

Train a Long Short-Term Memory Network for Predicting Displacement of CNC Machine Centre using Temperature Sensor Data

Use a Long Short-Term Memory (LSTM) network to predict z-axis error due to the thermal deformation of CNC machine tools.

```
% load data files for use with several Deep Learning apps
clear; clc; close all;

% change the file path to load a different csv file
datapath = "C:\Users\Mareim\OneDrive - Coventry University\Data\Data on CNC temp\data\2017-03-6";

dateOfDay = extractBetween(datapath,"data\",".csv");

[tsdata, ndata] = importfile1(datapath, [2, Inf]);
interval = 1:size(tsdata,1);
tsdata_interval = tsdata(interval,:);
tt1 = table2timetable(tsdata_interval);
% fix date and time
t = tsdata.Time;
d = datetime(dateOfDay);
t.Year = d.Year;
t.Month = d.Month;
t.Day = d.Day;

% Response and predictor (temperature sensor feeds) variables (pre-normalised)

X_pre = tsdata.X(interval);
Y_pre = tsdata.Y(interval);
Z_pre = tsdata.Z(interval);

predictors_pre = tsdata{interval,5:end};%
ts_1 = tsdata(interval,1);
% Response and predictor variables (post-normalised)

Xval = ndata.X;
Yval = ndata.Y;
Zval = ndata.Z;

%predictors = [interval, ndata{:,4:end}];
predictors = ndata{:,4:end};
% take a sample sensor as input (column 1:48 specifying sensor location in
% 6x8 grid; column 49:52 specifying sensor 1:4 around the spindle)
pred1 = predictors(:,6);

% Plot figures
ts_interval = tsdata.Time(interval);
d = datetime(dateOfDay);
```

```
ts_interval.Year = d.Year;
ts_interval.Month = d.Month;
ts_interval.Day = d.Day;
```

```
%plotdata();
```

Split the dataset into training and testing data

Create three two-hour-long sampling intervals, with random starting points

```
numSamplingIntervals = 3;
% calculate the length of each sample such that 25% of the timeseries is
% used for testing
numHours = t.Hour(end)-t.Hour(1)+1;
samplingMinutes = 0.25*numHours*120;
sampleDuration = samplingMinutes/numSamplingIntervals;
startTimes = sort(randsample(numHours-3,numSamplingIntervals)*sampleDuration);
% assign random start points for sampling
startTimes = startTimes - 2*randsample(60,numSamplingIntervals)
```

```
startTimes = 3×1
    102
    358
    926
```

```
for i = 1:size(startTimes,1)
    if startTimes(i) < 0
        startTimes(i) = startTimes(i)*-1
    end
end
endTimes = startTimes(:) + sampleDuration
```

```
endTimes = 3×1
    242
    498
    1066
```

Generate a subset of testing samples

Add an index to predictors so the desired data points can be selected by their relative index in the input data.

```
predictors(:,1);

for i = 1:numSamplingIntervals
    % calculate sampling interval duration
    intervalPoints = startTimes(i):endTimes(i);
    ezs = [intervalPoints', Zval(intervalPoints')];
    newStartPoint = startTimes(i);
    % starting at the first point in the interval + the interval
    newEndPoint = newStartPoint + intervalPoints(end);
    eps = [predictors(startTimes(i):endTimes(i),:)]';
    % set new start index
    startIndex = 1+(i-1)*sampleDuration
    extZSamples(startIndex:startIndex+sampleDuration,:) = ezs;
    extPredSamples(startIndex:startIndex+sampleDuration,:) = eps;
```

```

    %extPredSample() = eps;
    %Ztest((i-1)*240+1:i*240+i,1) = extSample;
end

```

```

startIndex = 1
startIndex = 141
startIndex = 281

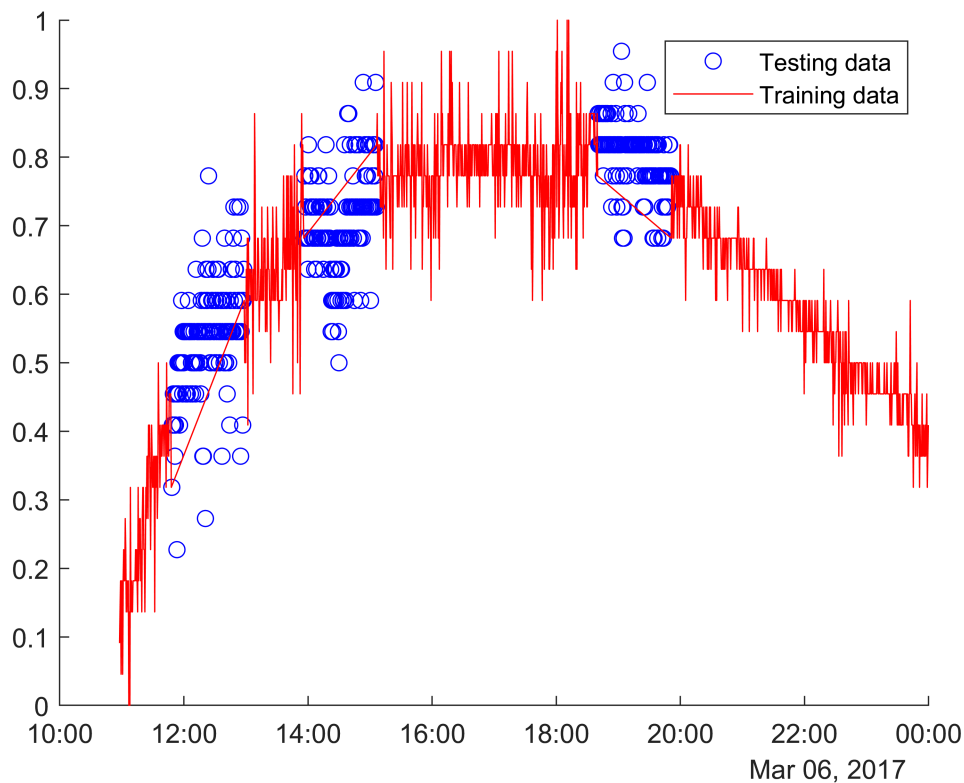
```

```

predictors_test = extPredSamples;
predictors_train = predictors;
indexesToRemove = extZSamples(:,1);
% remove indexes in indexesToRemove
predictors_train(indexesToRemove,:) = [];
% similarly, remove indexes in Zvals_train
Zvals_test = extZSamples;
Zvals_train = [interval', Zval];
Zvals_train(indexesToRemove,:) = [];

figure(3); clf reset;
testIndeces = Zvals_test(:,1);
trainIndeces = Zvals_train(:,1);
scatter(t(testIndeces),Zvals_test(:,2),'b');
hold on;
plot(t(trainIndeces),Zvals_train(:,2),'r');
legend('Testing data','Training data');

```



Step 1: Feature selection for regression using Neighborhood Component Analysis

Create a Feature Selection for Regression Neighborhood Component Analysis (FSRNCA) model to weight each feature based on a predefined threshold λ , equal to $0.5/\text{numObservations}$

```
lambda = 0.5/size(interval,2);
mdl = fsrnca(predictors, Zval, 'Verbose',1, 'FitMethod', 'Exact', 'Solver', 'lbfgs');
```

o Solver = LBFGS, HessianHistorySize = 15, LineSearchMethod = weakwolfe

ITER	FUN VALUE	NORM GRAD	NORM STEP	CURV	GAMMA	ALPHA	ACCEPT
0	9.603917e-02	1.052e-03	0.000e+00		5.703e+02	0.000e+00	YES
1	9.102973e-02	2.667e-03	1.625e+00	OK	1.781e+02	5.000e-01	YES
2	8.774561e-02	2.103e-03	1.051e+00	OK	2.951e+02	1.000e+00	YES
3	8.414418e-02	5.378e-04	2.497e+00	OK	4.224e+02	5.000e-01	YES
4	8.383733e-02	4.789e-04	3.816e-01	OK	1.085e+03	1.000e+00	YES
5	8.321317e-02	7.151e-04	1.530e+00	OK	1.092e+03	1.000e+00	YES
6	8.290021e-02	2.114e-04	6.471e-01	OK	3.475e+02	1.000e+00	YES
7	8.278288e-02	3.115e-04	7.406e-01	OK	1.315e+03	1.000e+00	YES
8	8.271017e-02	3.167e-04	6.743e-01	OK	3.151e+02	1.000e+00	YES
9	8.269814e-02	3.439e-04	6.241e-01	OK	2.743e+02	1.000e+00	YES
10	8.267506e-02	9.129e-05	2.724e-01	OK	2.161e+02	1.000e+00	YES
11	8.266842e-02	4.655e-05	1.147e-01	OK	6.469e+02	1.000e+00	YES
12	8.265333e-02	7.826e-05	4.573e-01	OK	8.649e+02	1.000e+00	YES
13	8.264446e-02	4.231e-05	1.501e-01	OK	5.269e+02	1.000e+00	YES
14	8.263843e-02	1.445e-05	2.195e-01	OK	2.583e+03	1.000e+00	YES
15	8.263470e-02	1.947e-05	1.396e-01	OK	2.379e+03	1.000e+00	YES
16	8.263012e-02	5.545e-05	2.880e-01	OK	6.904e+02	1.000e+00	YES
17	8.262761e-02	5.318e-05	1.892e-01	OK	3.715e+03	1.000e+00	YES
18	8.262170e-02	1.440e-04	3.603e-01	OK	3.750e+02	1.000e+00	YES
19	8.261862e-02	2.722e-04	5.823e-01	OK	7.548e+02	1.000e+00	YES

ITER	FUN VALUE	NORM GRAD	NORM STEP	CURV	GAMMA	ALPHA	ACCEPT
20	8.260315e-02	3.912e-05	3.256e-01	OK	2.761e+02	1.000e+00	YES
21	8.259643e-02	8.932e-05	2.052e-01	OK	5.125e+02	1.000e+00	YES
22	8.259060e-02	1.935e-04	3.333e-01	OK	6.178e+02	1.000e+00	YES
23	8.258346e-02	1.499e-04	1.006e-01	OK	4.314e+02	1.000e+00	YES
24	8.257346e-02	5.661e-05	3.700e-01	OK	1.560e+03	1.000e+00	YES
25	8.257126e-02	6.093e-05	1.180e-01	OK	2.581e+02	1.000e+00	YES
26	8.256994e-02	1.497e-05	1.397e-01	OK	3.786e+02	1.000e+00	YES
27	8.256948e-02	1.287e-05	3.131e-02	OK	1.948e+03	1.000e+00	YES
28	8.256710e-02	1.934e-05	1.950e-01	OK	1.856e+03	1.000e+00	YES
29	8.256658e-02	4.113e-05	1.918e-01	OK	9.819e+02	1.000e+00	YES
30	8.256518e-02	1.013e-05	6.371e-02	OK	6.513e+02	1.000e+00	YES
31	8.256463e-02	2.289e-05	6.595e-02	OK	6.812e+02	1.000e+00	YES
32	8.256407e-02	2.015e-05	8.268e-02	OK	2.882e+03	1.000e+00	YES
33	8.256353e-02	3.350e-05	1.226e-01	OK	1.021e+03	1.000e+00	YES
34	8.256319e-02	5.645e-06	5.969e-02	OK	4.341e+02	1.000e+00	YES
35	8.256309e-02	8.063e-06	3.346e-02	OK	2.259e+03	1.000e+00	YES
36	8.256294e-02	6.870e-06	4.605e-02	OK	2.222e+03	1.000e+00	YES
37	8.256285e-02	3.831e-06	5.365e-02	OK	2.283e+03	1.000e+00	YES
38	8.256280e-02	2.927e-06	3.052e-02	OK	9.133e+02	1.000e+00	YES
39	8.256277e-02	2.252e-06	2.822e-02	OK	7.989e+03	1.000e+00	YES

ITER	FUN VALUE	NORM GRAD	NORM STEP	CURV	GAMMA	ALPHA	ACCEPT
40	8.256274e-02	3.940e-06	5.565e-02	OK	6.619e+03	1.000e+00	YES

	41		8.256272e-02		6.417e-06		2.812e-02		OK		2.538e+03		5.000e-01		YES	
	42		8.256270e-02		5.058e-06		1.876e-02		OK		4.330e+02		1.000e+00		YES	
	43		8.256269e-02		1.947e-06		1.900e-02		OK		4.774e+02		1.000e+00		YES	
	44		8.256268e-02		7.175e-07		7.499e-03		OK		1.343e+03		1.000e+00		YES	

Infinity norm of the final gradient = 7.175e-07

Two norm of the final step = 7.499e-03, TolX = 1.000e-06

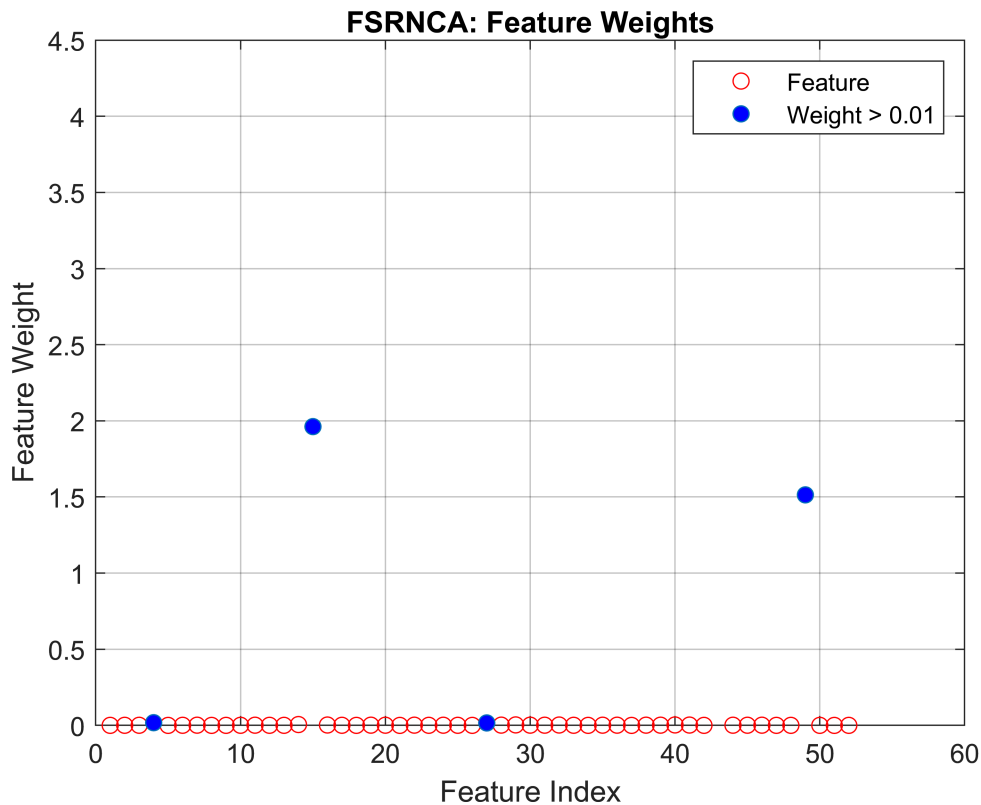
Relative infinity norm of the final gradient = 7.175e-07, TolFun = 1.000e-06

EXIT: Local minimum found.

```
[fi,fj,fs] = find mdl.FeatureWeights > 0.01;
```

Plot the results

```
figure(2); clf reset;
plot(mdl.FeatureWeights,'ro');
hold on;
scatter(fi,mdl.FeatureWeights(fi),'MarkerFaceColor','b');
legend('Feature','Weight > 0.01');
xlabel('Feature Index');
ylabel('Feature Weight');
grid on;
title('FSRNCA: Feature Weights');
```



Approach 2: Use the Diagnostic Feature Designer App to generate condition indicators

TODO

Approach 3: Use a simple LSTM layer to predict the output of the z-axis displacement taking in the file ensemble datastore as input

```
% Training Data
XTrain = predictors_train';
YTrain = Zvals_train(:,2:end)';
% Testing Data
XTest = predictors_test';
YTest = Zvals_test(:,2:end)';

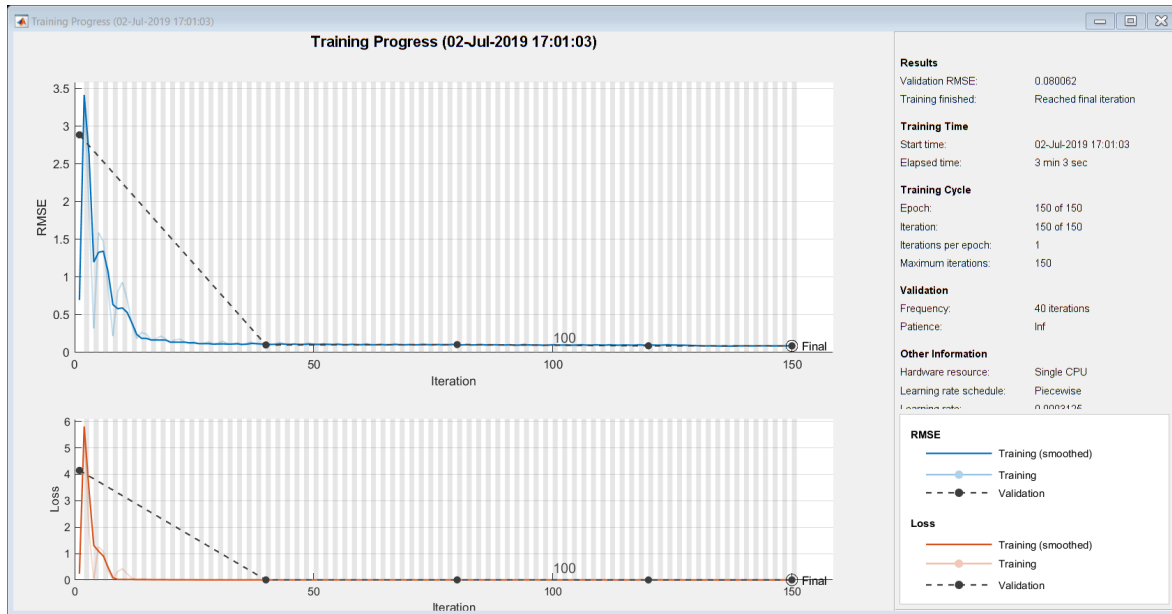
numFeatures = 52;
numHiddenUnits = 180;
numResponses = 1;

layers = [...
    sequenceInputLayer(numFeatures),...
    lstmLayer(numHiddenUnits,'OutputMode','sequence'),...
    fullyConnectedLayer(100),...
    dropoutLayer(0.4),...
    fullyConnectedLayer(numResponses),...
    regressionLayer;
];
options = trainingOptions('adam', ...
    'MaxEpochs',150, ...
    'GradientThreshold',1, ...
    'InitialLearnRate',0.0025, ...
    'LearnRateSchedule','piecewise', ...
    'LearnRateDropPeriod',125, ...
    'LearnRateDropFactor',0.125, ...
    'Verbose',0, ...
    "ValidationData",[XTest},{YTest}],...
    "ValidationFrequency",40,...
    'Plots','training-progress');
```

Designate the training and testing data and pre-train the model

Vary the training options to improve the performance, or try training the model for longer.

```
net = trainNetwork(XTrain, YTrain, layers, options);
```



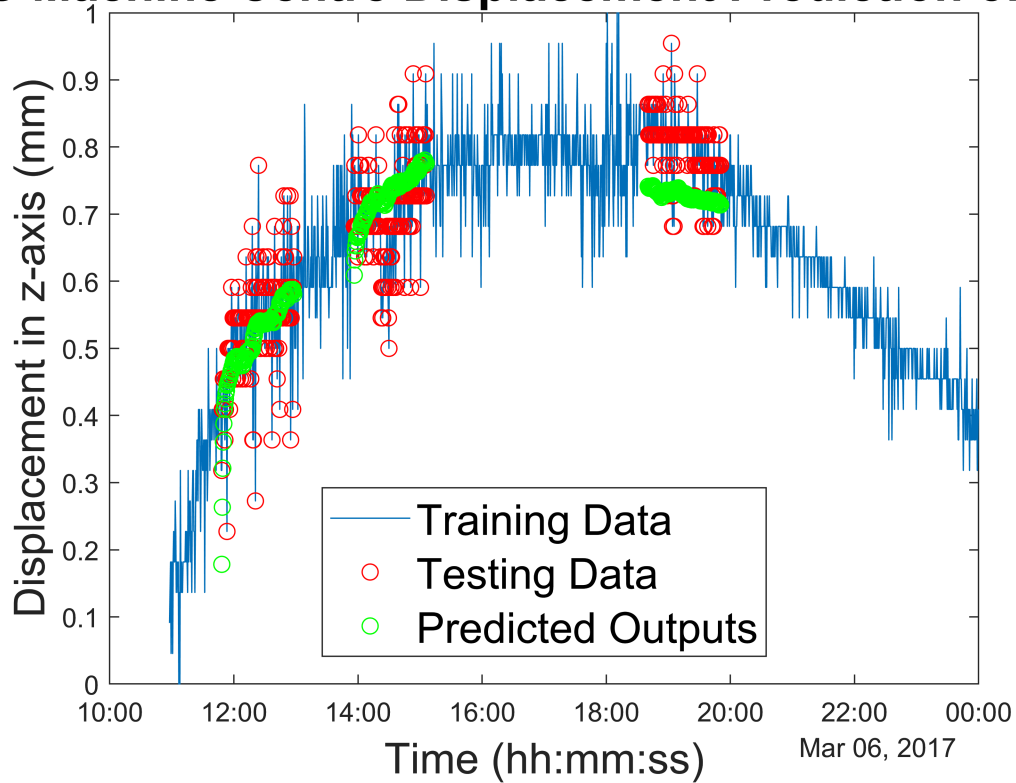
```
YPred = predict(net,XTest,'MiniBatchSize',1);
```

Plot the results

```
testData = [{t(testIndeces)}, {YTest}];
predData = [{t(testIndeces)}, {YPred}];

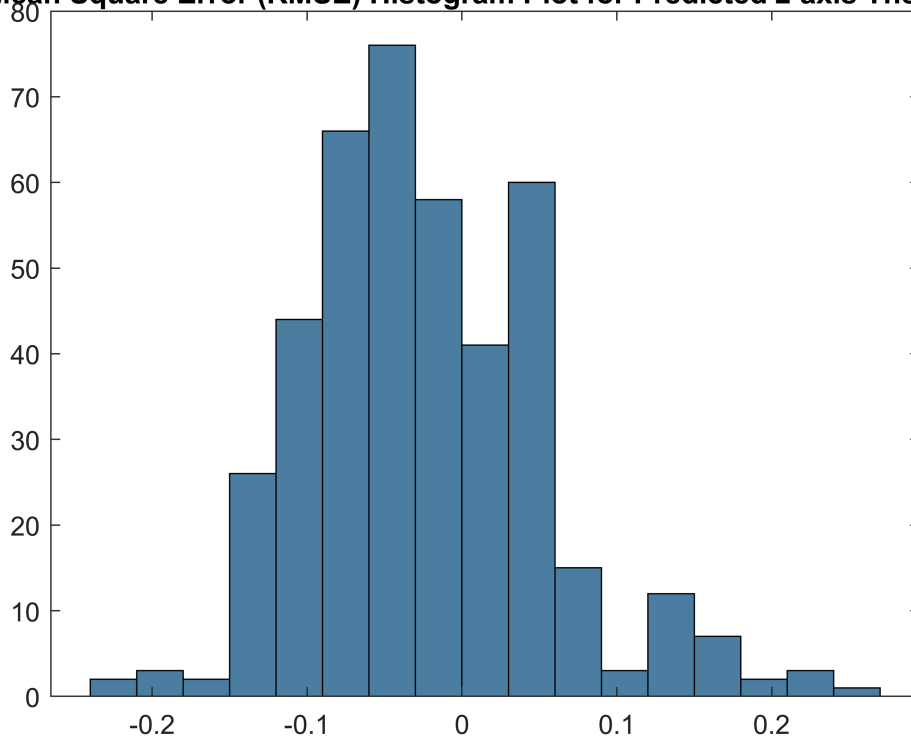
% Create a figure to show the prediction outputs
figure(4); clf reset;
plot(t,Zval(:,1));
hold on
scatter(testData(:,1),testData(:,2),'r');
scatter(predData(:,1),predData(:,2),'g');
hold off
legend('Training Data','Testing Data','Predicted Outputs','Location','Best','FontSize',16)
ylabel('Displacement in z-axis (mm)','FontSize',16);
xlabel('Time (hh:mm:ss)','FontSize',16);
title('LSTM z-axis CNC Machine Centre Displacement Prediction on 24-hour Sequence','FontSize',16);
```

IC Machine Centre Displacement Prediction on 24



```
% calculate RMSE and display it in the histogram for all
% predictions
RMSE = sqrt(mean(YPred - YTest.^2));
figure(4); clf reset;
h1 = histogram(YPred - YTest);
title('Root Mean Square Error (RMSE) Histogram Plot for Predicted z-axis Thermal Error');
```


Root Mean Square Error (RMSE) Histogram Plot for Predicted z-axis Thermal Err



```
acc_t = [0.10 0.20];  
errors = abs(YPred - YTest);  
% accuracy of estimation error magnitude  
numCorrect_1 = errors(errors < acc_t(1));  
numCorrect_2 = errors(errors < acc_t(2));  
acc_10 = size(numCorrect_1,2)/size(YPred,2)
```

```
acc_10 = 0.8385
```

```
acc_20 = size(numCorrect_2,2)/size(YPred,2)
```

```
acc_20 = 0.9857
```

Approach 3b: Use only the features identified from FSRNCA implementation

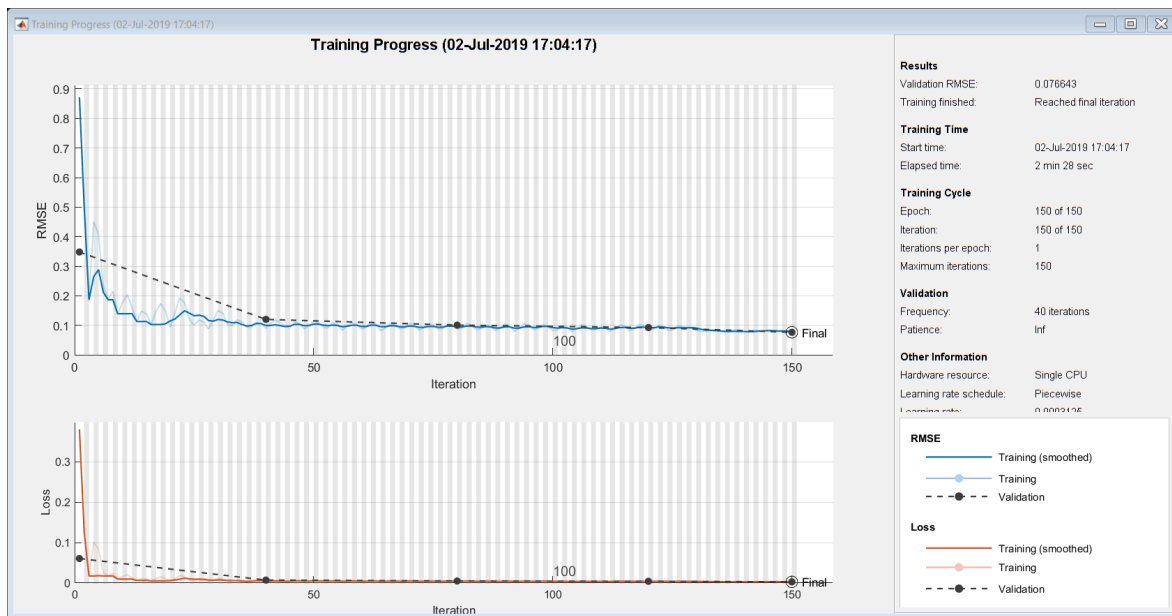
```
% Training Data  
fsrnca_features = fi;  
XTrain_fsrnca = predictors_train(:,fsrnca_features)';  
YTrain = Zvals_train(:,2:end)';  
% Testing Data  
XTest_fsrnca = predictors_test(:,fsrnca_features)';  
YTest_fsrnca = Zvals_test(:,2:end)';  
  
numFeatures_fsrnca = size(fi,1);  
numHiddenUnits = 180;  
numResponses = 1;
```

```

layers = [...
    sequenceInputLayer(numFeatures_fsrnca),...
    lstmLayer(numHiddenUnits,'OutputMode','sequence'),...
    fullyConnectedLayer(100),...
    dropoutLayer(0.4),...
    fullyConnectedLayer(numResponses),...
    regressionLayer;
];
options = trainingOptions('adam', ...
    'MaxEpochs',150, ...
    'GradientThreshold',1, ...
    'InitialLearnRate',0.0025, ...
    'LearnRateSchedule','piecewise', ...
    'LearnRateDropPeriod',125, ...
    'LearnRateDropFactor',0.125, ...
    'Verbose',0, ...
    "ValidationData",[XTest_fsrnca},{YTest}],...
    "ValidationFrequency",40,...
    'Plots','training-progress');

net2 = trainNetwork(XTrain_fsrnca, YTrain, layers, options);

```



```

YPred_fsrnca = predict(net2,XTest_fsrnca,'MiniBatchSize',1);

```

Plot the results

```

testData_fsrnca = [{t(testIndeces)},{YTest}];
predData_fsrnca = [{t(testIndeces)},{YPred_fsrnca}];

% Create a figure to show the prediction outputs
figure(5); clf reset;
plot(t,Zval(:,1));

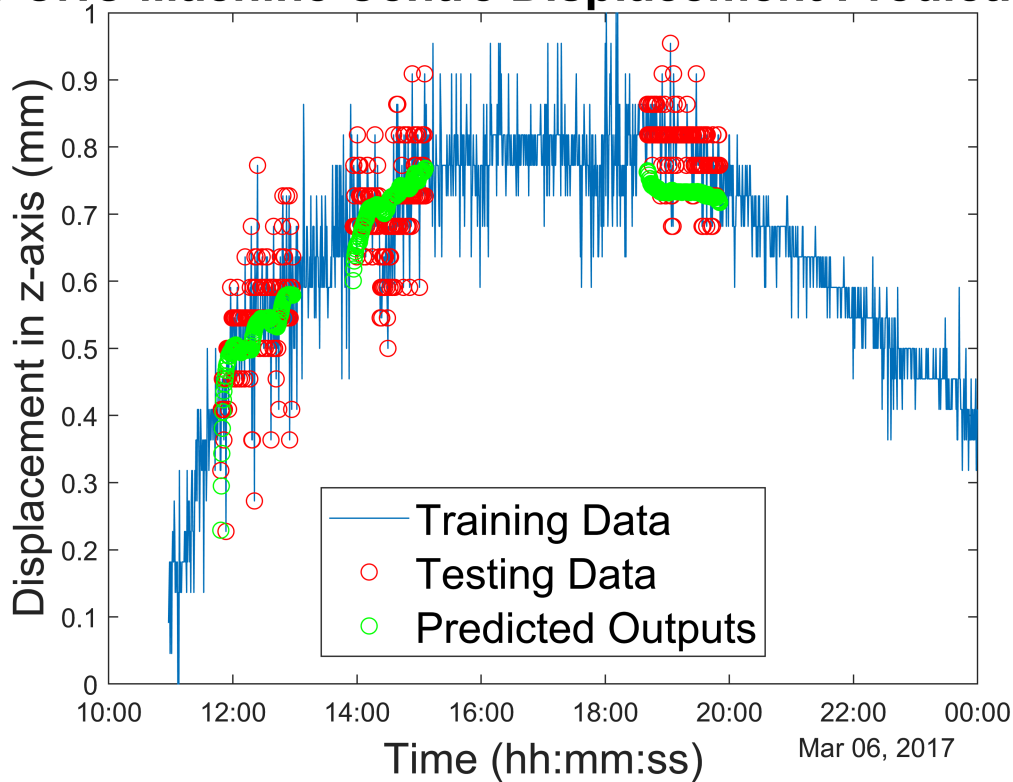
```

```

hold on
scatter(testData_fsrnca{:,1},testData_fsrnca{:,2},'r');
scatter(predData_fsrnca{:,1},predData_fsrnca{:,2},'g');
hold off
legend('Training Data','Testing Data','Predicted Outputs','Location','Best','FontSize',16)
ylabel('Displacement in z-axis (mm)','FontSize',16);
xlabel('Time (hh:mm:ss)','FontSize',16);
title('FSRNCA-LSTM z-axis CNC Machine Centre Displacement Prediction on 24-hour Sequence','Font

```

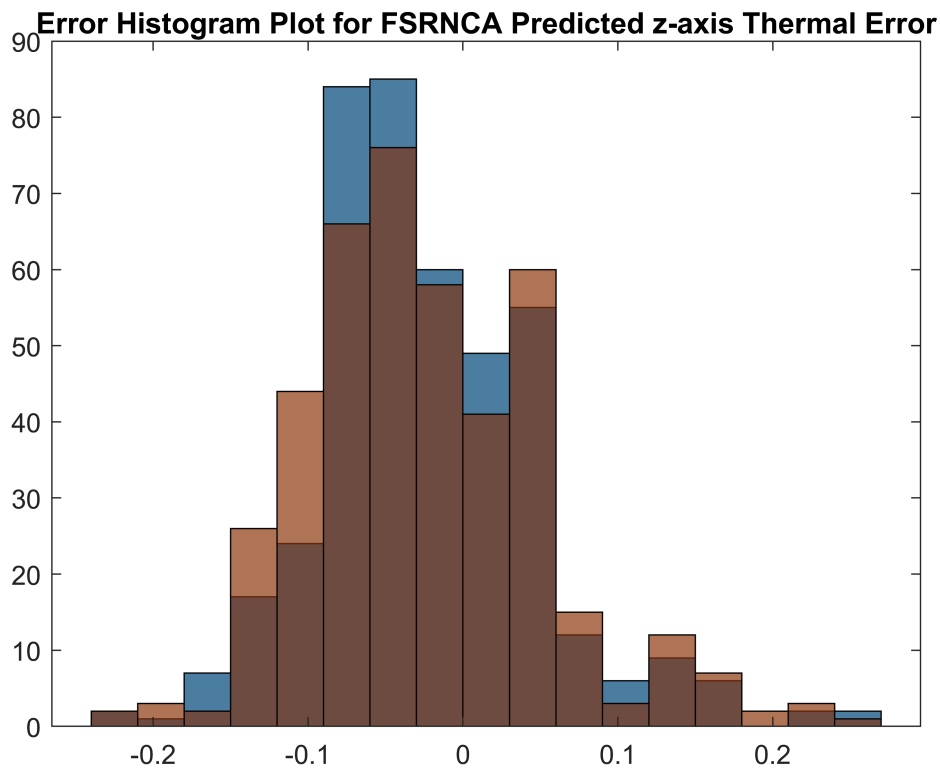
is CNC Machine Centre Displacement Prediction



```

% calculate RMSE and display it in the histogram for all
% predictions
RMSE = sqrt(mean(YPred_fsrnca - YTest_fsrnca.^2));
figure(6); clf reset;
h1 = histogram(YPred_fsrnca - YTest_fsrnca);
hold on;
h2 = histogram(YPred - YTest);
title('Error Histogram Plot for FSRNCA Predicted z-axis Thermal Error');

```



```
acc_t = [0.10 0.20];
errors_fsrnca = abs(YPred_fsrnca - YTest_fsrnca);
% accuracy of estimation error magnitude
numCorrect_1_fsrnca = errors_fsrnca(errors_fsrnca < acc_t(1));
numCorrect_2_fsrnca = errors_fsrnca(errors_fsrnca < acc_t(2));
acc_10_fsrnca = size(numCorrect_1_fsrnca,2)/size(YPred_fsrnca,2)
```

```
acc_10_fsrnca = 0.8480
```

```
acc_20_fsrnca = size(numCorrect_2_fsrnca,2)/size(YPred_fsrnca,2)
```

```
acc_20_fsrnca = 0.9857
```

As observed, we can increase the validation accuracy by 0.95% when using FSRNCA. Tuning this quantity further could help us further improve the prediction performance.