## **Supplementary Information for Manuscript Entitled:**

Accurate Virus Identification with Interpretable Raman Signatures by Machine Learning

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## **This PDF file includes:**

Figures S1 to S10 Tables S1 to S4



**Fig. S1.** The t-SNE plots of all viruses (Avian virus, Enterovirus and Human Respiratory viruses), before and after baseline correction. Each Raman spectrum is represented by a point in the plots. Observed from the comparison between the two plots, applying baseline correction makes the spectra of virus types (or subtypes) such as H3N2, H7N2, CVB1, RSV, EV71 more distinguishable by pulling tighter each cluster corresponding to spectra of the same virus while pushing the clusters of different viruses further apart.

 $\mathsf{A}$ 



 $\mathbf B$ 





**Fig. S2. A.** The CNN classification performance of Avian viruses on three metrics (Accuracy, Sensitivity and Specificity); **B.** The CNN classification accuracy for each type of Avian virus; **C.** Matching scores between Raman ranges important for identifying Avian viruses using ML and Raman peak ranges of biomolecules.

 $\mathbf c$ 



**Fig. S3. A.** The CNN classification performance of Enteroviruses on three metrics (Accuracy, Sensitivity and Specificity); **B.** The CNN classification accuracy of each type (subtype) of Enterovirus; **C.** Matching scores between Raman ranges important for identifying Enteroviruses using ML and Raman peak ranges of biomolecules.



A



 $\mathbf{L}_{\text{max}}$ 

 $\, {\bf B}$ 



**Fig. S4. A.** The CNN classification performance of FLU A virus subtypes on three metrics (Accuracy, Sensitivity and Specificity); **B.** The CNN classification accuracy of each subtype of FLU A virus; **C.** Matching scores between Raman ranges important for identifying Influenza A subtypes using ML and Raman peak ranges of biomolecules.





**Fig. S5. A.** The CNN performance on three classification tasks involving Avian and Human flu viruses (1. Avian FLUA vs. Human FLUA; 2. Avian FLUA, Human FLUA, Human FLUB; 3. Human FLUA vs. Human FLUB); **B.** Matching scores between Raman ranges important for each of the three classification tasks using ML and Raman peak ranges of biomolecules.





Fig. S6. A. The CNN performance on three classification tasks involving enveloped and nonenveloped viruses (1. Classification within enveloped viruses, including FLUA, FLUB, IBV, RSV; 2. Classification within non-enveloped viruses, including Reovirus, Enterovirus, Rhino; 3. Binary classification to identify a virus as either enveloped or non-enveloped; **B.** Matching scores between Raman ranges important for each of the three classification tasks using ML and Raman peak ranges of biomolecules.

 $\, {\bf B} \,$ 

A



 $\, {\bf B}$ 





**Fig. S7. A.** The CNN classification performance of Human Respiratory viruses on three metrics (Accuracy, Sensitivity and Specificity); **B.** The CNN classification accuracy for each type of Human Respiratory virus; **C.** Matching scores between Raman ranges important for identifying different types of Human Respiratory viruses using ML and Raman peak ranges of biomolecules.

C



 $\, {\bf B}$ 



Fig. S8. A. The overall CNN performance of classifying / identifying virus type (subtype) among all viruses in our dataset in one classification task; **B.** The classification accuracy for each type of virus, including Avian, Enterovirus and Human Respiratory viruses.



**Fig. S9.** Raman peak ranges of lipids (phosphatidylcholine, phosphatidylethanolamine and sphingomyelin), nucleic acids, proteins, amino acids and other chemical functional groups such as Carboxylic acid and Ketone. These peak ranges are used for matching score calculation to help us understand what biomolecules or chemical functional groups are important for virus identification tasks using ML.



**Fig. S10**. Learning curves of 5-fold cross validation for the classification task on Flu A subtypes (H1N1/H3N2/H5N2/H7N2). Each of the five folds is used as the hold-out validation set once, and the learning curves for the validation folds are shown in the figure. In each learning curve, the classification accuracy on the validation fold after each training epoch is plotted. Although with some fluctuations, the learning curves for the five folds are similar and they all converge when the training process gets close to 1000 epochs, which justifies our choice for the number of training epochs, one among many crucial hyper-parameters.

**Table S1:** Definition for ML classification performance metrics: Sensitivity, Specificity and Accuracy. Sensitivity is the percentage of positive cases correctly identified as positive. Specificity is the percentage of negative cases correctly identified as negative. Accuracy is the percentage of correctly identified cases.



**Table S2.** Information about a large dataset consisting of Raman spectra of various types of flu viruses, which is used to test the viral dose detection limit of our approach. For each flu virus strain, we have collected around 10,000 Raman spectra.



Table S3: The TCID50 and RNA copies present in 10  $\mu$ L of sample, the volume used for spectra collection.



**Table S4:** Accuracy of flu type and subtype classification for two testing strains, Indiana/08 and Nebraska/14, using spectra collected at different concentration levels. The trained ML model uses the CNN architecture as shown in Fig 1B in the manuscript. The reported accuracies are spectrabased accuracies, i.e., the percentage of all spectra for a virus sample that are correctly classified as the true label for the virus. The case-based prediction for the virus sample is also reported, which is the majority vote of all the spectra predicted labels.

