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EVALUATING GENERIC AUTOML TOOLS FOR COMPUTATIONAL PATHOLOGY

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MOTIVATION

- Choice of neural network architecture and training hyperparameters are key components of developing AI solutions
- AutoML approaches reduce efforts for typically exploratory search and manual optimization
- **Question:** How well does general-purpose AutoML for image classification perform for tasks in computational pathology? [6]

GENERIC AUTOML TOOLS

AUTOGLUON [1]

- runs on-premises
- open source
- used via python
- presets for some parameters
- limited hyperparameter optimization (HPO)

GOOGLE AUTOML VISION [2]

- runs in the cloud
- no access to internals
- used via web interface
- three presets + training time budget

COMPUTATIONAL PATHOLOGY USE CASES

TISSUE CLASSIFICATION [4]

- lung tissue: normal, adenocarcinoma (LUAD), and squamous cell carcinoma (LUSC)
- distinguish normal vs. tumor (binary); normal vs. LUAD vs. LUSC (ternary classification)
- assessed via area under receiver operating curve (AUROC)

MUTATION PREDICTION [5]

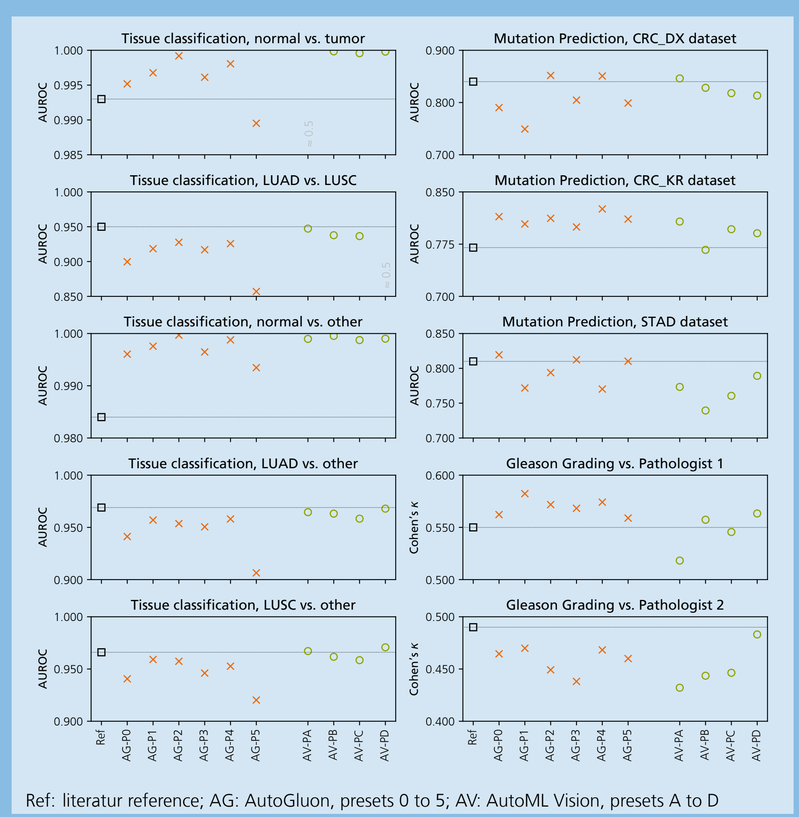
- colorectal cancer and gastric adenocarcinoma tissue
- predict microsatellite (in)stability (MSI vs. MSS): binary classification
- assessed via AUROC for three datasets

GLEASON GRADING [3]

- prostate biopsies, tissue microarray images
- predict grade 0, 3, 4, 5: quarternary classification
- assessed via Cohen's quadratically weighted kappa for annotations by two pathologists

RESULTS

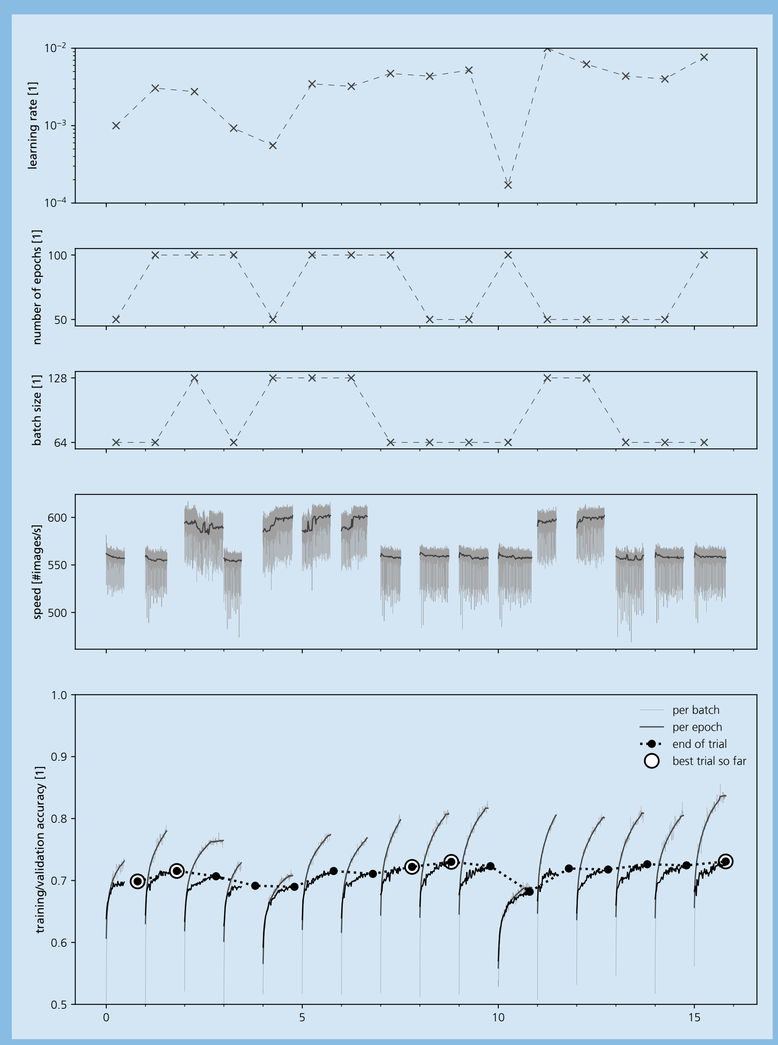
PERFORMANCE VS. REFERENCE



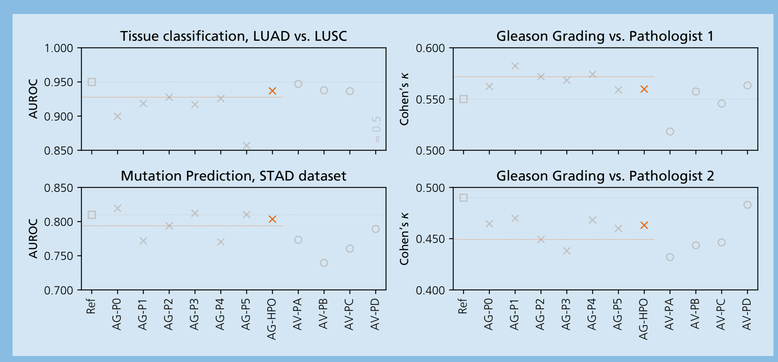
Ref: literatur reference; AG: AutoGluon, presets 0 to 5; AV: AutoML Vision, presets A to D

- generally on par with literature reference

HYPERPARAMETER OPTIMIZATION

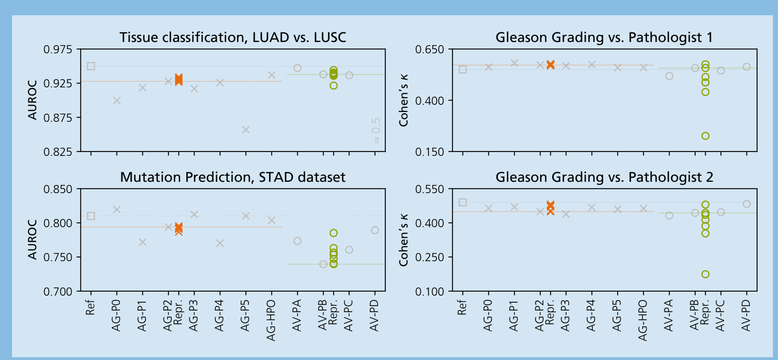


- tissue classification, LUAD vs. LUSC:
  - batch size influences speed
  - learning rate influences accuracy



- (limited) hyperparameter optimization has limited impact

RESULT VARIABILITY



- training is non-deterministic
- performance may vary substantially

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