Supplementary Documents

Neural Ordinary Differential Equations for Predicting the Temporal Dynamics of a ZnO Solid Electrolyte FET

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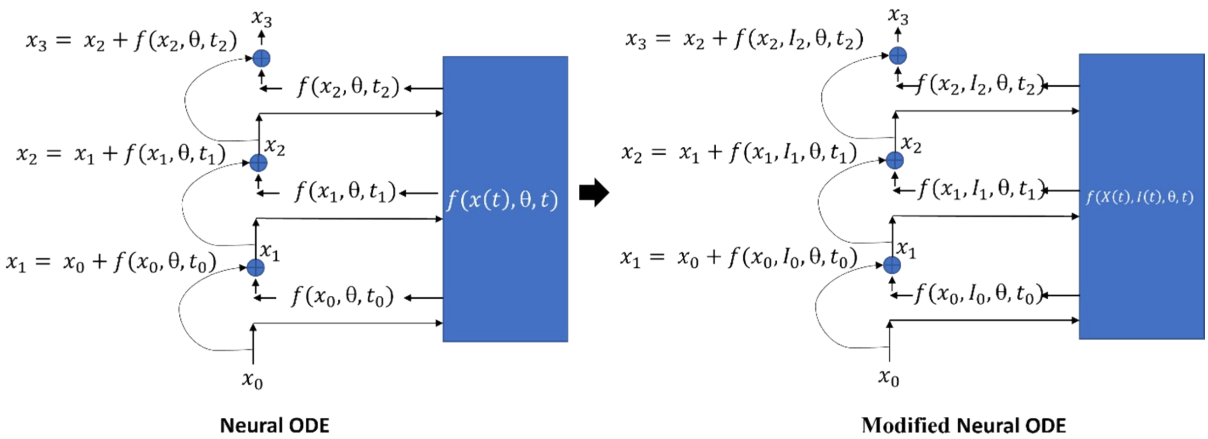
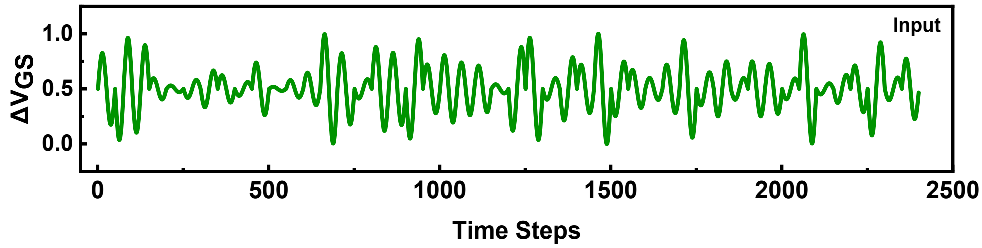
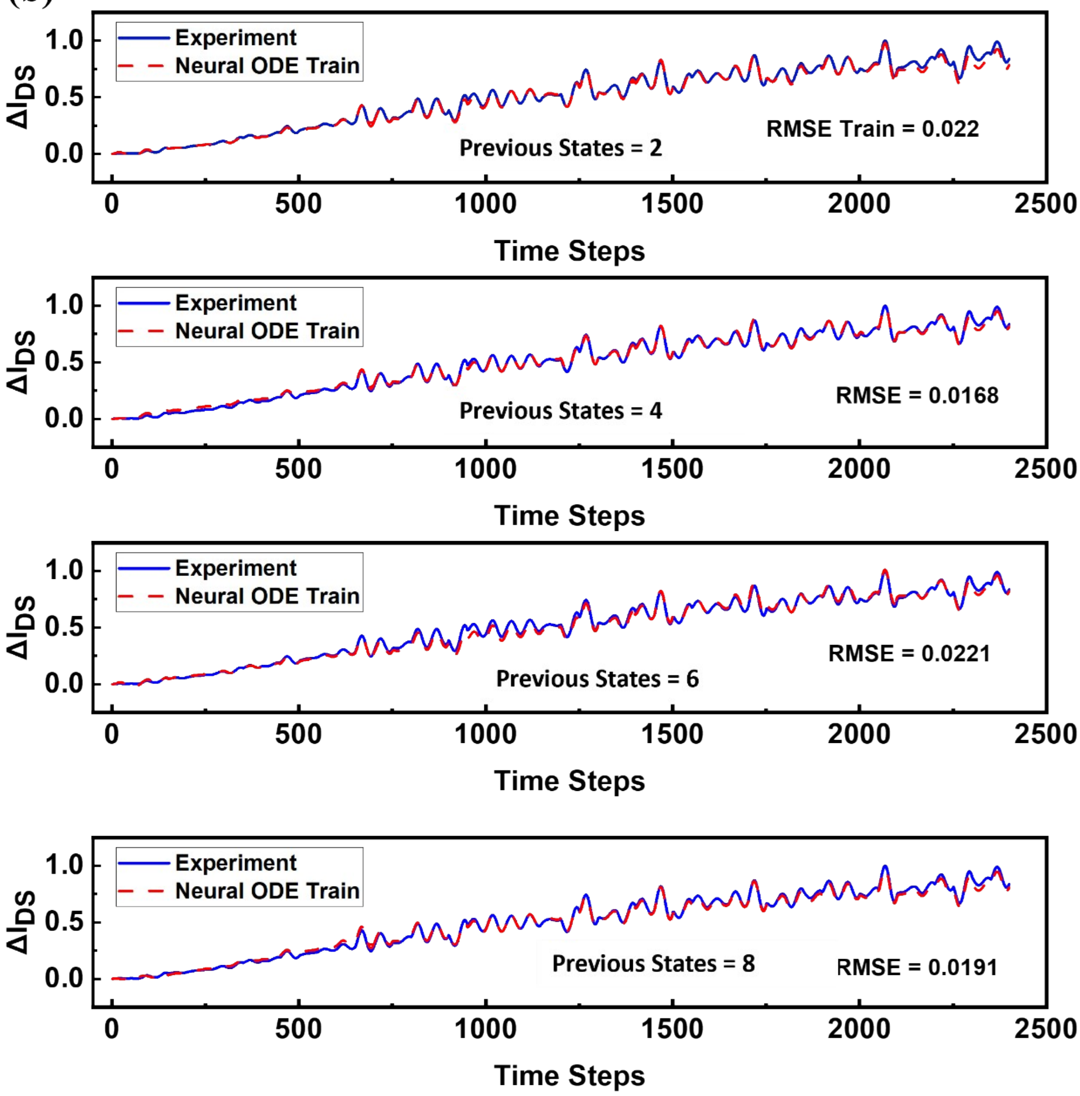


Supplementary Figure S1. The modified neural ODE network showing a continuous transformation of the input consisting of two parts, (1) observed system dynamics X(t), and (2) time-dependent external inputs I(t).

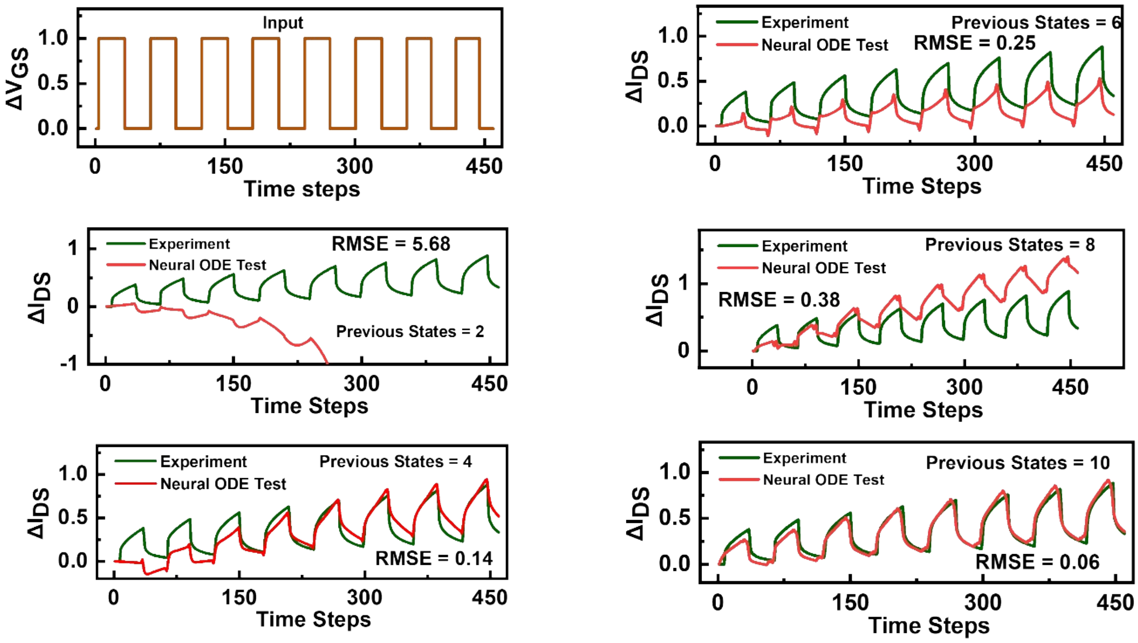
(a)



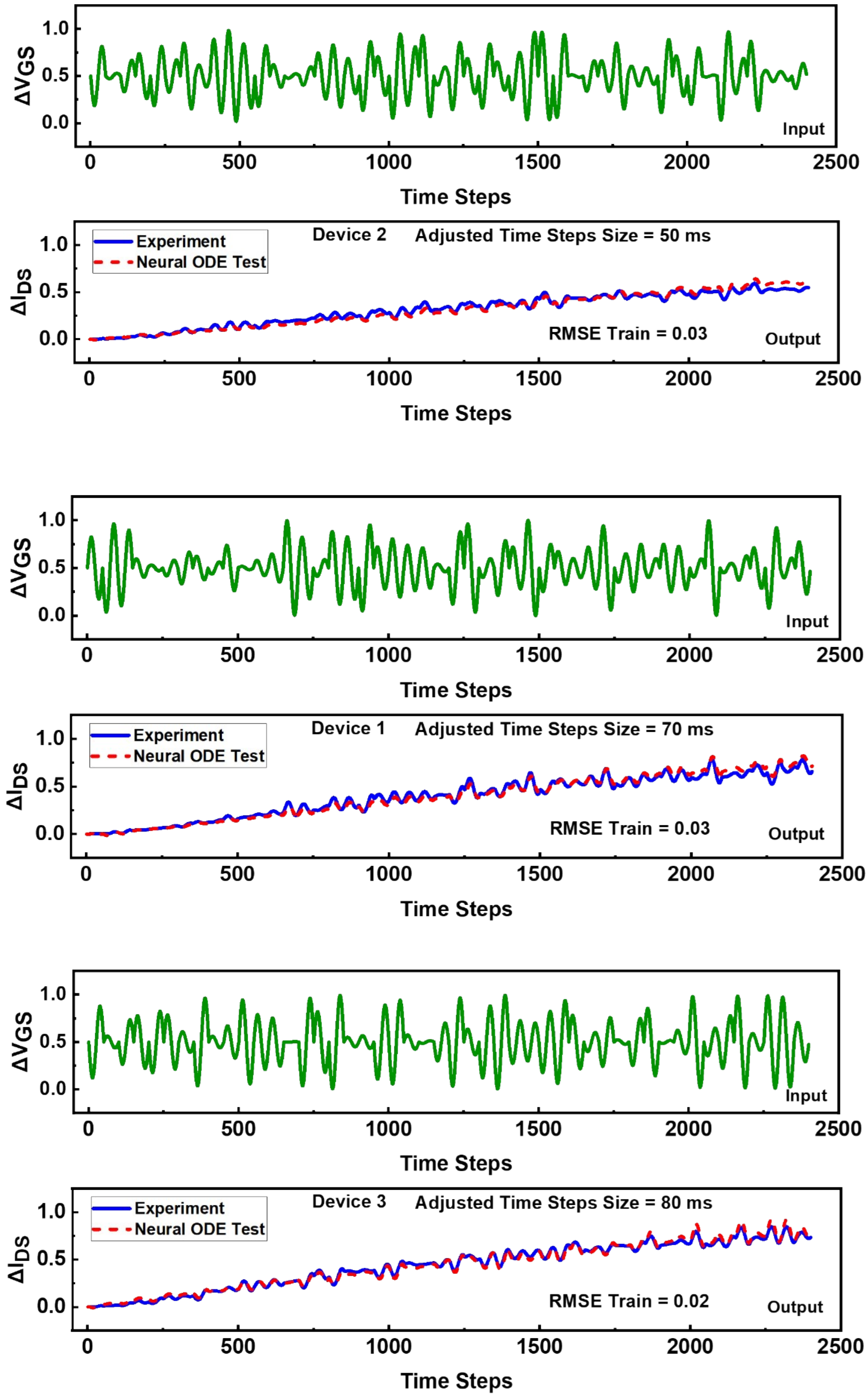
(b)



Supplementary Figure S2. Training performance of the Neural ODE to learn the dynamics of the SE-FET using a random gate to source voltage as input, with 2,4,6 and 8 previous states. All of these achieve a low training error of RMSE = 0.02 or lower. (a) Normalized random voltage, in the form of ΔV_{GS} (gate to source voltage) is given as input to the neural ODE. (b) The corresponding normalized ΔI_{DS} (drain to source current) experimentally measured data (blue line) is used to train the neural ODE and (red dotted line shows the performance during training).



Supplementary Figure S3. Testing the predictability of the dynamics of SE-FET with input not used in training, via the neural ODE model (for different previous states) to that of experiment. These results show that the neural ODE model with previous states = 10 can perform better, despite having similar training errors across all previous states. This is because a higher number of previous states is equivalent to the information provided by higher-order derivatives that leads to better performance.

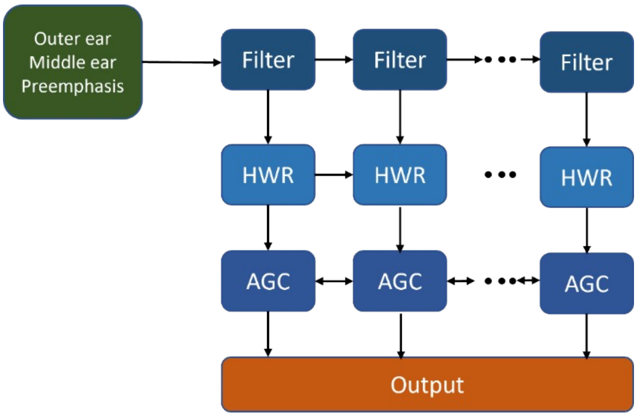


Supplementary Figure S4. Comparing the output of the neural ODE model to that of experiment from three different SE-FETs. The variation from device to device is achieved by adjusting the frequency (time steps size) of the neural model.

Supplementary Note 1: Classification of spoken digit – Methods

Before feeding the audio file of isolated spoken digits (0-9) from the NIST TI46 database[1] (which consists of 500 samples) into the reservoir as input, it is preprocessed using Lyon's passive ear model based on human cochlear channels. Lyon's passive ear model describes how a cochlea, a part of the inner ear, can convert acoustical energy into neural representations, which allow to capture the frequency and amplitude components of an audio signal as essential features for classification of speech. It uses a series of filters to divide the input signal into different frequency channels corresponding to pitch of the audio, half wave rectifiers (HWRs) to identify the actual information from the filtered signal , and automated gain control (AGC) to compress the signal as shown in the Supplementary Figure S5.

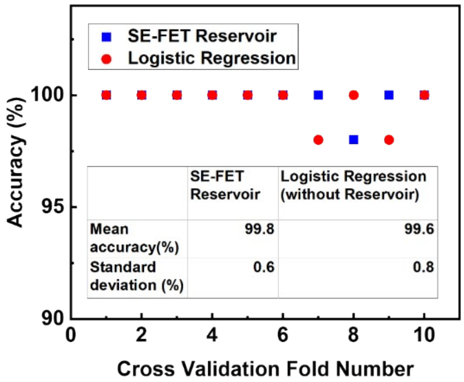
The processed audio file is then applied as an analog input to the neural ODE model of the SE-FET and its response periodically recorded after each time step of 100ms. The recorded response is then used to train the readout network. Our readout network is trained on 450 samples using logistic regression, and testing conducted on a 50-sample set that is not used for training. To prevent the system from overfitting to certain combinations of the training and testing, 10-fold cross-validation is used. As a result, training and testing are repeated ten times, each time with a different assignment of training and testing samples. classification accuracy is defined as the mean in a 10-fold cross- validation set-up.



Supplementary Figure S5. Schematic of Lyon's passive ear model

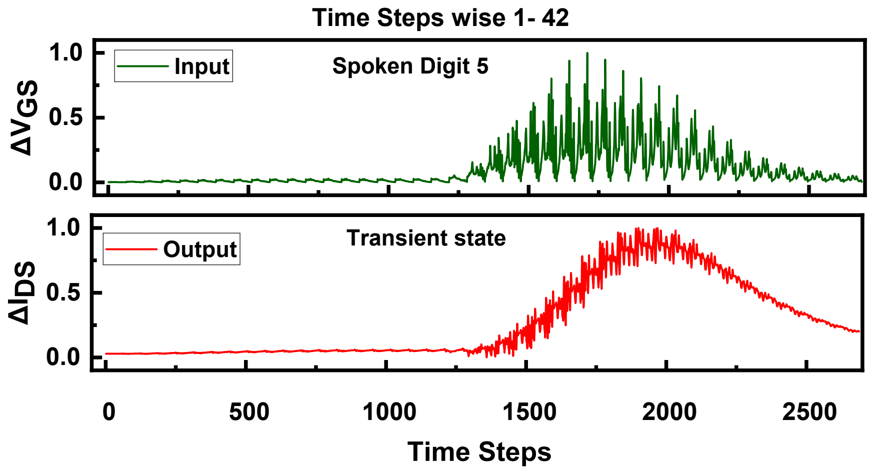
Supplementary Note 2: The SE-FET-based reservoir system using the neural ODE model of the device (additional details)

The performance benchmark of our dynamic SE-FET-based RC system with a conventional network with no hidden layer (reservoir), trained using the same algorithm (logistic regression) is shown in Supplementary Figure S9. Our dynamic SE-FET-based RC system outperforms the conventional machine learning algorithm and achieves the lowest error rate of 0.2% for the same network size. This improvement in performance shows the ability of the reservoir to convert the input into rich space-time-dependent features.



Supplementary Figure S6. The classification accuracy is defined as the mean in a 10-fold cross-validation set-up. Using the neural model the SE-FET based reservoir has better accuracy by 0.2% compared to conventional machine learning algorithm for the same network size.

In an alternative time step-based approach, the input data is fed in time steps rather than as a channel number to examine the effects of representation of sample data for spoken digit 5 as an example and the SE-FET response is shown in Fig.S5. In this implementation, an overall mean accuracy of 99.60% is achieved. This result shows that representation of samples in reservoir computing can affect the performance of the RC system. On the other hand, in the conventional approach (without reservoir) there is no effect on performance due to representation of the sample data in a different manner. This is because changing the position of the same input features in the conventional network does not have any impact on its performance.



Supplementary Figure S7. The temporal response of the SE-FET to an analog input for spoken digit 5 in both transient and steady state. When input is fed time steps wise.

The performance summary of the different approaches using a single SE-FET device-based reservoir and logistic regression (without any reservoir) for spoken digit classification task is shown in Supplementary Table 1. These results show that our dynamic single SE-FET- device based RC system in transient state outperforms all other approaches and has lowest error rate of 0.2%.

The performance summary of the different approaches using multi-SE-FET device-based reservoir computing for spoken digit classification task is shown in Supplementary Table S2.

Supplementary Table 1. Simulation result of single SE-FET device-based reservoir computing and logistic regression (without reservoir) for spoken digit classification task.

	Single device	**Single device**	**Logistic Regression (Without reservoir)**	**Logistic Regression (Without reservoir)**
Accuracy	**99.80%**	99.60%	99.60%	99.60%
Standard deviation	0.60%	1.33%	0.80%	0.80%
Representation of sample data	Channel number wise	Time step wise	Channel number wise	Time step wise

Supplementary Table.2. Simulation result of multi-SE-FET device-based reservoir computing for spoken digit classification task.

	Multi device	**Multi device**	**Logistic Regression (Without reservoir)**	**Logistic Regression (Without reservoir)**
Accuracy	99.00%	99.20%	99.60%	99.60%
Standard deviation	1.34%	0.98%	0.80%	0.80%
Representation of sample data	Channel number wise	Time step wise	Channel number wise	Time step wise

Our SE-FET based reservoir computing achieves the highest accuracy of 99.8% for a single device reservoir and 99% for a multi device reservoir which performs better or at par to earlier published work as shown in Table S3.

Supplementary Table.3. Comparison of SE-FET based reservoir computing with other reported work.

Ref.	**Device**	**Spoken digit classification task accuracy**
[2]	Memristor (WO_x)	99.2%
[3]	Memristor (TiO_x/TaO_y)	99.6%
[4]	Spintronic	99.6%
[5]	SE-FET (ZnO/Ta_2O_5)	99.4%
This work	SE-FET (ZnO/Ta_2O_5)	99.8% (for single device) 99% (for multi device)

References

1 Texas Instruments-Developed 46-Word Speaker-Dependent Isolated Word Corpus (TI46) NIST Speech Disc 7-1.1. (1991).

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