

# Paper Discussion Report

Lawrence Owusu, Jordan Sturtz, and Swetha Chittam

## I. SUMMARY

A paper authored by Gunasekaran, et al. uses deep learning methods to classify viruses by their DNA sequences[1]. Since DNA is composed of strings of nucleotides, the problem amounts to classifying viruses according to samples of nucleotide strings. The authors collect data from the public nucleotide sequence database, The National Centre for Biotechnology Information (NCBI) <https://www.ncbi.nlm.nih.gov>. They then encode this data using label encoding and kmer encoding. For each encoding type, they run three different deep learning models: CNN, CNN-LSTM, and CNN-Bidirectional-LSTM. The architectures of all three models start with embedding layers, then convolutional layers, then max pooling layers, and then from there diverge to either add LSTM layers or bidirectional LSTM layers before finishing with dense layers and a final output layer. The authors compare all six combinations of the two encoding methods with the three model types using several performance metrics. They also compare their results to current state-of-the-art approaches in the literature.

## II. PROBLEM STATEMENT

All DNA and RNA is composed of a string of nucleotides. A nucleotide refers to one of four compounds for DNA (adenine, cytosine, guanine, thymine) or four compounds for RNA (adenine, cytosine, guanine, uracil). For double-helix DNA or RNA, each nucleotide bonds with one and only one other nucleotide, forming what is called a base pair (Fig 1). Since these base pairs are fixed, then, a DNA or RNA sequence can be identified solely by one side of the double helix. Thus, every DNA virus can be identified by a single string of characters drawn from the set  $\{A, C, G, T\}$  and every RNA virus can be identified by a string of characters drawn from the set  $\{A, C, G, U\}$ . The task, then, is to build highly accurate models to classify a virus from its DNA or RNA sample.

## III. RELATED WORK

DNA classification and protein structure-sequence prediction remain some of the challenges in the field of computational biology. Determination of accurate protein structure and DNA sequence are important in developing deep understanding of the functions of protein, disease diagnosis, prevention of epidemics and assisting in drug design [2].

### A. Non-Machine Learning Methods

Although experimental methods of protein structure determination, including Cryogenic Electron Microscopy, X-ray Crystallography, Nuclear Magnetic Resonance Spectroscopy

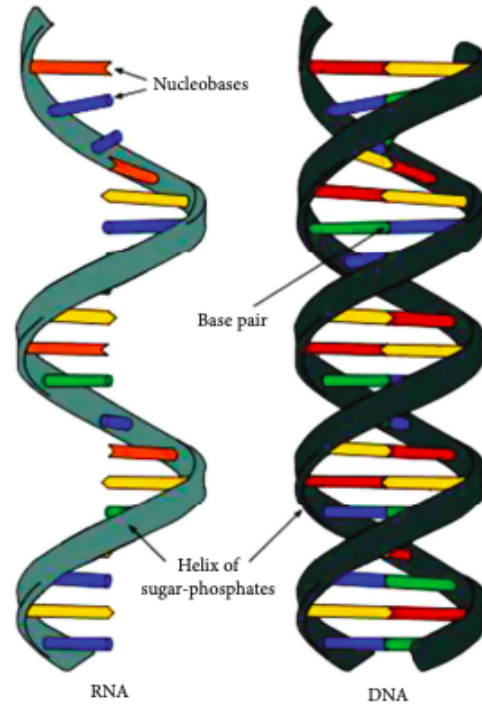


Fig. 1. Single or double-stranded DNA/RNA, borrowed from Gunasekaran, H., et al.[1]

and others have seen continuous advancement, such techniques are expensive, involve cumbersome and time-consuming procedures and require high level expertise. Similarly, DNA-based approaches such as DNA sequencing, DNA-DNA hybridization and DNA fingerprinting for the identification and classification of species of bacteria and viruses have some challenges. For example, these DNA sequencing technologies produce read length as short as 35-40 nucleotides, thus posing challenges for genome annotation and assembly [3]. To make the process less cumbersome, deep learning algorithms as well as hybrid deep learning models have been proposed for DNA and protein sequence classification [4].

### B. Machine Learning Methods

The use of CNN and LSTM models in protein sequence prediction, classification of miRNA and DNA sequence classification is highly researched in computational biology. Abdulkadir and Baha (2021) applied a hybrid deep learning model based on CNN and LSTM to classify miRNA with accuracy, sensitivity, specificity and F1 scores of 0.943, 0.935, 0.948 and 0.925 respectively, suggesting that the hybrid CNN and LSTM networks can be employed to achieve better performance for pre-miRNA classification [5]. Similarly, Chinju

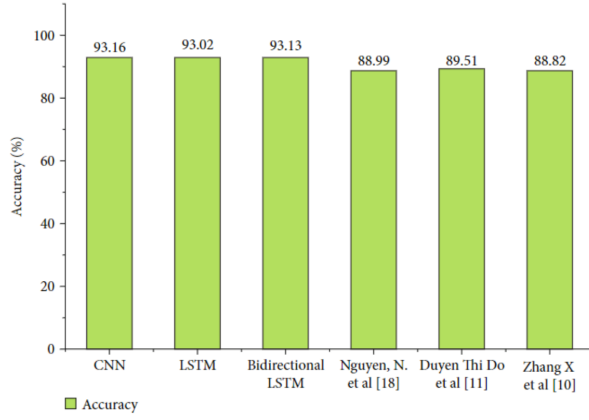


Fig. 2. Gunasekaran, H. et al, compared against state of the art methods, borrowed from Gunasekaran, et al. (2020)

and his colleagues (2022) developed a hybrid deep learning CNN-LSTM model that uses the convolutional neural network architecture and long short-term memory network to classify the protein sequences belonging to the five-member polo like kinase family with an accuracy score of 97.6% [6]. LSTM networks have been used tremendously in computational biology especially in protein structure prediction. For example, Soren and Winther (2019) reported 67.4% performance accuracy on protein structure prediction problems [7].

#### C. Model Performance Against State of the Art Methods

The authors compare their accuracy results to other state-of-the-art approaches to virus classification (Fig 2). Their results show that all three of their models show higher accuracy than that achieved by Nguyen, et al.[8], Do, et al.[9], and Zhang, et al.[10].

#### IV. DATA COLLECTION

The authors obtain complete genomic sequences from the National Centre for Biotechnology Information (NCBI) <https://www.ncbi.nlm.nih.gov/>. Sequence length ranges from 8 to 37971 nucleoids. They collected genomic sequences for six virus classes: COVID, MERS, SARS, Dengue, Hepatitis, and Influenza (Fig 3). Because the population of these viruses were unbalanced—for instance, there were 37272 samples of COVID and only 1418 samples of MERS—the authors opted to use Synthetic Minority Oversampling Technique (SMOTE) to get a more even distribution of all six classes in their dataset. The DNA sequence dataset used in this paper consists of 66,153 inputs which is divided into training, validation and testing sets with a ratio of 70%, 10% and 20% respectively. The training set consists of 46307, and the validation set consists of 6615, and the testing set consists of 13231 samples. The maximum sequence length is 2000, and the vocabulary size is 8972.

#### V. DATA PREPROCESSING

The authors encoded the data in two different formats for comparative analysis. In the first approach, they use label encoding, which replaces each nucleoid by a unique index

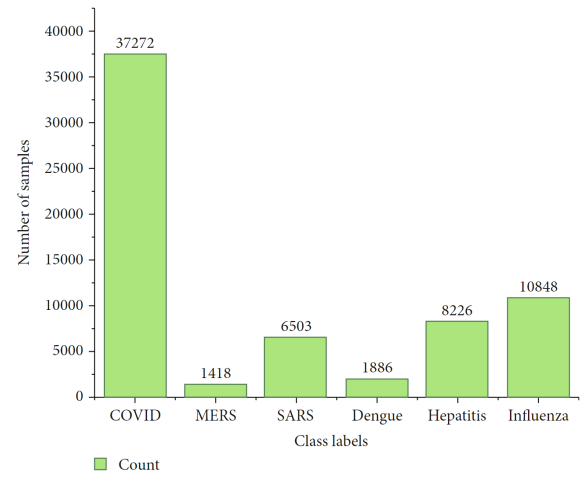


Fig. 3. Samples of virus classes retrieved from NCBI, borrowed from Gunasekaran, H., et al. (2020)

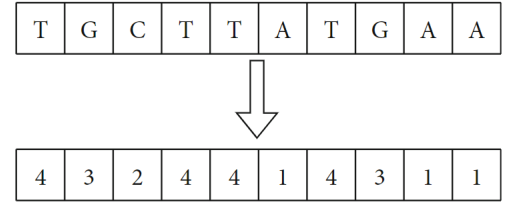


Fig. 4. Label encoding example, borrowed from Gunasekaran, H., et al. (2020)

value, preserving positional information (Fig 4). In the second approach, they used kmer encoding, which generates all kmers from a sequence and forms an English-like sentence onto which natural language processing techniques can be applied (Fig 5).

Once encoded, in both cases the input data is one-hot encoded and then fed into the first layer of the models, which is an embedding layer.

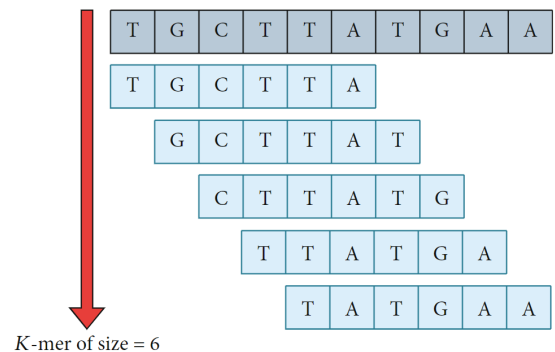


Fig. 5. Kmer encoding example, where k=6, borrowed from Gunasekaran, H., et al. (2020)

TABLE I  
HYPER PARAMETERS OF CNN MODEL

Layers	Units	Filters	Kernel	Act. Func	Output Shape	Params
Embedding	8				(None, 1000, 8)	128
Conv 1D		128	2*2	ReLu	(None, 1000, 128)	3200
Max Pool			2*2		(None, 500, 128)	0
Conv 1D		64	2*2	ReLu	(None, 500, 64)	24640
Max Pool			2*2		(None, 250, 64)	0
Flatten					(None, 16)	0
Dense	128				(None, 128)	2176
Dense	64				(None, 64)	8256
Dense	6			Softmax	(None, 6)	390

## VI. PROPOSED MODELS

In this paper, the authors use three different classification models to perform multi-classification of the DNA sequence: CNN, CNN-LSTM and CNN-bidirectional LSTM. All three models share the same initial layers: an embedding layer, convolutional layers, and max pooling layers. The raw data is first either label encoded or kmer encoded and then one-hot encoded to be fed into the embedding layer. The results of the embedding layer are then fed into the convolutional layers, each of which has a corresponding max pooling layer. From here, the three model types diverge. For the CNN model, the results are fed into the final dense layers and output layers. The LSTM and bidirectional LSTM models differ only in that they add LSTM or bidirectional LSTM respectively before the final dense layers.

### A. CNN

CNN is a popular deep learning technique that is widely used for feature extraction and to solve any classification problems. CNN can be used for any kind of datasets like text, image, or video datasets. The 2D CNN is often used for feature extraction from image datasets and 3D CNN is used for feature extraction from video datasets. The 1D CNN auto extracts the features from the input dataset and can therefore be used for text classification. Here in this paper, authors are using 1D CNN for feature extraction of the DNA sequence data. The proposed CNN model architecture has two 1D convolutional layers, each followed by a max pooling layer to reduce the feature map dimensions from the previous layers. Next, a flatten layer is used to convert feature maps to a single column vector followed by multiple dense layers. The output is passed to the final dense layer with softmax activation function to perform multi-classification.

Table I shows the hyper parameters for the proposed CNN model.

### B. CNN-LSTM

Long-short term memory (LSTM) is a recurrent neural network that can learn long term dependencies in a sequence and hence can be used for sequence classification or prediction. The LSTM model consists of three gates: forget gate, input gate and output gate (Fig 6). For the hybrid CNN-LSTM model, the authors add an LSTM Layer with 100 LSTM memory units between the final convolutional layer and the final dense layers.

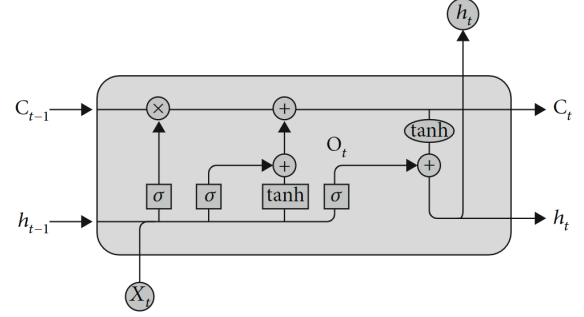


Fig. 6. LSTM Cell Architecture.  $\times$  is a multiplicative gate,  $+$  is additive, borrowed from Gunasekaran, H., et al. (2020)

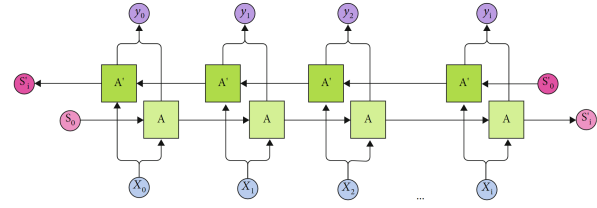


Fig. 7. Bidirectional LSTM Model Architecture, borrowed from Gunasekaran, et al. (2020)

### C. CNN-Bidirectional-LSTM

The bi-directional LSTM has two RNN's: One to learn dependencies in forward direction and the other to learn dependencies in backward direction (Fig 7). For the hybrid CNN-LSTM-Bidirectional model, the authors add the bidirectional LSTM layers after the final convolutional layers and before the final dense layers.

## VII. RESULTS AND DISCUSSION

The proposed models CNN, CNN-LSTM, CNN-Bi-LSTM models are tested by varying different hyperparameters listed in Table I. The authors use the grid-search cross-validation technique to find the best parameters of the model. The best parameters are listed in Table II.

The classification models are evaluated using different classification metrics like accuracy, precision, recall, F1 score, sensitivity, and specificity by obtaining the confusion matrix for both k-mer and label encoding techniques. The confusion matrix holds the values of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). Based on these values, classification metrics are calculated and

TABLE II  
BEST HYPERPARAMETERS

Parameters	Values
Size of Filter	2*2
Training Batch Size	100
Training Epochs	10
Embedding Dimensions	32
K-mer Size	6

TABLE III  
FORMULAS TO CALCULATE PERFORMANCE METRICS

Metric	Formula
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Specificity	$\frac{TN+FP}{TN+FP+FN}$
Sensitivity	$\frac{TP}{TP+FN}$
Precision	$\frac{TP}{TP+FP}$

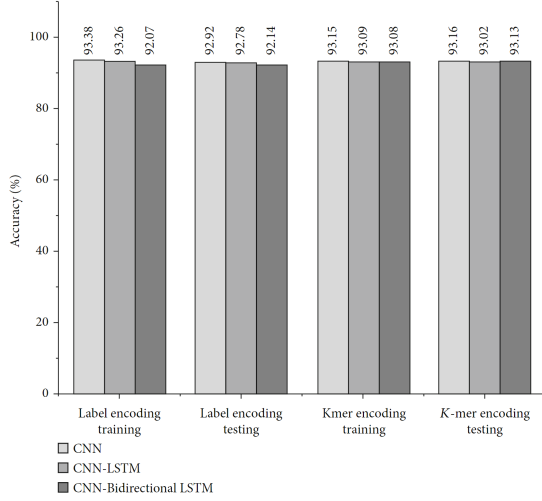


Fig. 8. Training and Testing Accuracies of all six models, borrowed from Gunasekaran, et al. (2020)

compared. Table III shows the formulas for calculating these classification metrics.

#### A. Model Comparison

Figure 8 shows the accuracy comparison for all three models for training and testing data using label and k-mer encoding. The testing accuracies for label encoding are less when compared to its training accuracy. For k-mer encoding testing accuracies are more significant than training. Therefore, the encoding technique plays an important role for achieving high accuracy.

Figure 9 shows the training and validation accuracies for all three models and both encodings. From Figure 9, we can observe that the accuracy of the model remains same after 10 epochs for all models except CNN-LSTM using k-mer encoding. This model has unstable accuracy as each epoch increases. CNN and CNN-Bi-LSTM have high accuracies of 93.16%, 93.13% respectively, when compared to LSTM.

#### B. Discussion

Figure 10 shows the model performance concerning six different classes using label and k-mer encoding techniques. Based on metrics in Figure 10, we make the following observations:

- If class samples are high, CNN with label encoding has high precision.
- If class samples are low, CNN with k-mer encoding has high precision.

- If recall is preferred, k-mer encoding has higher recall for all classes irrespective of the class samples.
- High sensitivity rate of 99.95% is obtained for class “a” using CNN+Bi-LSTM with label encoding.
- To obtain a high recall and sensitivity for class with more samples, Bi-LSTM with label encoding will be a good choice.
- CNN with label encoding offers high specificity irrespective of the class size.

CNN with label encoding outperforms other two models but their testing accuracies are low. K-mer encoding has achieved high validation and testing accuracy. We can conclude that, the best model can be chose not only based on the accuracy of the model but also other metrics such as sensitivity, specificity and precision must be considered.

### VIII. CONCLUSION

The authors’ results are promising when compared to existing non machine-learning and machine learning methods for virus classification. The various performance metrics reviewed here show that the right model may depend on the particular use case. If accuracy is the most important metric, then the authors’ results show that CNN outperforms CNN-LSTM and CNN-bidirectional LSTM. The high accuracy acheived in this paper demonstrates the effectiveness of deep learning models in performing complex tasks.

### REFERENCES

- [1] H. Gunasekaran, K. Ramalakshmi, A. Rex Macedo Arokiaaraj, S. Deepa Kanmani, C. Venkatesan, and C. Suresh Gnana Dhas. "Analysis of DNA Sequence Classification Using CNN and Hybrid Models." *Computational and mathematical methods in medicine*, 2021.
- [2] S. Shadab, M. T. Alam Khan, N. A. Neezi, S. Adilina, and S. Shatabda, "DeepDBP: deep neural networks for identification of DNA-binding proteins," *Informatics in Medicine Unlocked*, vol. 19, article 100318, 2020.
- [3] M. Pop and S. Salzberg. "Bioinformatics challenges of new sequencing technology." *Trends Genet.* vol. 24, no. 3, 142-149. 2008, doi: 10.1016/j.tig.2007.12.006.
- [4] S. C. Pakhrin, B. Shrestha, B. Adhikari, and D. B. Kc, "Deep learning-based advances in protein structure prediction," *Int. J. Mol. Sci.*, vol. 22, no. 11, 2021, doi: 10.3390/ijms22115553.
- [5] A. Tasdelen and B. Sen. "A hybrid CNN-LSTM model for pre-miRNA classification." *Scientific reports*, vol. 11, no. 1, 1-9. 2021.
- [6] J. Chinju, O. Matthew, and J. Sahoo. "CNN-LSTM based classification of polo like kinase family of Proteins: An emerging cancer drug target." *Materials Today: Proceedings*, 2022.
- [7] S. K. Sønderby and O. Winther, "Protein Secondary Structure Prediction with Long Short Term Memory Networks," 2014, [Online]. Available: <http://arxiv.org/abs/1412.7828>.
- [8] N. G. Nguyen, V. A. Tran, D. L. Ngo et al., "DNA sequence classification by convolutional neural network," *Journal of Bio- medical Science and Engineering*, vol. 9, no. 5, pp. 280-286, 2016.
- [9] D. T. Do and N. Q. K. Le, "Using extreme gradient boosting to identify origin of replication in *Saccharomyces cerevisiae* via hybrid features," *Genomics*, vol. 112, no. 3, pp. 2445-2451, 2020.
- [10] X. Zhang, B. Beinke, B. Al Kindhi, and M. Wiering, "Comparing machine learning algorithms with or without feature extraction for DNA classification" 2020, <http://arxiv.org/abs/2011.00485>

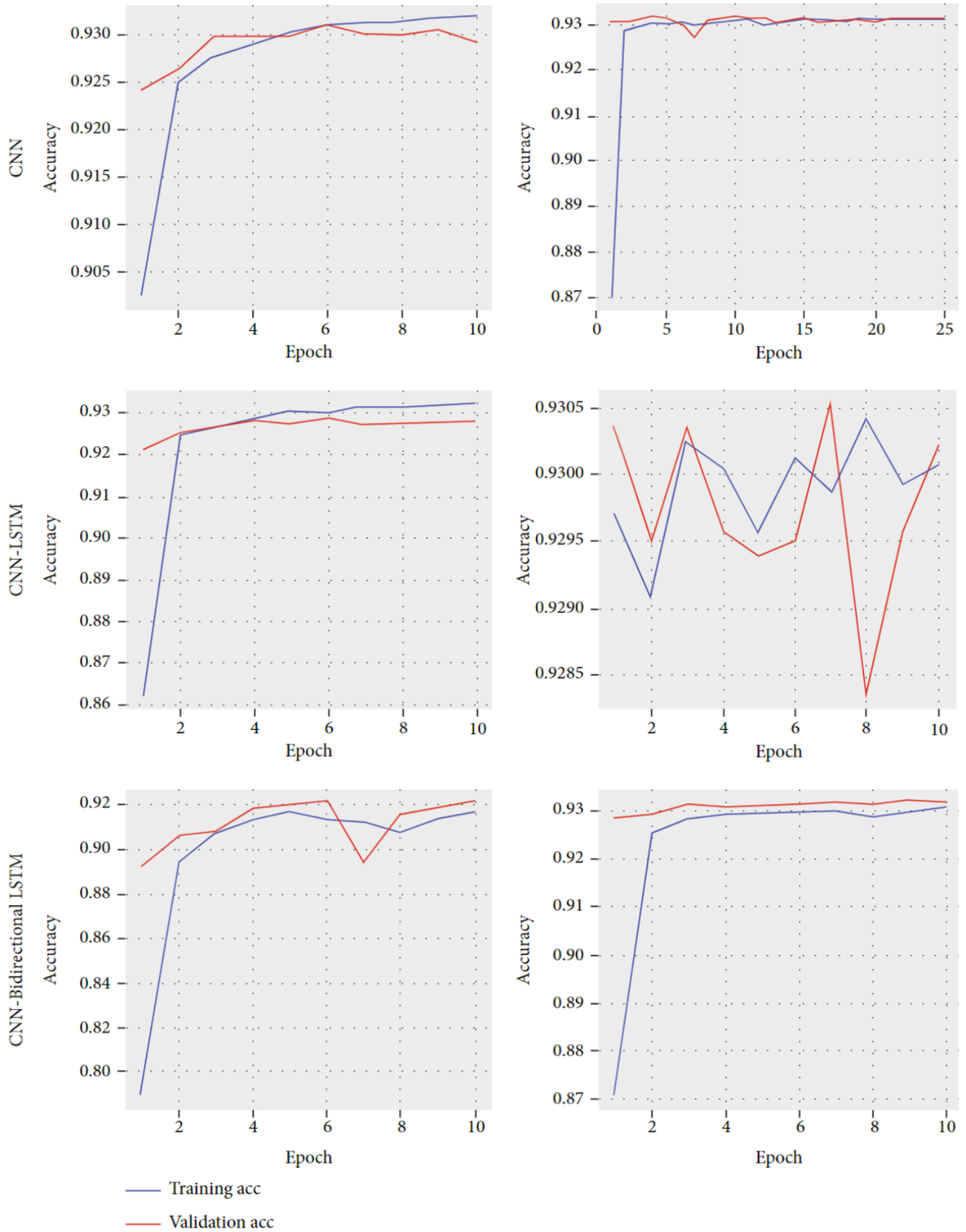


Fig. 9. Training / Validation accuracies for all six models, borrowed from Gunasekaran, et al. (2020)

Fig. 10. Performance Metrics for all Models, borrowed from Gunasekaran, et al. (2020)

Model class		Label encoding						K-mer encoding					
		a	b	c	d	e	f	a	b	c	d	e	f
CNN	Accuracy	0.93	0.99	0.92	0.99	0.99	0.99	0.93	0.99	0.93	0.99	0.99	0.99
	Precision	0.90	0.97	0.77	0.99	1.00	0.99	0.89	0.97	0.94	1.00	0.99	0.99
	F1	0.94	0.93	0.5	0.99	0.99	0.99	0.94	0.96	0.49	0.99	0.99	0.99
	Sensitivity	0.98	0.90	0.37	0.99	0.99	0.99	0.99	0.96	0.33	0.99	0.99	0.99
	Specificity	0.86	0.99	0.98	0.99	1.00	0.99	0.84	0.99	0.99	1.00	0.99	0.99
CNN-LSTM	Accuracy	0.93	0.99	0.92	0.99	1.00	0.99	0.93	0.99	0.93	0.99	0.99	0.99
	Precision	0.89	0.98	0.82	0.99	1.00	0.99	0.89	0.94	0.93	0.98	0.99	0.99
	F1	0.94	0.95	0.49	0.99	1.00	0.99	0.94	0.95	0.48	0.99	0.99	0.99
	Sensitivity	0.98	0.93	0.35	0.99	1.00	0.99	0.99	0.96	0.32	0.99	0.99	0.99
	Specificity	0.85	0.99	0.99	0.99	1.00	0.99	0.84	0.99	0.99	0.99	0.99	0.99
CNN-bidirectional LSTM	Accuracy	0.93	0.99	0.92	0.99	0.99	0.99	0.93	0.99	0.93	0.99	0.99	0.99
	Precision	0.89	0.95	0.84	0.93	0.98	0.99	0.89	0.98	0.94	0.99	0.99	0.99
	F1	0.94	0.82	0.40	0.96	0.99	0.99	0.94	0.96	0.48	0.99	0.99	0.99
	Sensitivity	0.99	0.72	0.26	0.99	0.99	0.99	0.99	0.95	0.33	0.99	0.99	0.99
	Specificity	0.84	0.99	0.99	0.99	0.99	0.99	0.84	0.99	0.99	0.99	0.99	0.99