Using Random Hiveminds to Predict Solar Energetic Particles (SEPs)

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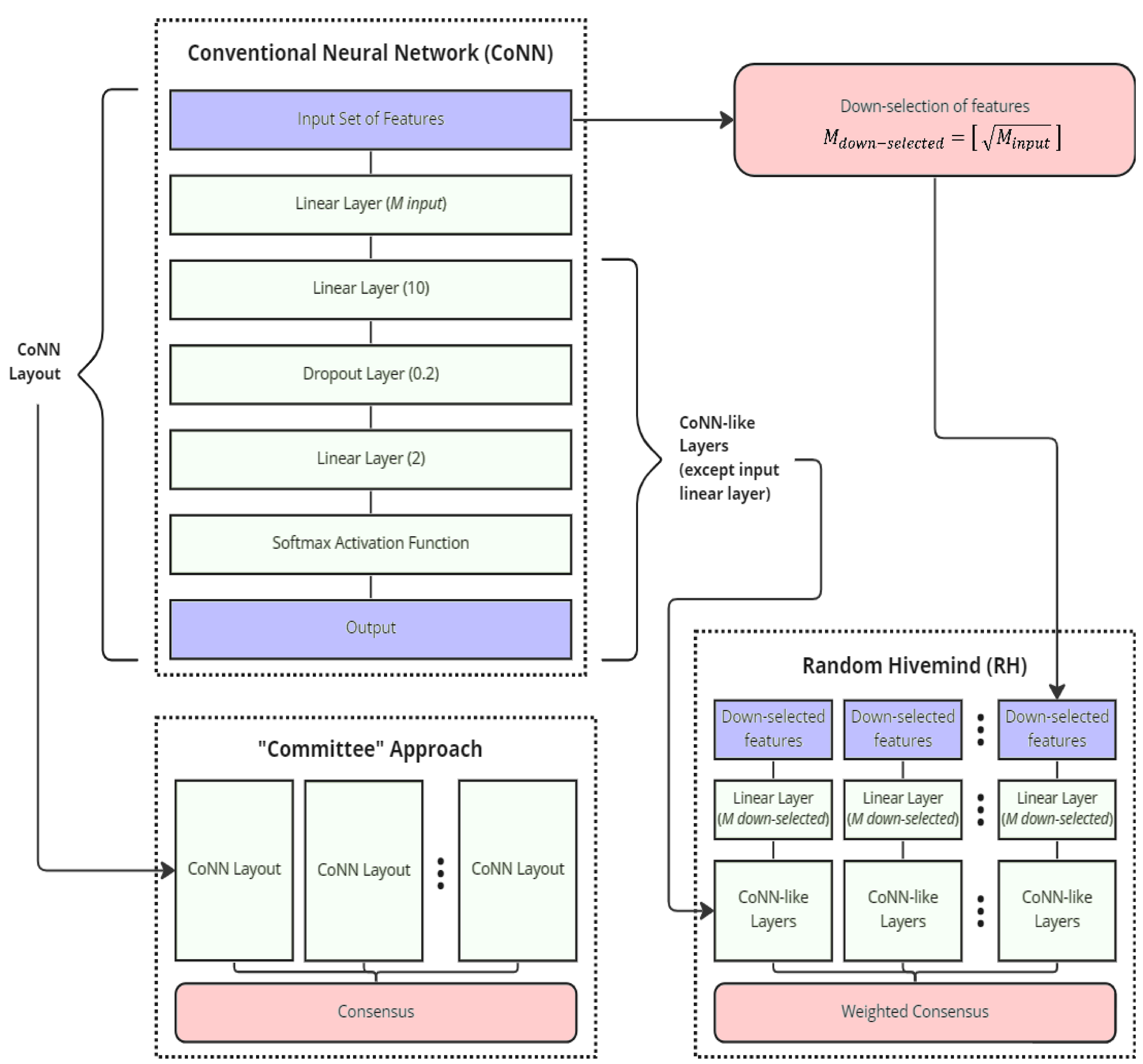
The Problem

The use of conventional neural networks (CoNNs) to predict SEPs has become popular, but neural network models do not follow one-size-fits-all approaches and their chaotic natures can yield completely different results on identical data sets. Committees of neural networks identical in input features have been used to solve this problem by (Aminalragia et al., 2021), but they have the possibility of all agreeing together in lockstep and missing crucial information.

Machine Learning Methodology

The estimators are organized in each approach according to this diagram. Each test uses a separate 70%-30% split of training and testing data, but to accommodate for class imbalance, only blocks of roughly average GOES class C4.05 to M3.37 are available for use as training data, since these correspond to the "liar's poker thresholds" mentioned by (O'Keefe et al., 2023) and each estimator uses cross-entropy loss with balanced class weights. Each non-RH neural network estimator has an epoch count and learning rate of 10 and 0.01 respectively, whereas each RH estimator has a linearly weighted epoch count and logarithmically weighted learning rate as (O'Keefe et al., 2023) prescribe in their paper, with these same values being used as base values for each weighting. The Adam optimizer is used in all neural networks.



The Solution

(O'Keefe et al., 2023) propose a solution consisting of neural network estimators in an ensemble, but with features randomly removed from them in a layout known as a random hivemind (RH). The decision weight, learning rate, and epoch count of each member in this ensemble are boosted in relation to how well its individual features perform in a chi-square test.

Results

The results displayed below consist of averages obtained after 10 tests using different train-test splits as mentioned previously.

Metric	CoNN	Committee	RH
Accuracy	0.72 ± 0.20	0.77 ± 0.09	0.77 ± 0.07
Balanced Accuracy	0.80 ± 0.10	0.87 ± 0.04	0.88 ± 0.03
TSS	0.60 ± 0.21	0.75 ± 0.08	0.76 ± 0.06
HSS	0.02 ± 0.02	0.03 ± 0.02	0.03 ± 0.01
ROC_AUC	0.91 ± 0.17	0.95 ± 0.03	0.97 ± 0.01
TN	4423.1 ± 1248.3	4712.5 ± 535.0	4724.2 ± 413.1
FP	1716.6 ± 1243.7	1427.2 ± 535.0	1415.5 ± 413.9
FN	2.3 ± 4.3	0.5 ± 0.8	0.4 ± 0.8
TP	20.0 ± 8.6	21.8 ± 6.3	21.9 ± 5.8
Missed Event Rate	0.12 ± 0.22	0.02 ± 0.03	0.01 ± 0.02
False Alarm Rate	$4.12 \times 10^{-4} \pm 7.53 \times 10^{-4}$	$9.74 \times 10^{-5} \pm 1.59 \times 10^{-4}$	$7.95 \times 10^{-5} \pm 1.59 \times 10^{-4}$
Precision	0.02 ± 0.01	0.02 ± 0.01	0.02 ± 0.01
Recall	0.88 ± 0.22	0.98 ± 0.03	0.99 ± 0.02

Data Preparation

Flares from the observations from the Solar Proton Events Affecting the Earth Environment list at https://umbra.nascom.nasa.gov/SEP/ provided by the NOAA Space Environment Services Center are organized into 90-minute blocks, with the average duration, temperature, peak X-ray flux, emission measure, and rise and decay time for the latter three features in each block used as features to predict whether an SEP occurs within a given block. This grouping is done to facilitate forecasting "all-clear" periods, with future blocks' aforementioned features able to be predicted using a time series forecaster. Only flares with temperatures of < 100 MK and with non-negative values for each numerical feature are used in all blocks and all blocks without any flares occurring within them are excluded.

Conclusion

RH is largely superior than CoNNs and committees of neural networks identical in input features and is a viable method of predicting "all-clear" periods. In the vast majority of metrics, RH produces a better average, a lower standard deviation, or both when compared to the alternate approaches.

References

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