Liquid State Machine

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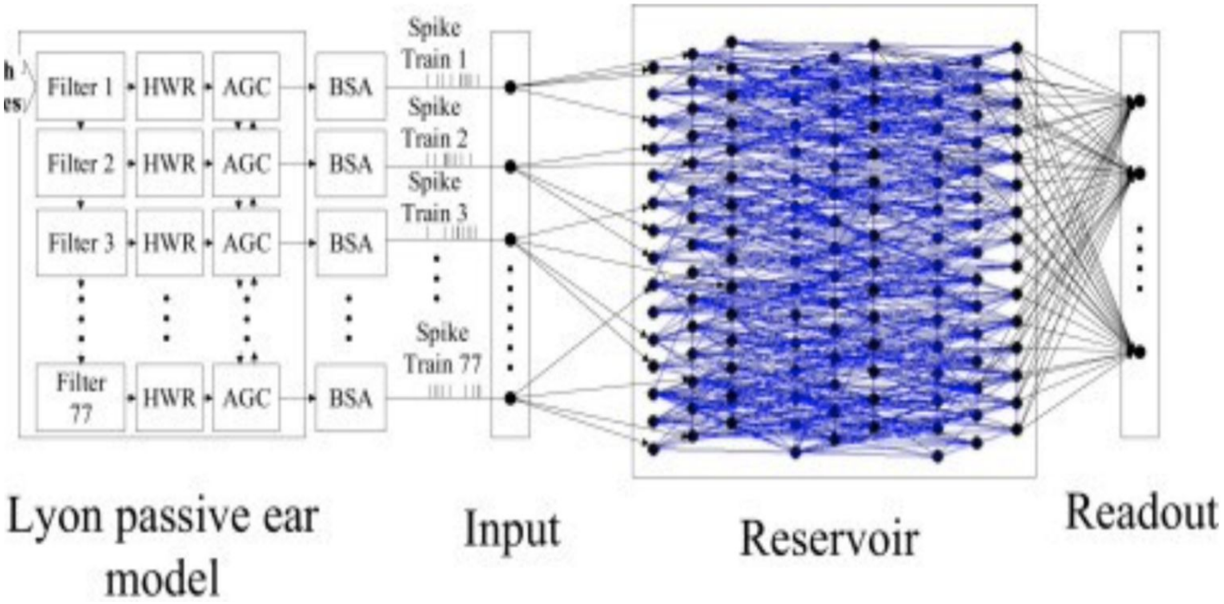
Motivation

- An LSM is a type of machine learning algorithm that is based on Spiking neural networks. These spiking neurons resemble our brain more closely than traditional neurons.
- A reservoir is a collection of randomly connected neurons used in LSM. It creates a mapping to a high-dimensional space
- They have lower training complexity than their counterparts like CNN but achieve a high accuracy
- In my DPP project I have tried to scale the reservoir size in an LSM architecture and apply it on different speech dataset. I have also tried to predict optimal size for the reservoir for different classes.
- I have demonstrated how weight scaling in reservoir affect the accuracy and spiking of neurons in the reservoir.

LSM architecture

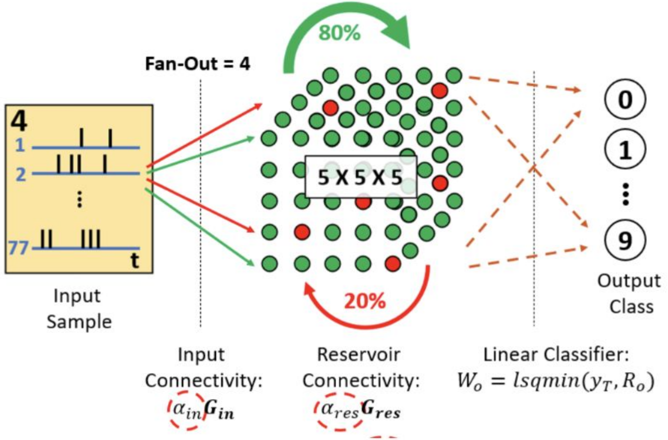
- Lyon passive ear model converts audio signals into 77 audio classes
- Each spike stream is applied to F_out neurons
- The spikes generated are then scaled and then connected to f_out no of neurons.
- The reservoir is then connected to a readout layer with trainable weights.
- Output is the neuron of output layer with most spikes.



Reservoir

- The neurons in the reservoir follow LIF neuron model.
- The neuron in the reservoir are of two type Excitatory Neuron and Inhibitory Neurons. Due to this there are four types of weights connecting different type of neurons.
- Whether a connection exists between two neurons depend on the distance between them:

$$P(N1, N2) = K.e^{-\frac{D^2(N1,N2)}{\lambda^2}}$$

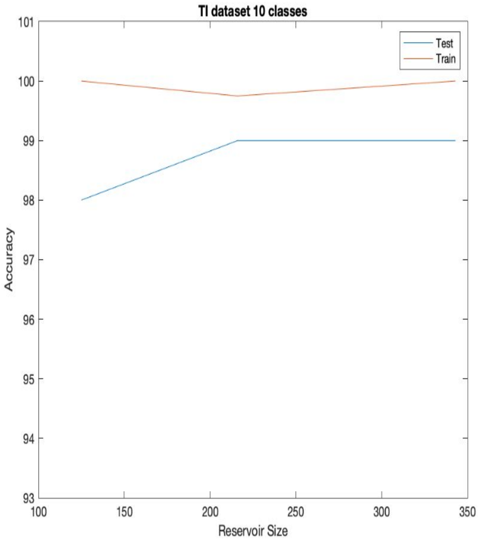


- In LSM the weight training happens only in outermost layer and is done through minimizing following loss equation using lsqlin function.

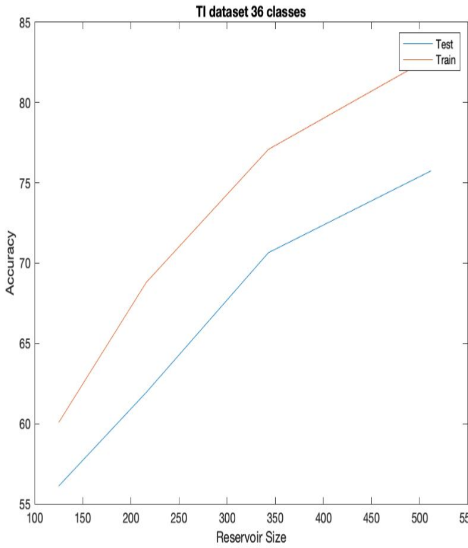
$$\frac{1}{2}\left| \sum_{i=Train} \left(\sum_{j=N^{res}} n_{ij}^{spike} W_{jk} - Y_{ik} \right) \right|$$

Results

- **TI data set:** The dataset comprises of 26 spoken alphabet and 10 digits. I have taken 150 samples of each class with test train ratio of 1:9.
- TI dataset has a total of 16 speakers(8M, 8F).
- We can see here that that accuracy increases as we increase the size of the reservoir
- We also see that as class size increase the classification problem becomes more difficult and it requires a larger liquid.



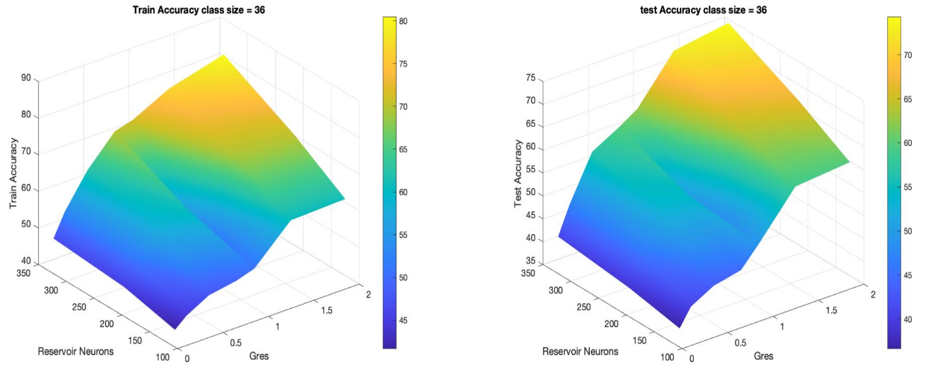
(a) Class size 10



(b) Class size 36

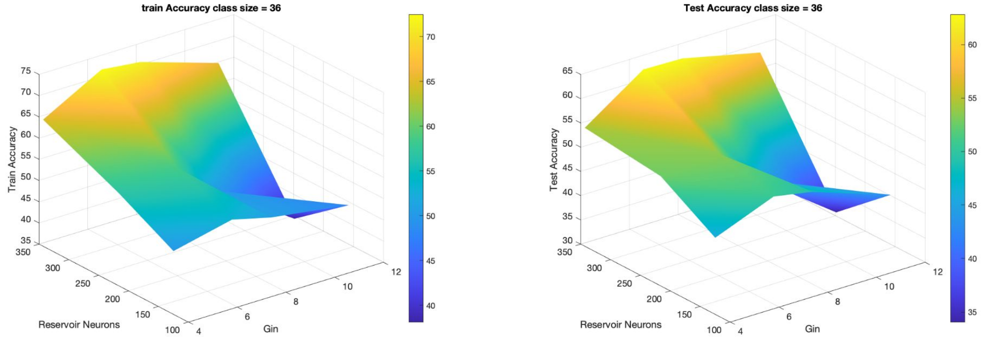
- **Ti 36 dataset:** As we increase the no of classes the complexity req. by classifier increases. To find the optimal parameter for the reservoir I have scaled the weights within the reservoir by Gres and weights between the reservoir and preprocessing layer by Gin.
- When we increase the weights we see that spiking in the reservoir increases. Ideally we want the reservoir
- The testing and training accuracy achieved after doing 5 folds was:

Train accuracy	80.9954
Test accuracy	73.0555



(a) Training Accuracy (b) Testing Accuracy

Figure 4.4: How accuracy varies with reservoir size and α_{Gres}

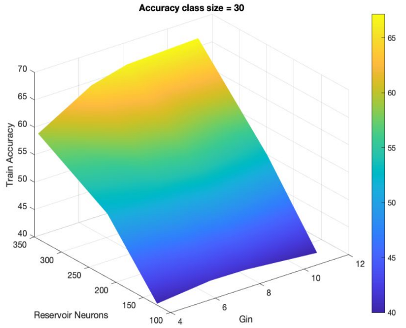


(a) Training Accuracy (b) Testing Accuracy

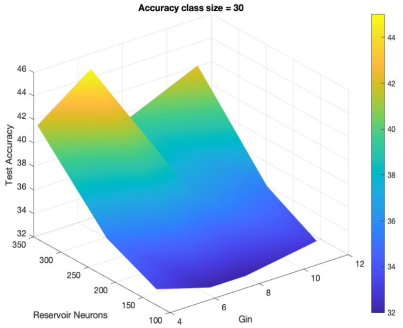
Figure 4.3: How accuracy varies with reservoir size and α_{GIn}

- **Google keyword Dataset:** It is a mixture of 30 most commonly spoken words by various speakers
- The reservoir weights were varied to get the optimal parameters.
- We see that there is a gap between training and testing accuracy. This suggests that the network has not generalized well. In this dataset almost every datapoint is spoken by a different speaker making it difficult for network to generalize.
- The testing and training accuracy achieved after doing 5 folds was:

Train accuracy	55
Test accuracy	40

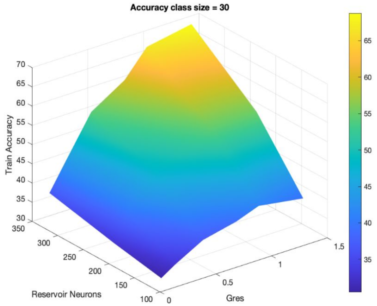


(a) Training Accuracy

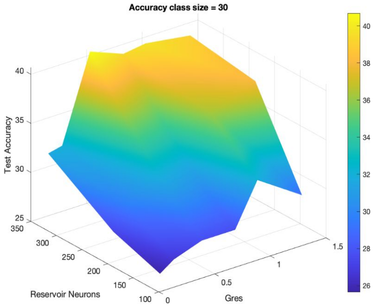


(b) Testing Accuracy

Figure 4.6: How accuracy varies with reservoir size and α_{Gin}



(a) Training Accuracy



(b) Testing Accuracy

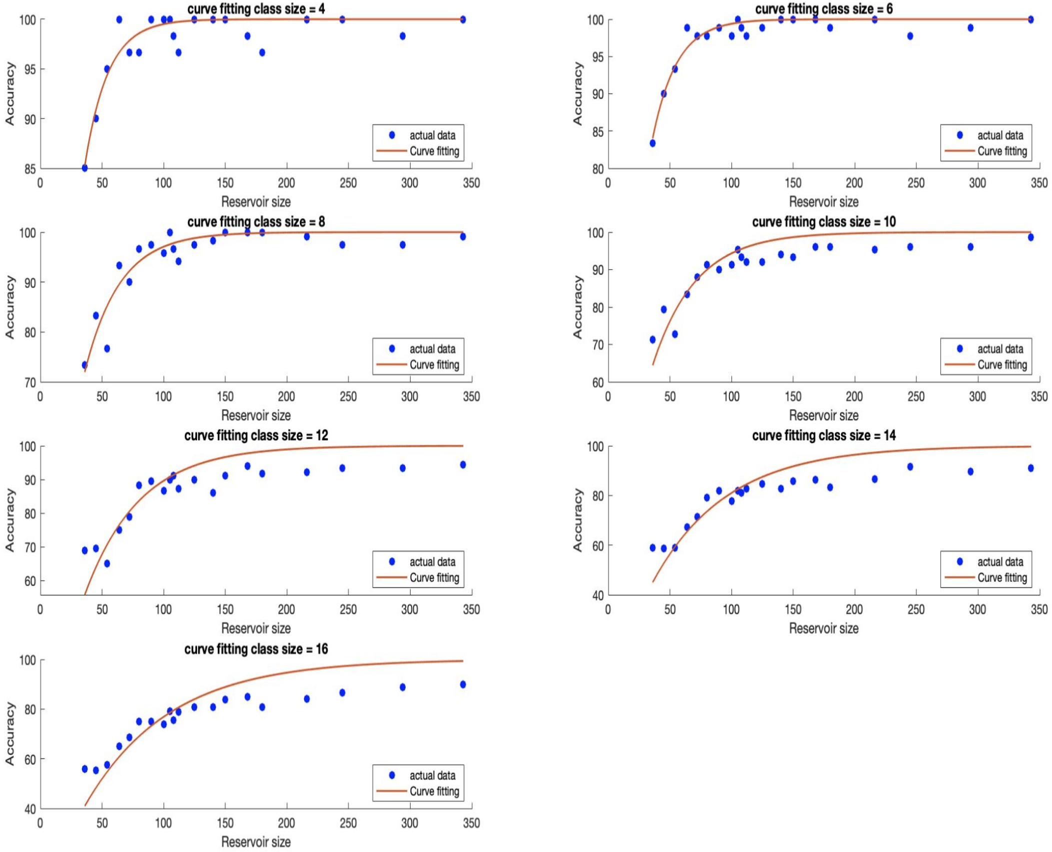
Figure 4.7: How accuracy varies with reservoir size and α_{Gres}

Reservoir size and class size

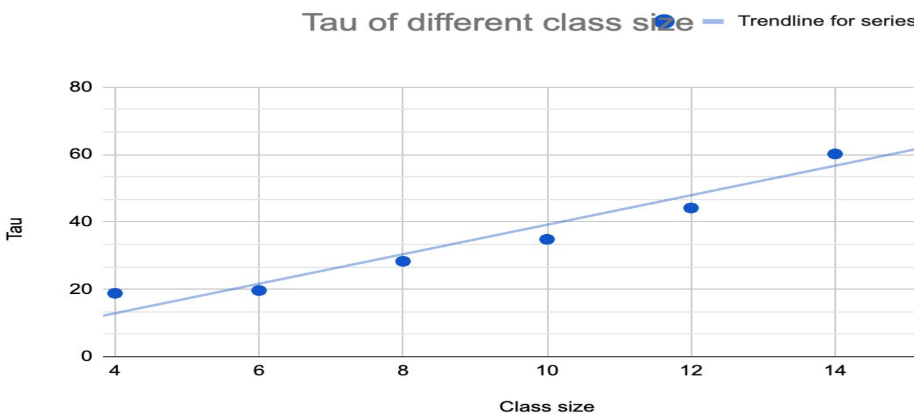
- The testing accuracy vs the reservoir size can be approximated through:

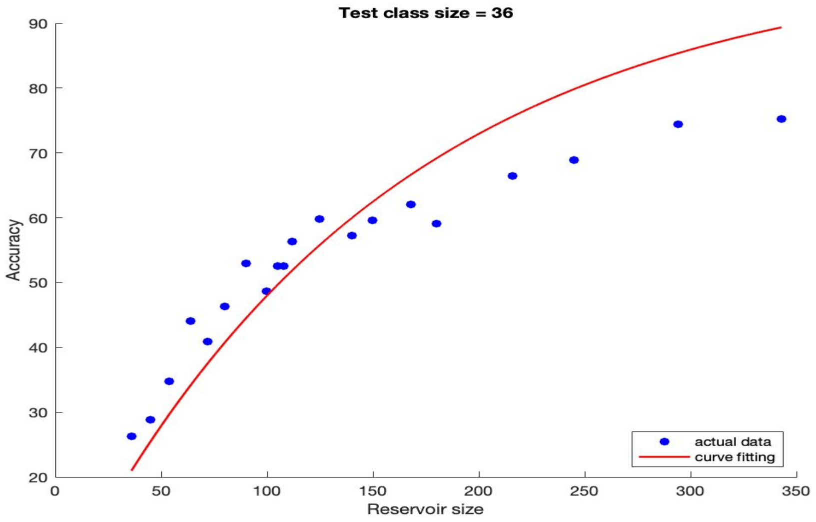
$$100(1 - \exp(-1 * \frac{ReservoirSize}{tau})))$$

- Here tau is the function of class size. We can have tau values for different class by trying to fit the curve on the data



- To approximate the accuracy for any higher class we can plot the tau for the smaller class and then estimate the tau for higher class through linear interpolation.
- To test this hypothesis I plotted the tau for different classes and fitted a straight line(y = mx + c) and predicted the tau value with that.
- To test this hypothesis I varied the reservoir size for a class size of 36 and see how well the data fits the predicted curve.

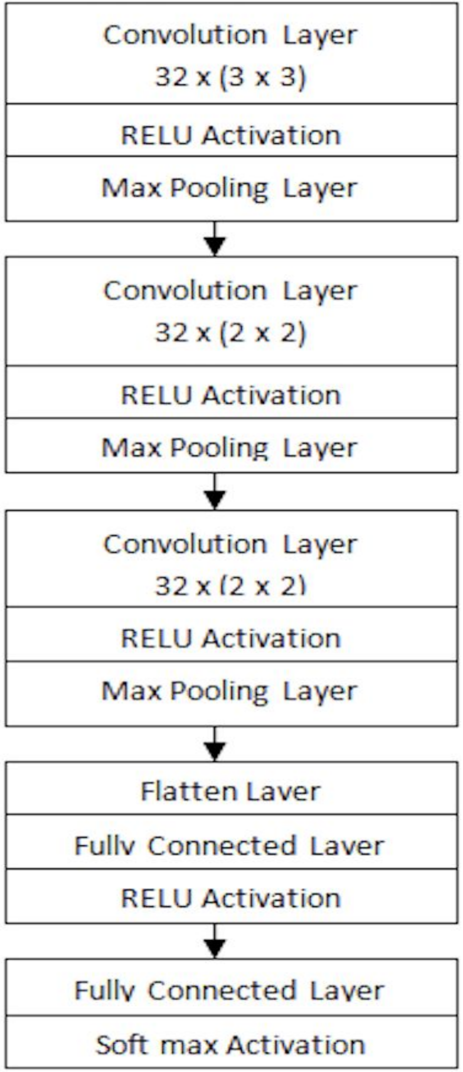




Comparison with CNNs

- We can see that both CNn and LSM achieve high accuracy when we compare with TI-10(spoken digits dataset)
- We can see that LSM has a lot less trainable parameter but the dip in accuracy is only 3 %

	LSM	CNN
Train Accuracy	100	99
Test Accuracy	95	98
No of parameter	1250	18500
Epoch	1	70
Kfolds	5	1



Future Work

- Adding a convolution layer in between reservoir and preprocessing layer.
- Convolution networks are very good at capturing spatial and temporal information. And it would be able to capture relation between different audio classes from lyon ears.
- To apply convolution filters on audio classes we can rearrange them into grids. And apply convolution filter through time.
- For training we can use unsupervised training through STDP to train the network from input to reservoir. This method was already used for implementing CNN in an LSM architecture for doing image classification.

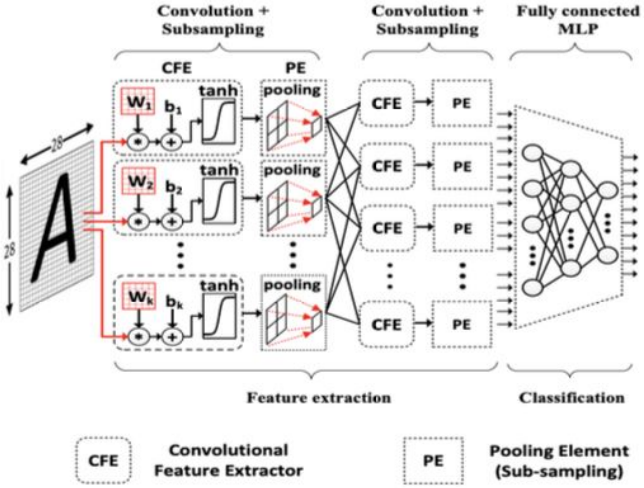


Figure 6.1: CNN in LSM for Mnist(15)