

COVID-19 detection from thermal image and tabular medical data utilizing multi-modal machine learning

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COVID-19

- A disease caused by the SARS-CoV-2 virus and can lead to severe respiratory syndromes
- It has caused a global pandemic
- The standard method for COVID-19 detection is the PCR-based DNA test
- The test requires analysis of respiratory specimens



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Different Data for COVID-19 detection

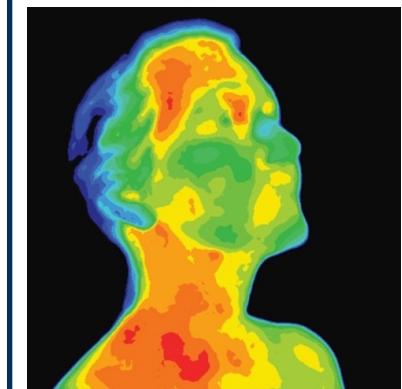
- Machine learning and deep learning techniques are used to detect COVID-19
- Utilizing textual, imaging, categorical, and numerical medical data
- Researchers have specifically explored medical imaging, most notably X-ray
- Chest CT and lung-ultrasound have also been investigated



[2]

Thermal Image for COVID-19 detection

- ❑ Thermal imaging captures infrared light emitted by warm surfaces
- ❑ It detects temperature variations across different body areas
- ❑ Thermal imaging is non-invasive, contactless, and commonly used in machine learning for detection tasks
- ❑ It can be useful for medical diagnosis, including COVID-19 detection
- ❑ It can provide remote, low-cost, and contactless solutions if performance is satisfactory



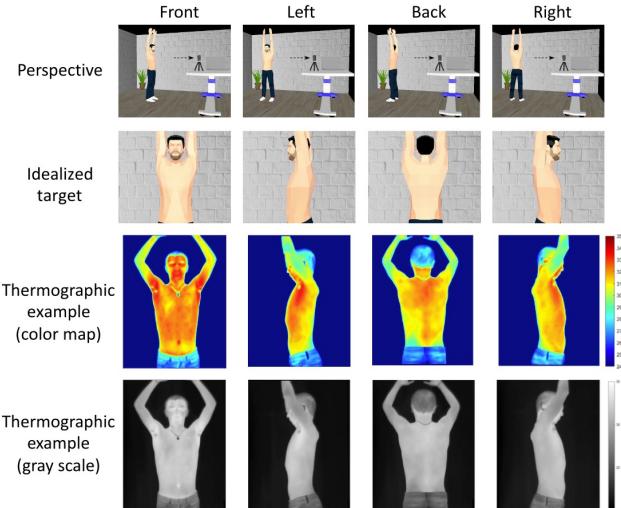
[3]



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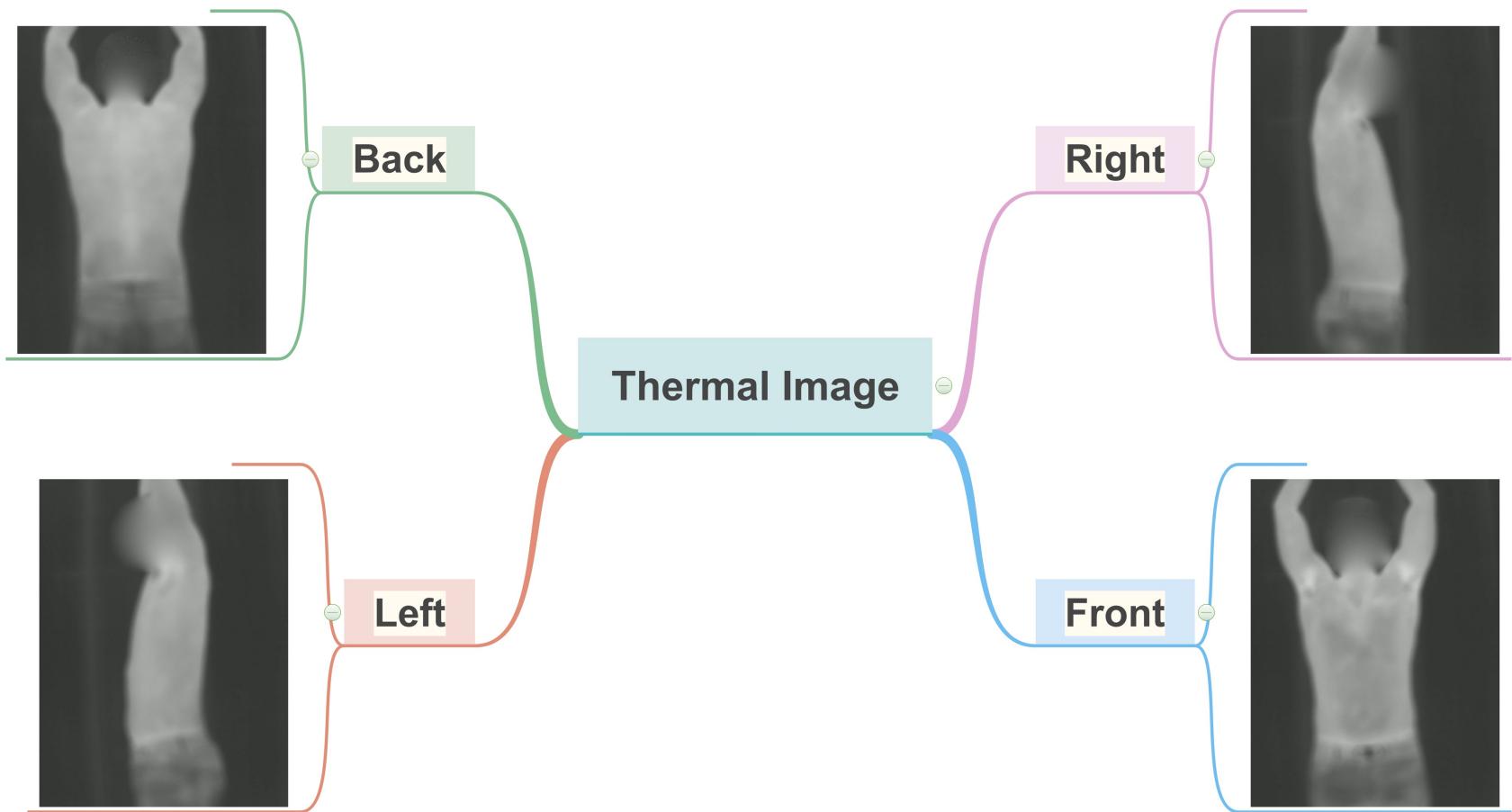
Thermal Image Covid-19 Dataset

- "Upper body thermal images and associated clinical data from a pilot cohort study of COVID-19" (version 1.1)
- 251 subjects, with 192 negative and 59 positive COVID-19 cases
- Thermal videos were recorded from four positions: front, back, left, and right for each subject
- Includes extracted signal moment, signal texture, and shape moment features in tabular format from the thermal video
- It also contains other medical information about the subjects along with their COVID-19 results

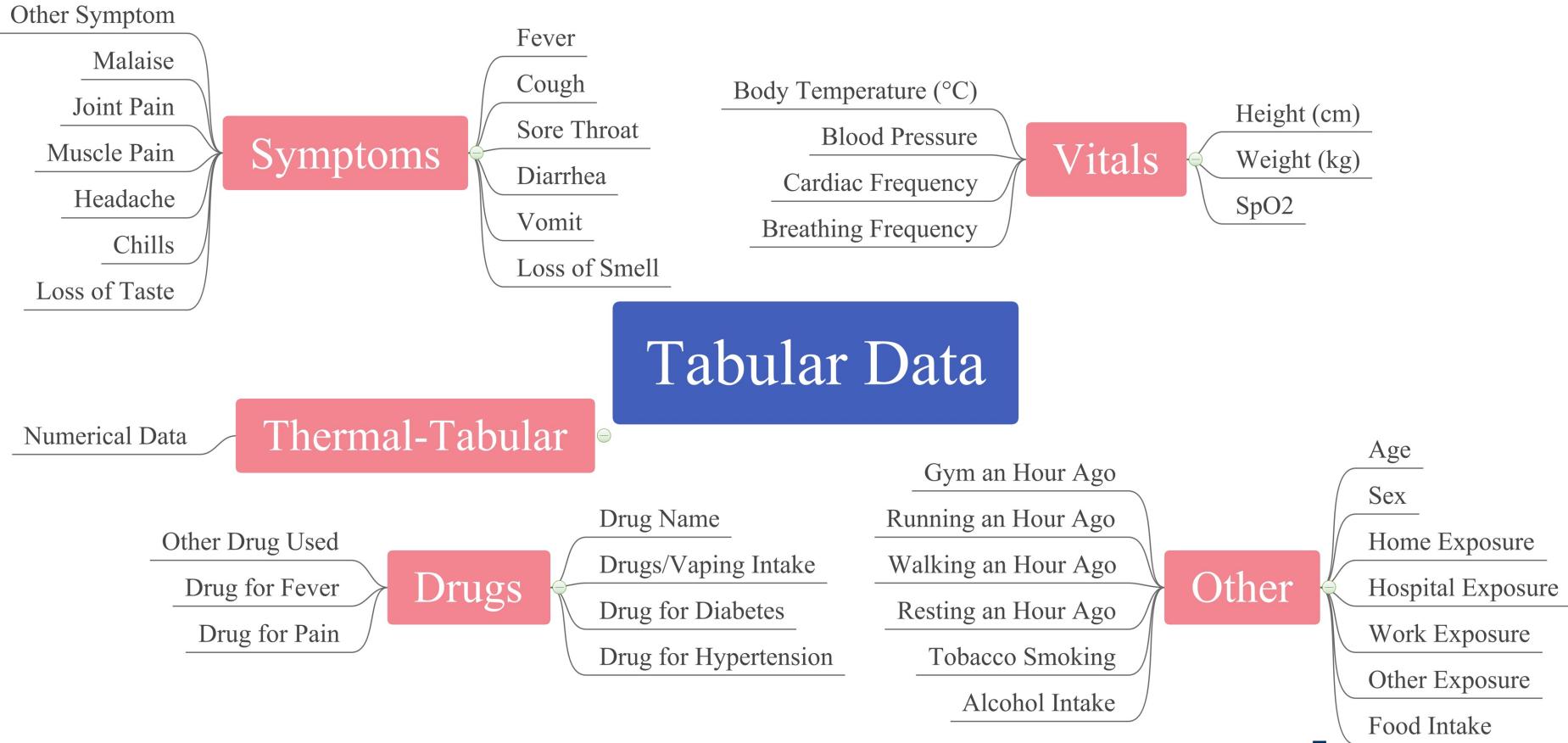


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Multi-Modal Data



Multi-Modal Data



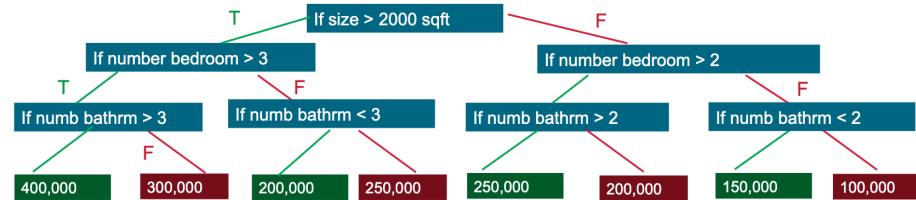
Random forests & XGBoost (Extreme Gradient Boosting)

Decision trees

- Predict label by evaluating if-then-else questions
- Estimate minimum questions for correct decision probability

Gradient boosting

- Improves weak model by combining with other weak models using a gradient descent algorithm
- Sets targeted outcomes based on gradient of error



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Random forest

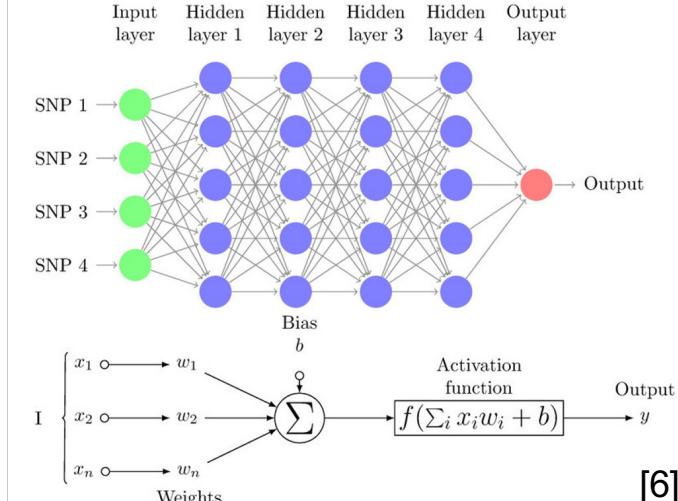
- Builds decision trees in parallel
- Final prediction is an average of all tree predictions

XGBoost

- Scalable and highly accurate implementation of gradient boosting

MLP (Multilayer Perceptron)

- Deep neural network with multiple layers of interconnected nodes called neurons
- Can learn complex relationships between inputs and outputs, making them useful for tasks like classification and regression
- MLPs use backpropagation to adjust weights based on prediction errors, improving performance over time

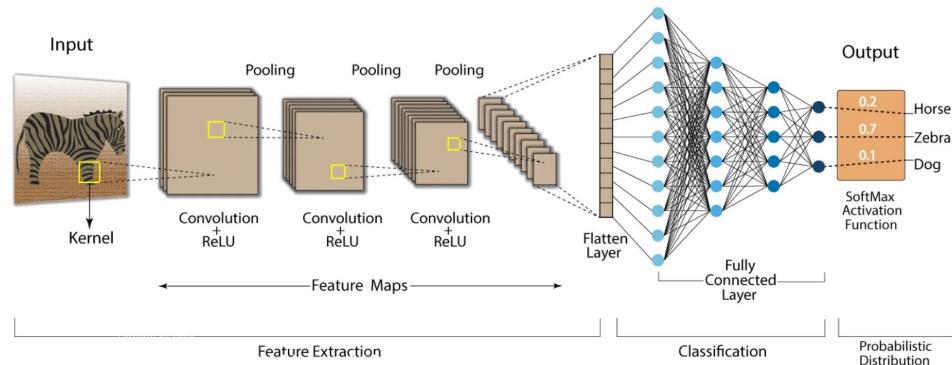


[6]



CNN (Convolutional Neural Network)

- ❑ Particularly useful for tasks involving spatial data, such as images
- ❑ Utilize convolutional layers that perform operations to capture spatial patterns in the data
- ❑ The convolutional layers apply filters to identify features in different spatial locations of the input data

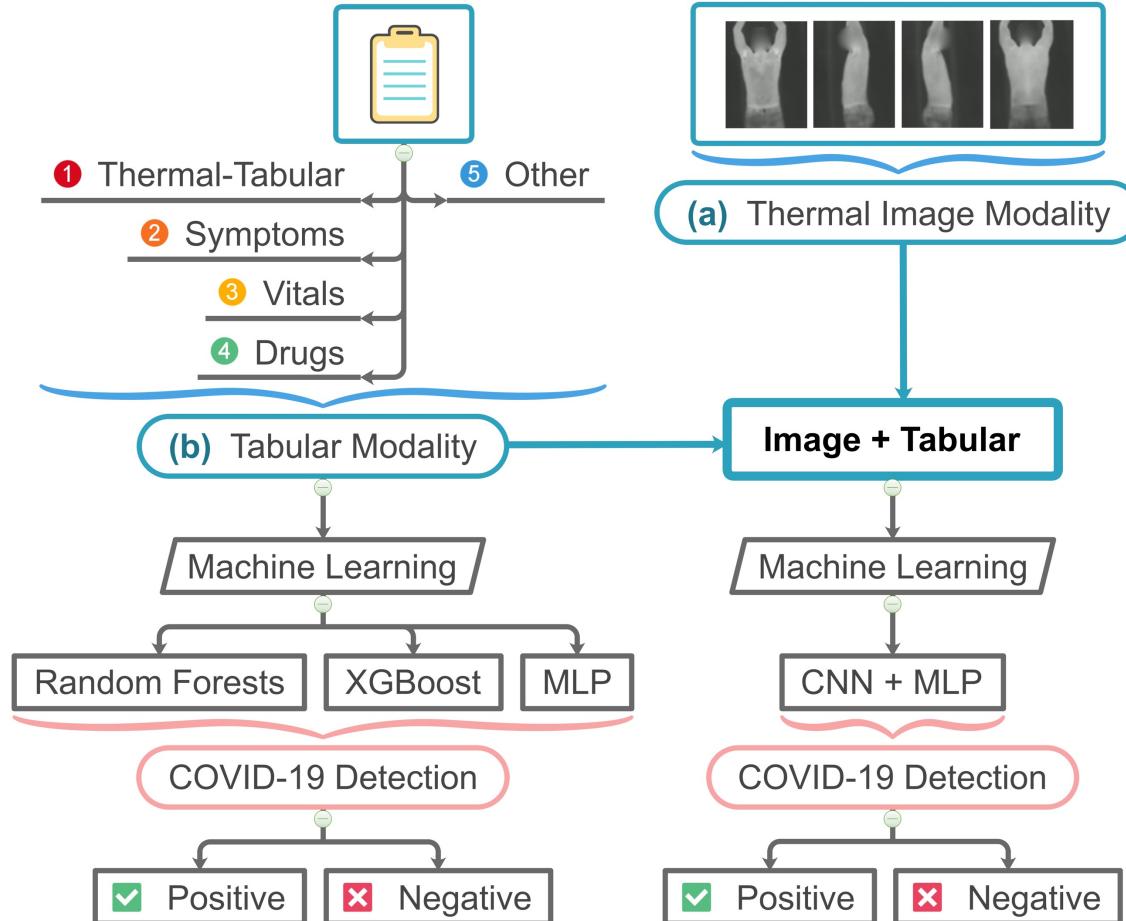


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Our Multi-Modal Approach



Experimental Setup

Dataset Split

- |Training|Validation|Test| :
|80%|10%|10%| of total data
- Same COVID-19 positive-negative ratio in all splits

Experiments

- Thirty-one experiments with different combinations of five Tabular data modalities

Reproducibility

- Specific seed values used for data splits and trials

Model Fine-tuning using validation data

- Grid search for random forests and XGBoost to find best-tuned model
- 100 Hyperparameter trials to obtain best-tuned models for MLP and CNN+MLP

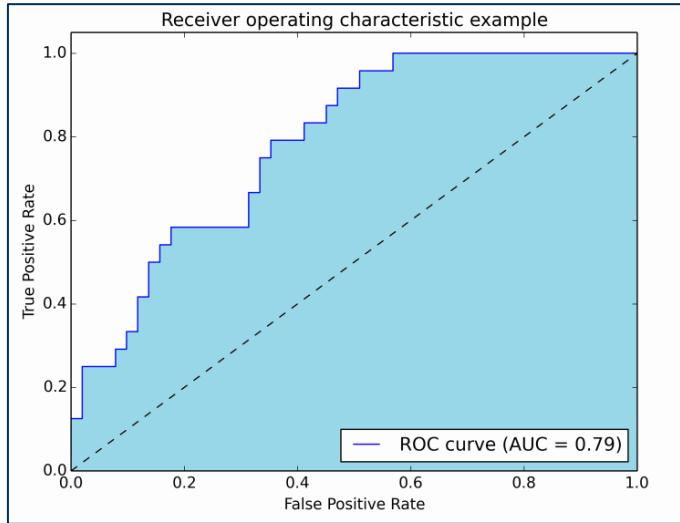
Leave-one-positive-instance-out Cross-validation

- Combined training and validation data
- Hyperparameter values from best-tuned model
- Average evaluation scores for all folds

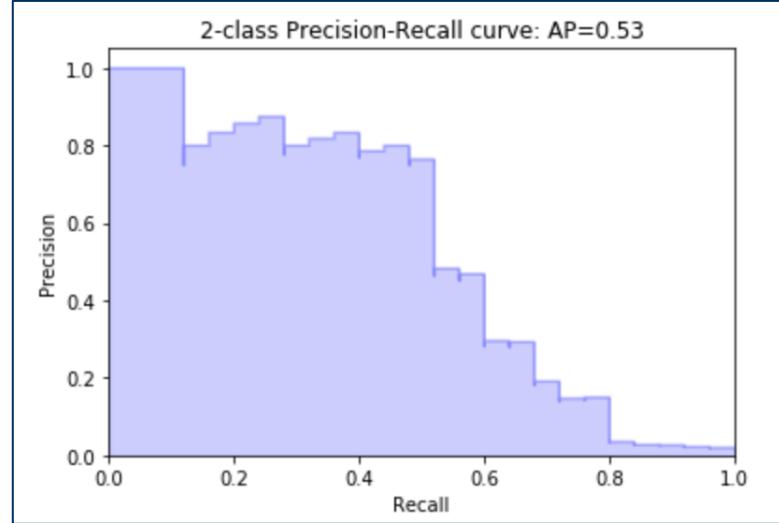
Testing

- Best-tuned model tested using test data

Evaluation Metrics : AUROC & AUPRC



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Area Under the Receiver Operating Characteristics (AUROC or AUC)

- Probability with which the classifier will assign a larger score to the positive than to the negative data point

Area Under the Precision-Recall Curve (AUPRC or AP)

- Average of precision across all recall values

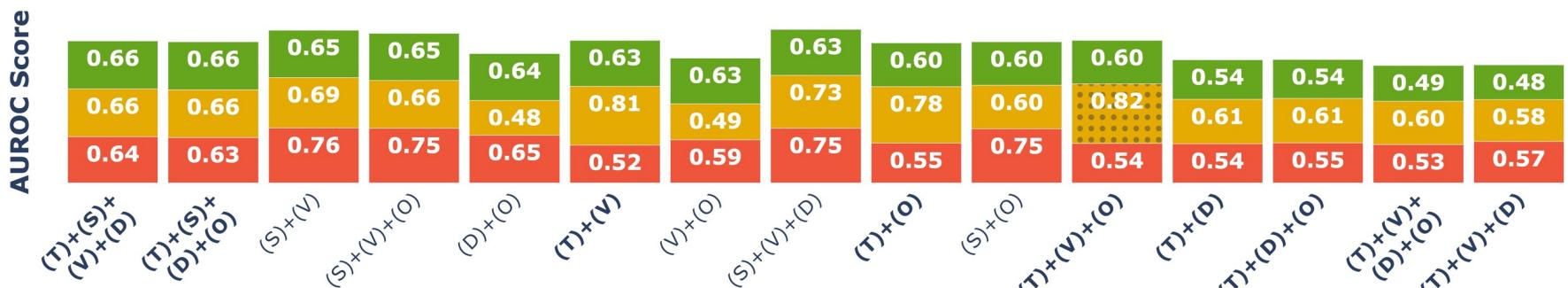
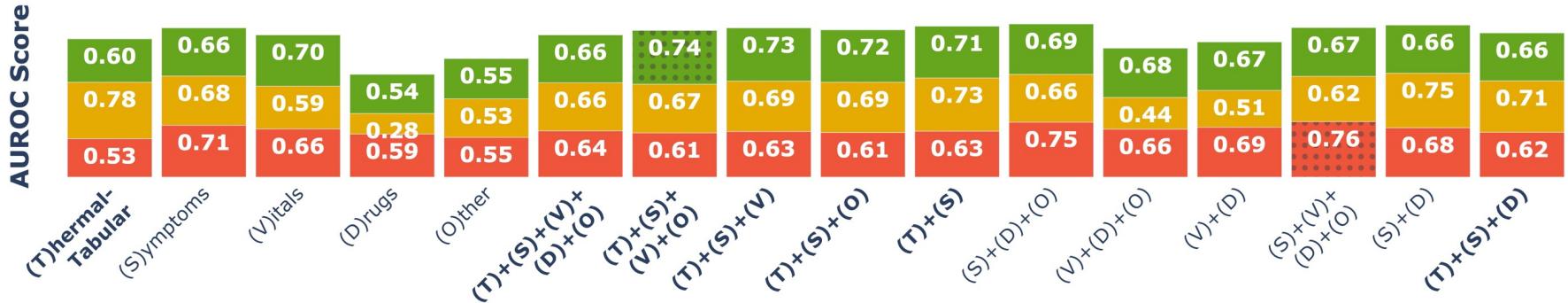
Multi-Modal COVID-19 Detection AUROC Results using Random Forests with Tabular Medical Data

Best Test Score: 0.74

Overall Best Validation Score: 0.82

Best Average of Leave-One-Positive-Instance-Out Cross-Validation Scores: 0.76

■ **Test Score** ■ **Best Validation Score** ■ **Average of Leave-One-Positive-Instance-Out Cross-Validation Scores**



Multi-modal Tabular Medical Data

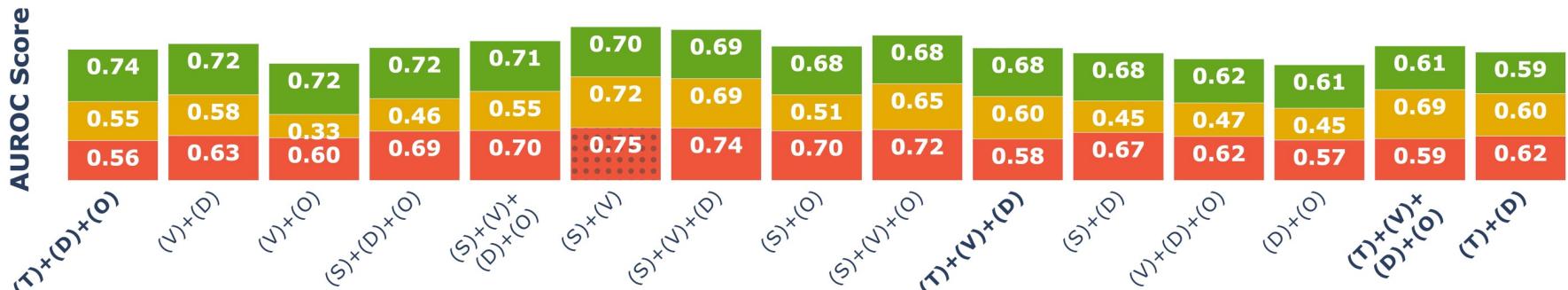
Multi-Modal COVID-19 Detection AUROC Results using XGBoost with Tabular Medical Data

Best Test Score: 0.91

Overall Best Validation Score: 0.76

Best Average of Leave-One-Positive-Instance-Out Cross-Validation Scores: 0.75

■ **Test Score** ■ **Best Validation Score** ■ **Average of Leave-One-Positive-Instance-Out Cross-Validation Scores**



Multi-modal Tabular Medical Data

Multi-Modal COVID-19 Detection AUROC Results using MLP with Tabular Medical Data

Best Test Score: 0.84

Overall Best Validation Score: 0.92

Best Average of Leave-One-Positive-Instance-Out Cross-Validation Scores: 0.69

■ Test Score ■ Best Validation Score ■ Average of Leave-One-Positive-Instance-Out Cross-Validation Scores

AUROC Score



AUROC Score



Multi-modal Tabular Medical Data

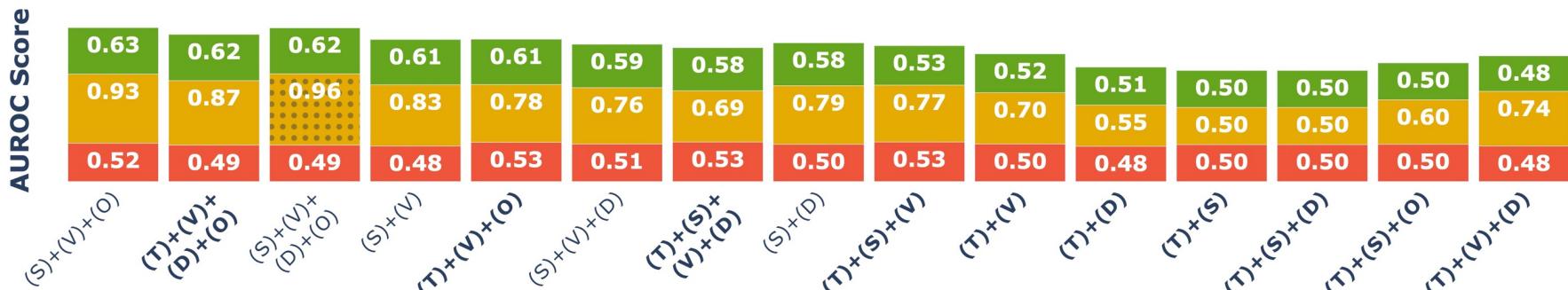
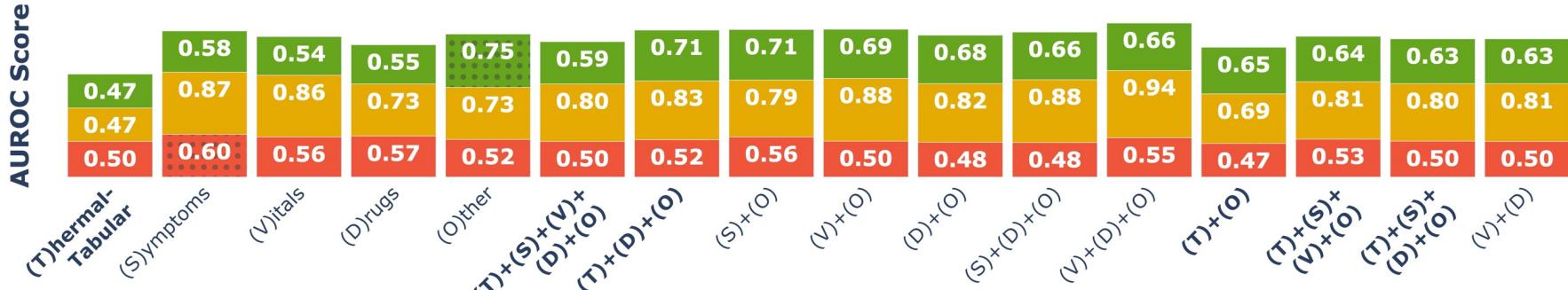
Multi-Modal COVID-19 Detection using CNN+MLP with Thermal Image & Tabular Medical Data

Best Test Score: 0.75

Overall Best Validation Score: 0.96

Best Average of Leave-One-Positive-Instance-Out Cross-Validation Scores: 0.60

■ **Test Score** ■ **Best Validation Score** ■ **Average of Leave-One-Positive-Instance-Out Cross-Validation Scores**



Multi-modal Thermal Image & Tabular Medical Data

Multi-Modal COVID-19 Detection AUPRC Results using XGBoost with Tabular Medical Data

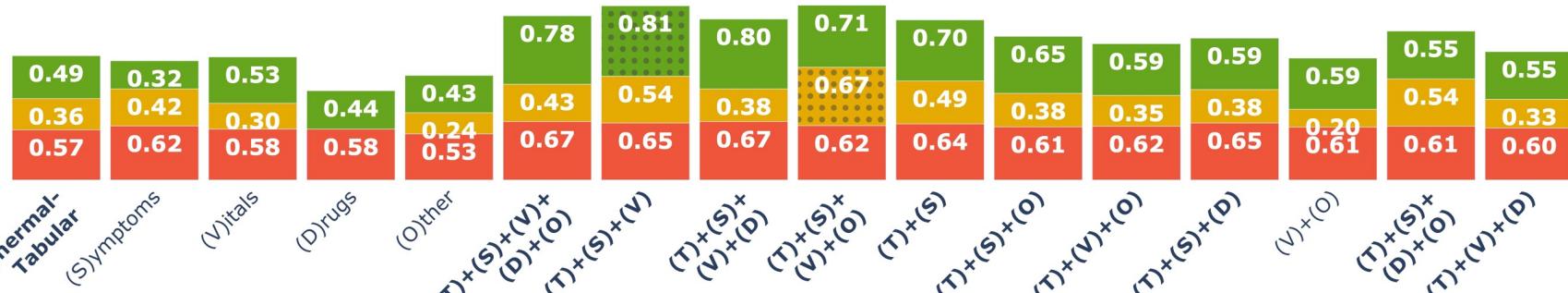
Best Test Score: 0.81

Overall Best Validation Score: 0.67

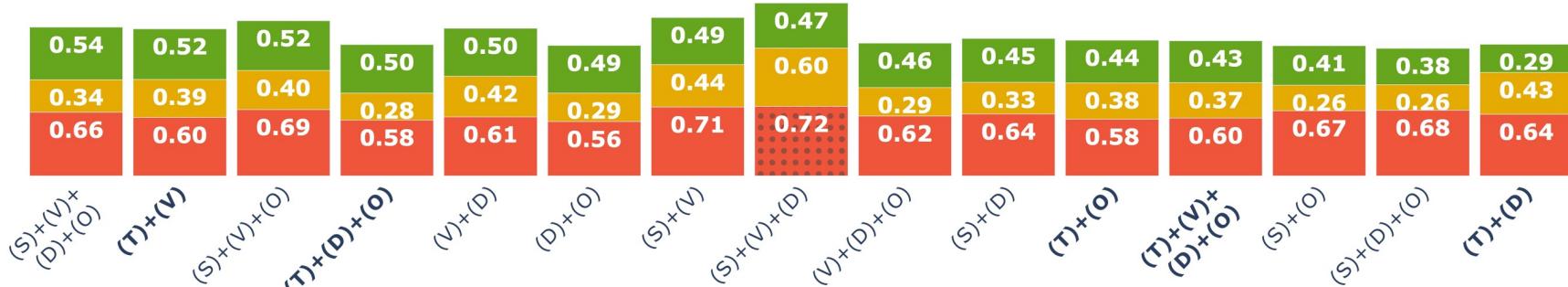
Best Average of Leave-One-Positive-Instance-Out Cross-Validation Scores: 0.72

■ **Test Score** ■ **Best Validation Score** ■ **Average of Leave-One-Positive-Instance-Out Cross-Validation Scores**

AUPRC Score



AUPRC Score



Multi-modal Tabular Medical Data

Key Insights

Machine Learning Techniques

- ❑ Utilized XGBoost, random forests, MLP, and CNN+MLP models
- ❑ Decision driven by research on limited data performance and advantages of gradient boosting algorithms for tabular data

Experimental Results

- ❑ Multi-modality showed better performance than single modalities with thermal image information
- ❑ XGBoost and random forests models outperformed MLP and CNN+MLP models for COVID-19 detection
- ❑ Leave-one-positive-instance-out cross-validation did well with small dataset
- ❑ AUPRC scores indicated robust performance despite imbalanced data

Benefits

- Safe, low-cost, non-invasive, and fast detection technique
- Remote deployment with minimal human contact for monitoring and diagnosis
- Potential effectiveness in pandemic situations
- Increased robustness and modularity in the system
- COVID-19 detection can be achieved even with missing data
- Flexibility in using various devices and data sources

Future Possibilities

- Utilizing Internet of Medical Things (IoMT) and wearable sensors for real-time COVID-19 detection
- Integration of vital signs, symptoms, clinical records, and thermal imaging
- Remote machine learning training and detection using low-cost edge devices
- Secure aggregation of devices and training models using federated learning or swarm learning approaches

Image Source

- [1] https://www.who.int/health-topics/coronavirus#tab=tab_1
- [2] <https://demigos.com/blog-post/healthcare-data-visualization/>
- [3] <https://www.securitysales.com/surveillance/thermal-imaging-trends-looking-up/>
- [4] <https://doi.org/10.1111/1.JBO.27.5.056003>
- [5] <https://www.nvidia.com/en-us/glossary/data-science/xgboost/>
- [6] [https://www.researchgate.net/publication/334609713 A Guide for Using Deep Learning for Complex Trait Genomic Prediction](https://www.researchgate.net/publication/334609713_A_Guide_for_Using_Deep_Learning_for_Complex_Trait_Genomic_Prediction)
- [7] <https://nafizshahriar.medium.com/what-is-convolutional-neural-network-cnn-deep-learning-b3921bdd82d5>
- [8] <https://riptutorial.com/machine-learning/example/14446/area-under-the-curve-of-the-receiver-operating-characteristic--auroc->
- [9] <https://stackoverflow.com/questions/53772249/how-to-evaluate-accuracy-on-highly-unbalanced-data-using-naive-bayes-model>



Thank You!

