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A Comparative Analysis of Automated Machine Learning Libraries for Electricity Price Forecasting

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1 OVERVIEW:

- Accurate electricity price forecasts can be used to **generate schedules** for energy consumption and electricity trading.
- Through Ireland's *Integrated Single Electricity Market* (**I-SEM**), traders can **buy and sell electricity** at hourly rates. Day-ahead prices are published at approximately 13:00 GMT day-1.
- Access to earlier price predictions provides stakeholders with additional time to facilitate energy cost-aware scheduling.
- Existing machine learning (ML) and statistical methodologies tend to be bespoke or require in-depth knowledge regarding implementation. This is not unique to time-series forecasting, and research into mitigating such limitations exists in the form of **Automated Machine Learning (AutoML)**.
- AutoML aims to optimise ML pipelines by automating various steps such as preprocessing, model selection, hyperparameter optimisation, validation, etc.
- This study applied **eight Python-based AutoML libraries** to day-ahead electricity price forecasting on an excerpt of I-SEM data from 01/01/2020 to 31/12/2020.
- The eight examined AutoML libraries were the following: **AutoGluon**, **AutoKeras**, **AutoTS**, **ETNA**, **FEDOT**, **FLAML**, **PyCaret** and **Ludwig**.

2 AUTOML LIBRARIES:

- The selected libraries are **open-source, Python-based and have time series-specific functionality**, e.g. auto-sklearn is excluded as it does not have classes or functions for handling time series.
- Models from previous works were implemented as a **baseline** with **XGBM** [1] having the best overall performance.

Table 1: AutoML library parameters

Library	Parameter	Values
AutoGluon	time_limit preset	Integer best_quality, high_quality, medium_quality, fast_training
AutoKeras	epochs tuner	10, 50, 100, 150 greedy, bayesian, hyperband, random
AutoTS	max_generations generation_timeout model_list	Calculated as time limit divided by generation_timeout 1, 2, 4, 8, 16, 32 minutes superfast, fast, fast_parallel, default, all
ETNA	tune_size* n_trials*	Integers sampled from 1-500 Integers sampled from 1-500
FEDOT	timeout preset	Integer fast_train, ts, gpu, stable, best_quality, auto
FLAML	time_budget	Integer
Ludwig	config.epochs	10, 50, 100, 150, 200
PyCaret	budget_time	Integer

All configurations for ETNA resulted in the same model output.

[1] Lynch et al., C. O'Leary, P. G. K. Sundareshan, and Y. Akin, "*Experimental Analysis of GBM to Expand the Time Horizon of Irish Electricity Price Forecasts*", Energies, vol. 14, no. 22, p. 7587, Jan. 2021

3 RESULTS:

- For readability, *Table 2* compares the best performing configuration of each AutoML library* and the XGBM model using Mean Absolute Error (**MAE**), Spearman Rank Correlation (**SRC**) and the geometric mean of MAE and SRC (**GM-MAE-SR**).

* ***Two results for AutoKeras are included: (1) most accurate overall and (2) most accurate that finished within 1 hour.***

Table 2: Best performing configuration for each library ordered by GM-MAE-SR

Library	Configuration	GM-MAE-SR	Duration (sec.)	MAE	SRC
AutoKeras	60 trials, 50 Epochs, Random Optimiser	1.91	23,162	15.36	0.75
AutoKeras	60 trials, 50 Epochs, Hyperband Optimiser	2.12	2,131	19.36	0.74
XGBM model	(Baseline Model)	2.17	1,855	14.88	0.68
PyCaret	Default Settings	2.40	2,853	16.02	0.64
Ludwig	Max. 100 Epochs	2.76	82	17.31	0.56
FLAML	Default Settings	2.84	3,563	23.23	0.65
FEDOT	Best-quality	2.92	6,306	22.72	0.62
AutoGluon	High-quality	3.44	801	23.02	0.49
ETNA	N/A	3.66	37	27.11	0.51
AutoTS	'fast' preset, 60 second trials	4.08	347	21.50	0.23

4 CONCLUSIONS:

- **AutoKeras** was found to produce the most accurate forecasts but required careful configuration to avoid long runtimes, e.g. only the Hyperband optimiser produced results that finished within 1 hour. ✓
- **PyCaret** and **FLAML** also produced favourable results while requiring little configuration, thus presenting a much lower barrier to entry for early-stage programmers. ✓
- **FEDOT**, **AutoGluon** and **Ludwig** produced results of reasonable accuracy. ✓
- **Ludwig's** time series forecasting documentation is poor relative to its other classes and to other libraries. ✗
- **ETNA** produced the same output regardless of configuration and runs into many internal runtime errors. ✗
- **AutoTS** showed suboptimal performance given the presented dataset which may be partially attributed to the small dataset size and AutoTS API limitations. ✗
- Existing Python-based AutoML libraries may produce accurate day-ahead electricity price forecasts, but some still require careful installation and configuration.
- Future works could investigate the proficiency of such technologies in other forms of forecasting such as multivariate and global forecasting.

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