function of Dataset Characteristics

Due to a low number of data points (N=9), only a Spearman-ρ statistics was computed, and the findings should be treated as a source of directional hypothesis for future research rather than an evidence of a strong relationship.
The differences in energy and time prediction efficiency seems to diminish with the rise of the number of instances in the training set and the number of features. Both effects could be partially explained by other characteristics of the dataset such as existence of solely numeric data for MNIST, however the data warrants future research on whether the prediction time benefit diminish with the rise of the models complexities.
It is also an interesting, however a subtle effect, that the Class Imbalance influences the $F1$ of Tsetlin Machines negatively as compared to the Deep Neural Networks. This may mean that TMs indeed do not perform well for under-represented classes.
This hypothesis gains support when looking at the training energy efficiency as seen in the Figure below as less complex thus less performing model should require less energy to train.



Topic Overview





Conclusions and Future Work

The research focused on the comparison of two machine learning models: Tsetlin Machines and Deep Neural Networks in terms of energy efficiency and model performance as a relation of the dataset characteristics. The relationships between the Dataset Characteristics should serve as an input to the continuing research, where especially experiments for tasks with imbalanced classes should be performed, perhaps by removing subsets of the classes from complete datasets.

QR Code for Recording