1 Supplementary material for viral genome sequence Data

This supplementary document provides additional experimental results, including mean values and standard deviations computed over 5 runs.

Table 1: impact of clause count on classification accuracy

We analyze how varying the number of clauses affects classification accuracy across increasing class complexities. The model was trained for 10 epochs with the following settings: T = 2000, s = 1, Max include literals = 200, Number of symbols = 64, Hypervector size = 512, Message Hypervector size = 512, and Depth = 2. The Clause counts range from 500 to 2000, and classification tasks include 2 to 5 virus classes:

- 2 classes: SARS-CoV-2, Influenza A virus.
- 3 classes: SARS-CoV-2, Influenza A virus, Dengue virus.
- 4 classes: SARS-CoV-2, Influenza A virus, Dengue virus, Zika virus.
- 5 classes: SARS-CoV-2, Influenza A virus, Dengue virus, Zika virus, Rota virus.

Table 1: Scalability analysis of GraphTM with increasing clause size and class complexity levels.

CLASSES	500	700	1000	2000
2	100.00 ± 0.00	100.00 ± 0.00	100.00 ± 0.00	100.00 ± 0.00
3	95.09 ± 0.53	96.80 ± 0.71	96.66 ± 0.54	97.31 ± 0.29
4	89.16 ± 1.69	91.96 ± 0.42	92.64 ± 0.83	94.67 ± 0.33
5	90.52 ± 1.07	92.72 ± 0.68	93.85 ± 1.08	95.14 ± 1.05

Table 2: accuracy with varying sequence length

Using a 5-class classification task, we varied the input sequence length and evaluated accuracy. The model was trained for 20 epochs with the following settings: Clauses = 2000, T = 2000, s = 1, Max include literals = 200, Number of symbols = 64, Hypervector size = 512, Message Hypervector size = 512, and Depth = 2.

Table 2: Classification accuracy with increasing sequence length.

Sequence Length	500	1000	1500	2000	4000	6000
Accuracy	95.58 ± 1.05	95.88 ± 0.76	95.15 ± 0.89	95.16 ± 0.39	93.30 ± 1.27	92.99 ± 1.09

Table 3: Training and testing time vs. sequence length

Reported in seconds.

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Sequence Length	500	1000	1500	2000	4000	6000
Train Time (s)	162.61 ± 2.11	272.05 ± 0.75	343.86 ± 1.77	414.64 ± 2.33	645.93 ± 3.02	855.59 ± 2.93
Test Time (s)	31.28 ± 0.40	58.34 ± 0.15	75.92 ± 0.16	93.43 ± 0.91	151.17 ± 0.58	204.08 ± 0.28

Table 4: Accuracy with increasing sample size

Five-class classification using 80/20 train/test split. Each category had 1799 samples, and training data was randomly sampled. The model was trained for 10 epochs with the following settings: Clauses = 2000, T = 2000, s = 1, Max include literals = 200, Number of symbols = 64, Hypervector size = 512, Message Hypervector size = 512, and Depth = 2.

Table 4: Classification accuracy with increasing sample size.

Samples	10000	15000	20000	25000
Accuracy	94.55 ± 0.58	94.60 ± 0.65	96.23 ± 0.48	96.99 ± 0.56

Table 5: Training and testing time vs. sample size

Reported in seconds.

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Samples	10000	15000	20000	25000
Train Time (s)	83.86 ± 0.53	167.85 ± 0.28	224.88 ± 1.09	276.61 ± 1.12
Test Time (s)	15.67 ± 0.16	15.81 ± 0.09	16.18 ± 0.11	16.25 ± 0.11

Table 6: Comparison of methods

All models were trained for 10 epochs, the GraphTM was trained with following settings: Clauses = 2000, T = 2000, s = 1, Max include literals = 200, Number of symbols = 64, Hypervector size = 512, Message Hypervector size = 512, and Depth = 2.

Table 6: Performance comparison of GraphTM and baseline methods.

Methods	Train Accuracy (%)	Test Accuracy (%)	Training Time (s)
GRAPHTM (depth: 1)	60.74 ± 0.14	59.81 ± 0.21	62.47 ± 0.08
GRAPHTM (depth: 2)	95.17 ± 0.47	95.14 ± 0.81	84.37 ± 0.42
BILSTM	94.43 ± 1.19	92.69 ± 0.23	50.39 ± 2.28
LSTM	88.70 ± 1.65	87.29 ± 0.91	26.02 ± 0.49
GRU	94.68 ± 0.26	94.05 ± 1.31	25.47 ± 0.20
BILSTM-CNN	96.77 ± 0.42	95.44 ± 0.52	32.65 ± 0.68
GRAPHCNN	96.64 ± 0.19	96.35 ± 0.13	226.36 ± 1.59