Use of Hyphal Image Analysis and Machine Learning to Classify Mucoromycota Soil Fungal Isolates

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Introduction

- Fungi in the group Mucoromycota are valuable
- Plant growth promotion (Osorio and Habte 2001)
- Industrial production of lipids (Sakuradani et al. 2013)
- Study system of bacterial endosymbiosis (Desirò et al. 2018)
- Isolates obtained from culturing of soil samples
- Computational methods including Fast Fourier Transform (FFT) and machine learning are useful classification tools (Mennitt, Sherrill, Fristrup, 2014; Orlov et al., 2008)

Problem

- Identification of fungal isolates is slow, expensive
- Fungal morphological identification often relies on features absent in culture

Design Goal

- Hyphae have few identifiable features, but have patterns which may be classifiable
- Create an image classifier using a database of sequence verified images to separate Mucoromycota from other fungi
- Obtain a usefully high precision and recall
- Implement a script capable of rapid classification using only hyphae

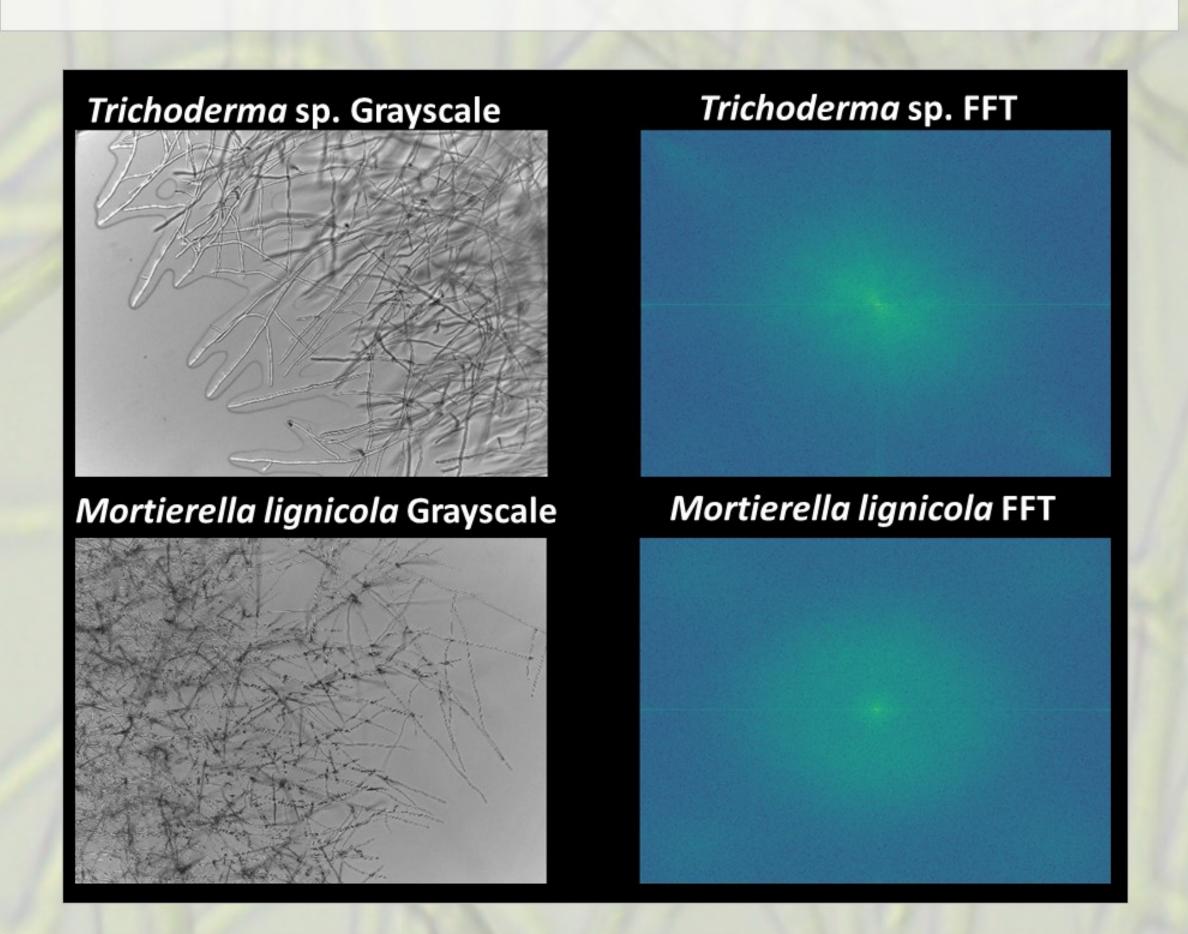


Figure 1. Grayscale and Fast Fourier Transforms (FFTs) of Brightfield Hyphal Images. FFT captures frequencies in the image, with low frequency (more structural) features in the center and high frequency (more detail) near the perimeter.

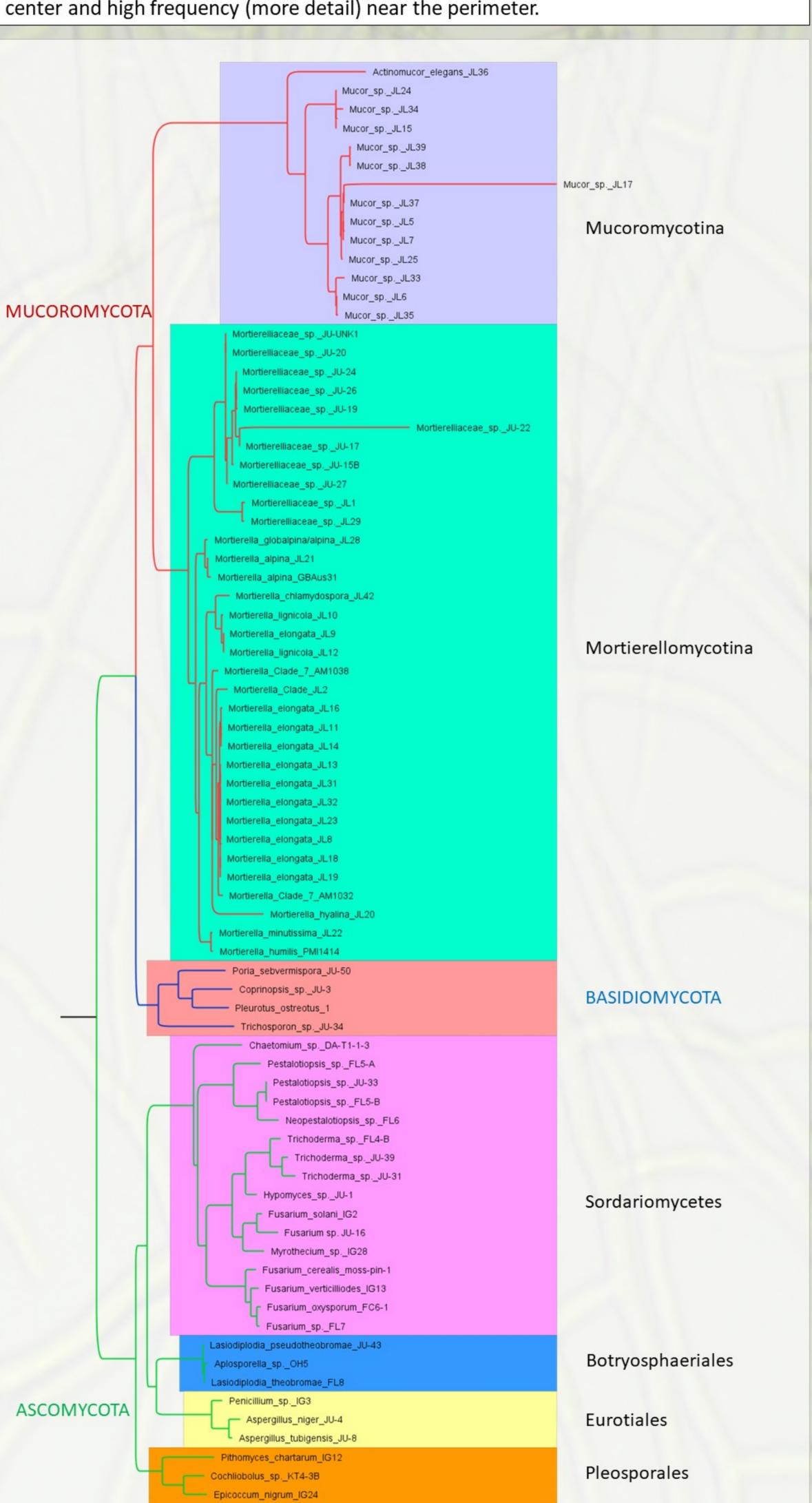
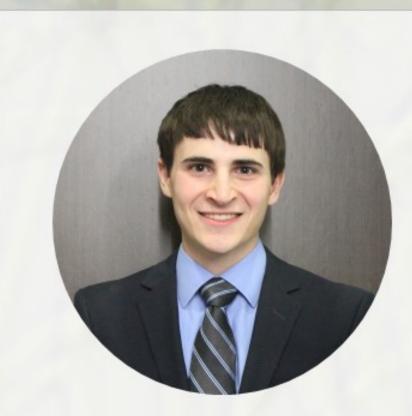
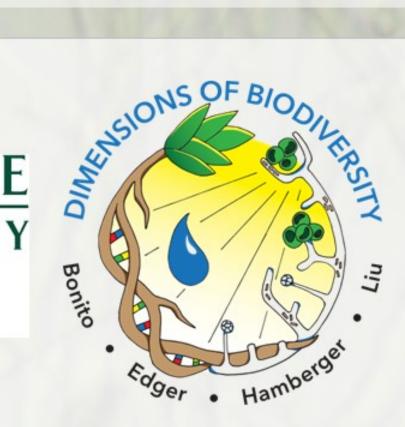


Figure 3. Maximum Likelyhood Phylogeny of Fungal Strains. Most micrographs were obtained from Mucoromycota isolates, but a diverse range of isolates were used to ensure validity of the classifier.

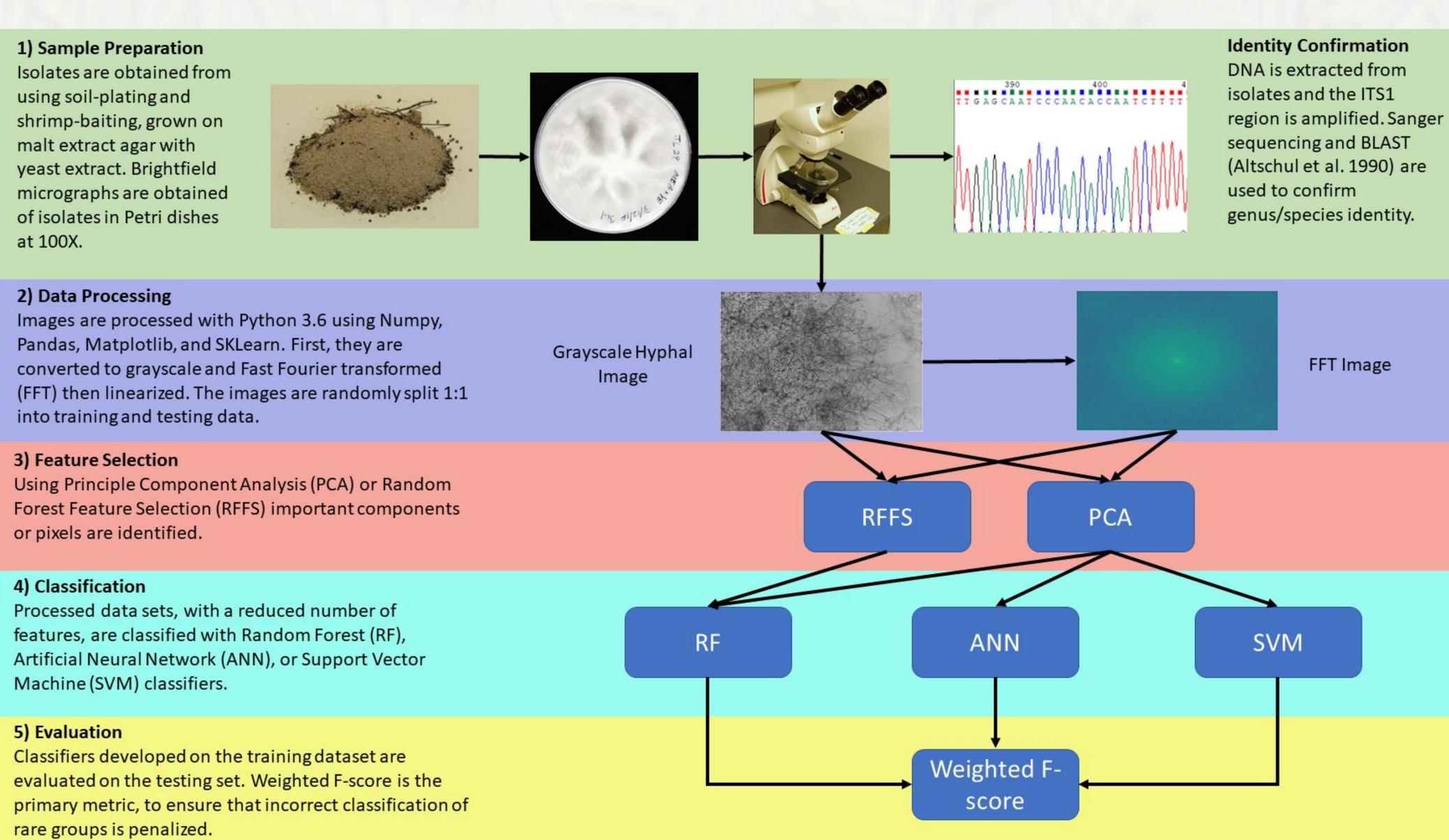








Methods



A) Random Forest (RF)

B) Artificial Neural Network (ANN) C) Support Vector Machine (SVM) SVC with linear kernel

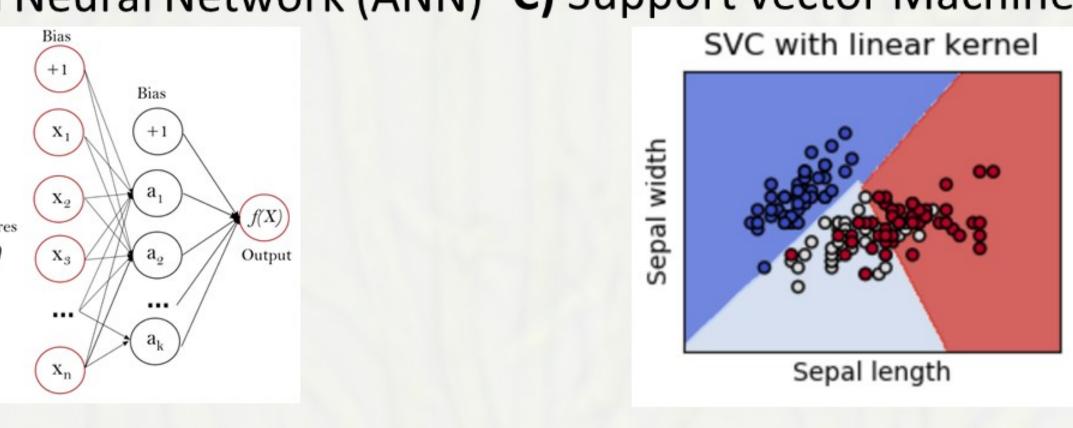


Figure 2. Classification Methods. A) Random Forest classifiers operate by constructing a series decision trees and compiling results into a class prediction. B) Artificial Neural Networks use a neuron-like method of activation based on input data to produce an output. C) Support Vector Machine attempts to linearly separate the data into groups. Figures retrieved from Mennitt, Sherrill, Fristrup, 2014, and SKLearn documentation.

Results

- 568 images included, 398 Mucoromycota
- Classification methods varied in success, measured by weighted F-score, compared using ANOVA
- Mucoromycota vs. other fungi (F = 29.42, $p = 3.25e^{-12}$)
- Mucormycotina vs. Mortierellomycotina (F = 326, p < 2e⁻¹⁶)
- Best method combines FFT, PCA, and RF

Conclusion

- Hyphal characteristics are sufficient for high-level classification of fungal isolates
- Greater than 90% F-score is sufficient to inform collection process
- Creation of useable classifiers and pipeline for creating classifiers
- Future Work
 - Improve phylogenetic resolution
 - Apply to detecting effects of environment on fungus as method of rapid phenotyping
 - Compare endobacteria hosting and non-hosting strains

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RF+FFT+PCA RF+FCA RF+FFT+RFFS RF+RFFS ANN+FFT+PCA ANN+PCA SVM+FFT+PCA SVM+PCA Classification Method Without FFT RF+PCA+FFT RF+PCA RF+RFFS+FFT RF+RFFS ANN+PCA+FFT ANN+PCA SVM+PCA+FFT SVM+PCA

Figure 4. Performance of Classification Methods. Performance significantly varies between methods, and letter annotations are different at p < 0.05 with Tukey's HSD test. Error bars indicate standard error of classifications with n trials. The combination of Random Forest, Fast Fourier Transform, and Principal Component Analysis provides the best classification. A) Classification between Mucoromycota and other fungi (n=5). **B)** Classification between Mucormycotina vs. Mortierellomycotina fungi (n=10).

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