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Submission date: 16-Sep-2020 11:26AM (UTC+0530)

Submission ID: 1388357172

File name: Control_Chart_Patterns_Recognition_Using_CNN_Final_Report.pdf (1.64M)

Word count: 4997

Character count: 25991

Control Chart Patterns Recognition Using Convolutional Neural Network

Summer Internship

Report by

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1.Introduction

Product quality is a key factor in the market competition of enterprises. Statistical process control (SPC) has brought significant improvements to the production quality of many enterprises, covering the industries of machining, chemical, electronic, etc. The fundamental idea of SPC is to use mathematical statistics methods to monitor various stages of production process, so the production anomalies can be detected timely and measures can be implemented to eliminate potential hazards.However, recognition of unnatural patterns is a critical task in statistical process control (SPC)

The primary objective of process quality control is to achieve and maintain an acceptable level of the desired process quality characteristic consistently. In this connection, accurate monitoring and control of the manufacturing system is very important.In order to manufacture products with the desired quality, production processes need to be monitored for any unnatural deviation in the state of the process and Control chart is important statistical process control tools for determining whether a process is running in its intended mode or in presence of unnatural patterns. The patterns displayed on the control charts can provide important information about the process and thus recognition and analyzation of CCPs is helpful to identify quality failures and find root abnormal causes in time.Control charts predominantly in the form of X chart are widely used to identify situations when control actions will be needed for the manufacturing systems.

The 8 basic patterns are normal (NOR), cyclic (CYC), systematic (SYS), stratification (STA), uptrend (UT), downtrend (DT), upward shift (US), and downward shift (DS)

1. **Normal Pattern(NOR)**: The normal pattern indicates the production process in-control.

2. **Systematics Pattern(SYS)**: The systematic pattern appears as a high point always follows a low point and vice-versa. So the point-to-point fluctuations can be predicted.

3.**Stratification Pattern(STR)**: This shows that the data is more concentrated and variance of data becomes smaller.

4. **Cyclic pattern**: Periodic occurrence of peaks and troughs can be found in cyclic pattern.

5. **Trend pattern**: In trend patterns, the data shows a continuous rise or fall, named upward trend and downward trend respectively.

6. **Shift pattern**: The shift patterns appear as a sudden rise or fall in the mean of data, named upward shift and downward shift respectively.

The patterns can be classified as natural/normal and unnatural/abnormal. The basic significance of a natural pattern is that it indicates a process under control. An unnatural pattern identifies a process when it is out of control.The abnormal CCPs in the production process usually correspond to some specific causes. Hence, the recognition of abnormal patterns can not only help to find the problems in time, but also narrow the scope of abnormal causes.

In the early period of control chart applications, human experience is required to judge whether the production process is abnormal and find the corresponding cause. With the development of industrial automation, the rule-based discriminant system partially replaces the role of manual observation. The discriminant rules of control charts are based on small probability events and can be easily implemented. However, it is difficult to cover all abnormal patterns with rules due to the complexity of the production process.An efficient automated control chart pattern (CCP) recognition system can compensate this gap and ensure consistent and unbiased interpretation of CCPs leading to lesser number of false alarms and easier implementation of control charts.

The advantage with neural networks is that it does not require the provision of explicit rules or templates. Rather, it learns to recognize patterns directly through typical example patterns during a training phase. A neural network also has the ability to identify an arbitrary pattern not previously encountered. However, there is no guarantee that it will identify such patterns correctly. One disadvantage with neural networks is that the information it contains is implicit and virtually inaccessible to the user.

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2. Literature Review

Many methods have been applied to the recognition of CCPs. Some methods directly feed the raw CCPs data into the recognition model, while others first use statistical knowledge to extract features from raw data, such as mean square amplitude, standard deviation, peak, average, etc. Then these extracted features are fed into the model.

Pham et al. (1997) propose that different CCPs have different geometric characteristics, so it is helpful to improve CCPs recognition accuracy by constructing features. However, there are lots of different features that can be constructed, making it a challenge to select the appropriate feature subset so as to reduce the computational complexity and improve the classification accuracy of the model. Gauri et al. (2007) have applied classification and regression tree (CART) to select feature subset. Addeh et al. (2018) apply the association rules (AR) to select the best feature subset. But some of the features selected by these methods are still highly correlated, leading to redundancy. Thus, some dimension reduction methods such as independent component analysis (ICA) (Lu et al., 2011) and principal component analysis (PCA) (Tai-Fu et al., 2012) are used to reduce redundancy between features. After determining the input form of data, whether it is raw data or extracted feature data, a model will be built to realize accurate recognition of different CCPs. Some classical methods such as fuzzy inference systems (FIS), support vector machines (SVM), artificial neural networks (ANN) have been applied in CCPs recognition systems.

Gulbay et al. (2007) propose a fuzzy method for recognition of unnatural CCPs. Zaman et al. (2018) combine the fuzzy c mean (FCM) with adaptive neuro-fuzzy inference system (ANFIS) to realize the CCPs recognition and get comparable classification accuracy. Ebrahimzadeh et al. (2011) apply SVM method to CCPs recognition for its excellent generalization performance. However, it is difficult to select appropriate parameters for SVM. Therefore, some optimization algorithms such as genetic algorithms (GA) (Zhao et al., 2017) and particle swarm optimization (PSO) (Yongman et al., 2013) are used to automatically optimize the parameters of SVM models. In addition, many studies have introduced ANN into the CCPs recognition. Cheng et al. (1997) construct a modular neural network using a multilayer perceptron (MLP) trained by back-propagation (BP) algorithm and realize the recognition of two kinds of CCPs. The CCPs recognition module designed by Ghomi et al. (2011) combines two types of neural network, one is learning vector quantization (LVQ) and another is MLP. Considering the continuity of control chart data over time, Awadalla et al. (2012) apply the spiking neural network (SNN) to the CCPs recognition.

Based on existing research, it can be found that the CCPs recognition method based on feature extraction usually has better performance. But the construction of features depends on human experience, thus, feature screening methods are needed to select the best feature subset.

Deep learning has been extensively studied for its outstanding performance. Deep learning establishes a mapping from inputs to outputs by a network structure (Zhang et al., 2018). As a multi-level representation learning method, the deep learning model is composed by simple but non-linear modules of which can transform a lower level representation to a higher and slightly more abstract level representation (Lecun et al., 2015). The structure of deep learning makes it automatically extract features from raw data. There are many typical deep learning methods such as deep belief network (DBN), deep neural network (DNN), convolutional neural network (CNN), recurrent neural network (RNN) and etc. CNN is a classical deep learning model and has been applied in many fields, such as image recognition.

In recent years, CNN has been used to recognize one dimensional (1D) signals. Kiranyaz et al. (2016) apply the 1D-CNN to the real-time classification of patient-specific electrocardiogram (ECG). Malek et al. (2017) propose a new method to analyze the chemometric data based on 1D-CNN. The literature above shows that CNN can extract features from raw data and has great advantages in the processing of complex classification.

3. Objective

The objective of our project is to recognize the Unnatural Control Chart Patterns that occur on statistical quality Control charts to detect the unnatural deviation in state of process as well as to identify quality failure and root abnormal cause in time.

4. Methodology

We have divided the methodology in two parts i.e; data preparation using data simulation and Feature extraction using Deep neural networks.

1) Data Preparation using Monte carlo simulation

Data simulation is one of the widely used techniques for control chart pattern recognitions. It is the process to generate thousands of random samples following a particular distribution using original data. In this project we have used raw eye tracking datasets and obtained its distribution, mean and variances to generate data of various patterns.

➢ Monte Carlo Simulation

In this project We have used Monte Carlo simulation of Data simulation on eye tracking datasets and its obtained the mean and variances and generate data of various patterns by changing various parameters as shown in the Table1 :

Table1: Parameters and formulas of Data simulation

class	Description	equations	Remarks
0	Normal, NOR	$y_t = \mu + r(t) \times \delta$	$\mu = 0,\ \sigma = 1$
1	Cyclic, CYC	$y_t = \mu + r(t) \times \delta + a \times sin(2/T)$	$r(t) \sim N(0, 1)$
2	Systematic, SYS	$y_t = \mu + r(t) \times \delta + d \times (-1)^t$	$\delta = 1\sigma$
3	Stratification, STR	$y_t = \mu + r(t) \times \delta'$	$\delta' \in (0.2\sigma, 0.4\sigma)$
4	Upward Trend, UT	$y_t = \mu + r(t) \times \delta + t \times g$	$d \in (1\sigma, 3\sigma)$
5	Downward Trend, DT	$y_t = \mu + r(t) \times \delta - t \times g$	$a \in (1.5\sigma, 2.5\sigma)$
6	Upward shift, US	$y_t = \mu + r(t) \times \delta + k \times s$ $k = 1\ if\ t \geq P, else = 0$	$T = 16$ $g \in (0.005\sigma, 0.25\sigma)$
7	Downward Shift, DS	$yt = \mu + r(t) \times \delta - k \times s$ $k = 1\ if\ t \geq P, else = 0$	$P \in (10, 20)$ $s \in (1\sigma, 3\sigma)$ $t = 1, 2, 3, ...L$

- μ and σ are the mean and standard deviation estimate of the controlled production process
- $r(t)$ represents the inevitable accidental fluctuation which is subject to gaussian distribution $N(0,1)$.
- d indicates the degree of system state departure.
- a is the amplitude of cyclic pattern.
- T is the period of the cycle.
- g is the gradient of a data trend.
- P represents the time point when the shift anomaly occurs.
- s is the amplitude of the shift pattern.

The sequence length of simulation data 'L' should not be too long, because longer window width data means larger lag of anomaly recognition. Generally window length is set to "16-64" sampling points.

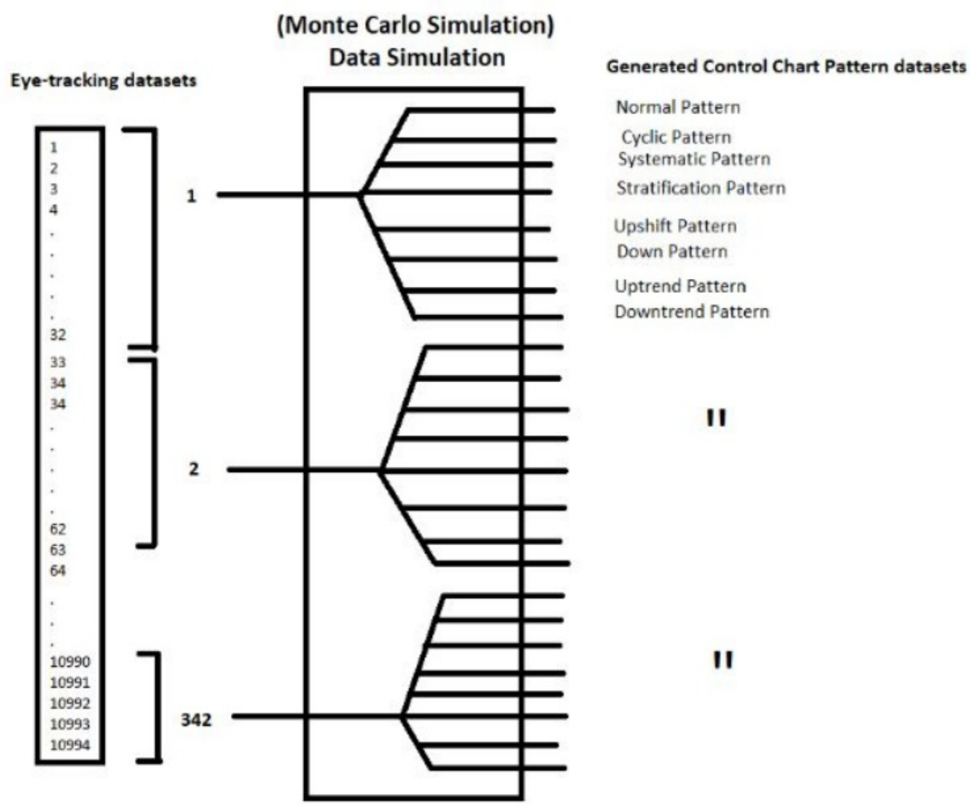
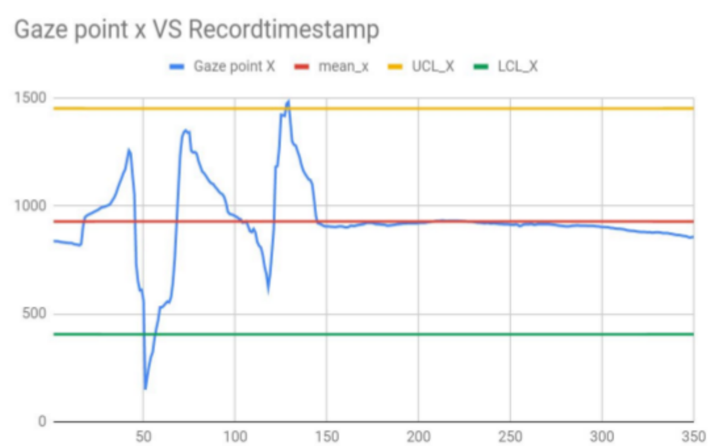


Figure1: Flowchart for Monte carlo simulation

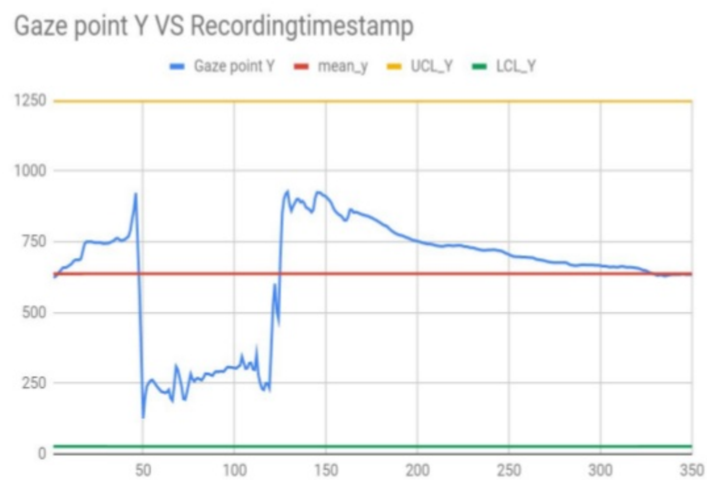
1. For the given sample of eye tracking gaze point datasets shown in the table2, we have done Data Simulation using monte carlo simulation on approx 10,944 raw eye gaze points data and prepared 8 different control chart pattern datasets with window length of 32 sampling points i.e; we make 342 datasets from 10944(342*32) data having 32 sampling points each.
2. For that first dataset we took the first 32 sampling points and generated 8 different patterns datasets using monte carlo simulation of the same window length of 32 sampling points.
3. Similarly we have done for next dataset having 32 sample length, and like that from 10944 (342*32) eye tracking data we have prepared 342 pieces for each 8 control chart patterns having sample length of 32.
4. We have written code in python using pandas and numpy for monte carlo simulation.

Visualization of raw eye tracking datasets

I. Gaze point X VS Recording timestamp

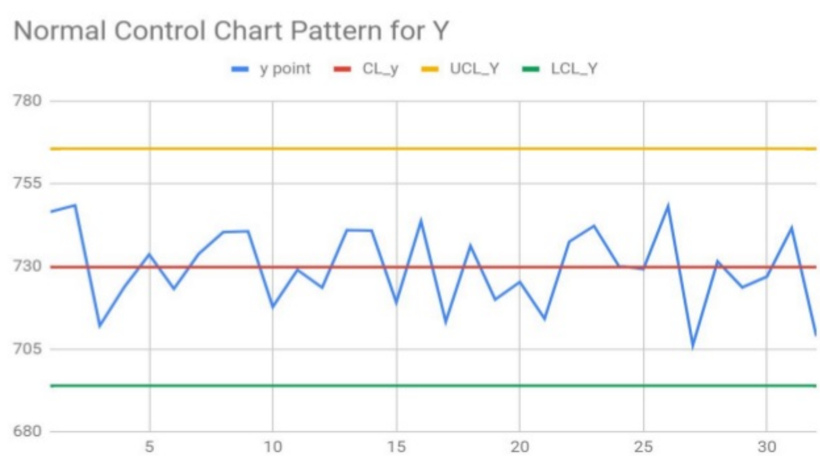


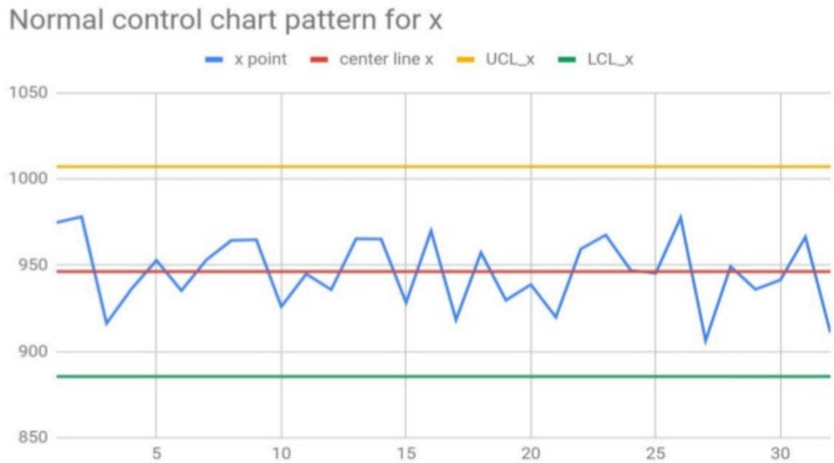
II. Gaze point Y VS Recording timestamp



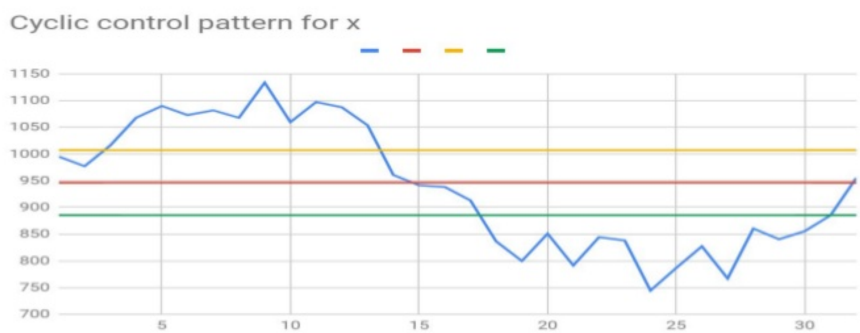
Visualization of Generated data of control chart patterns

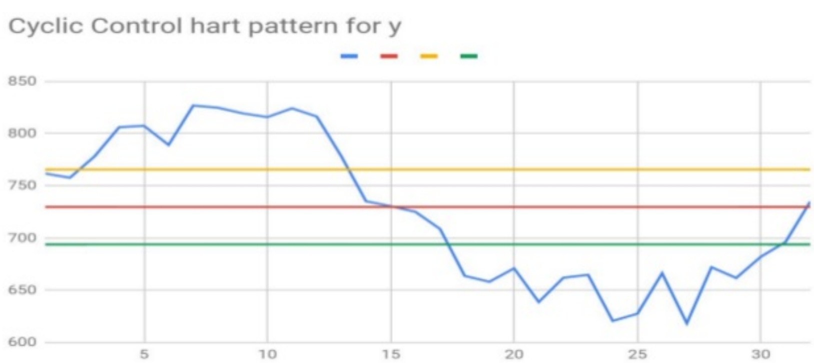
I. Normal Pattern



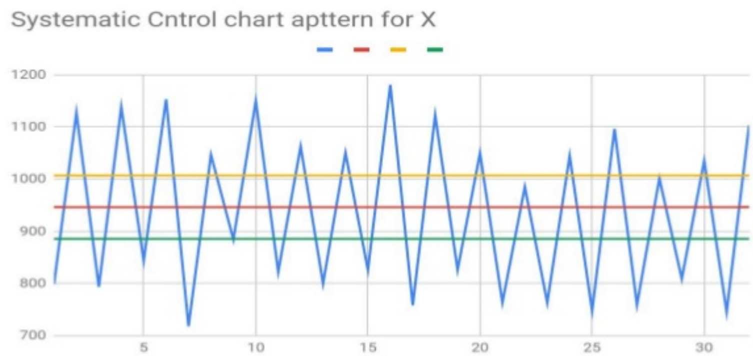


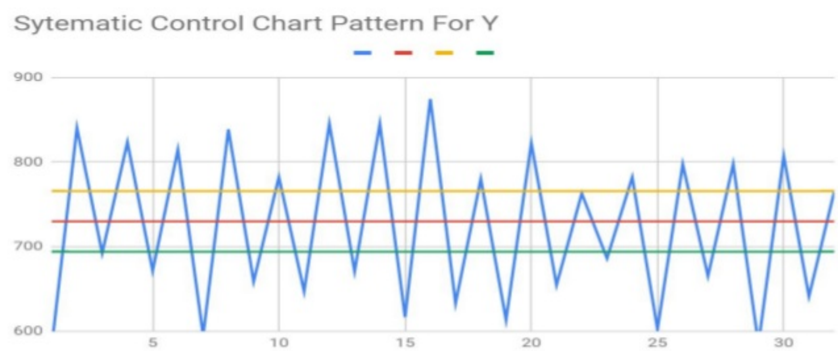
II. Cyclic pattern



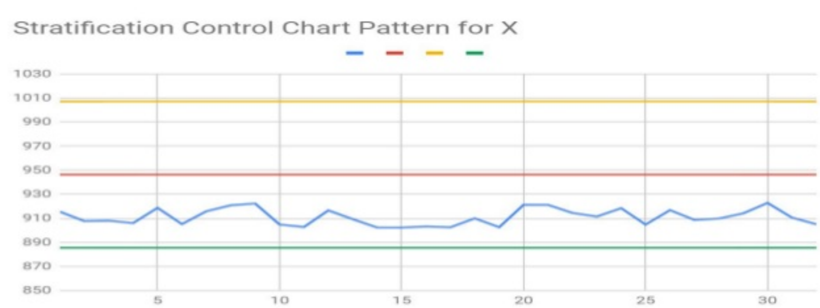


III. Systematic pattern

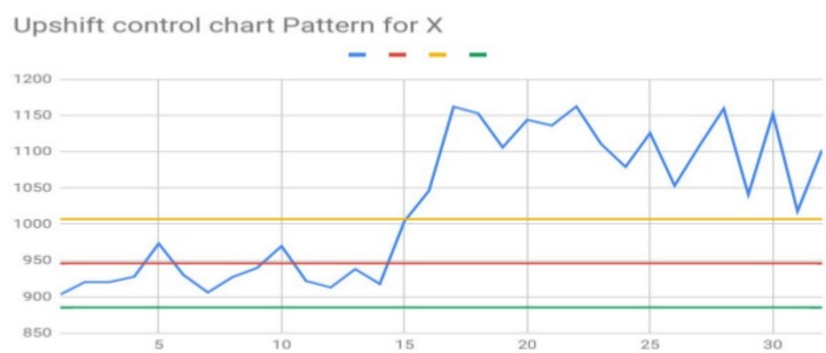


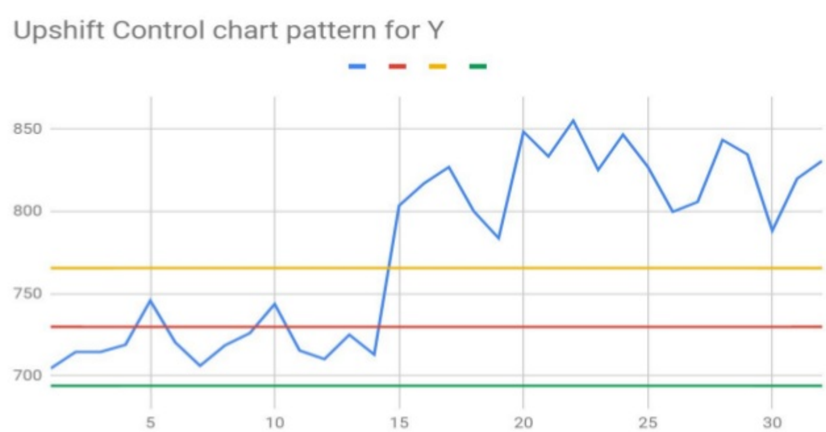


IV. Stratification pattern

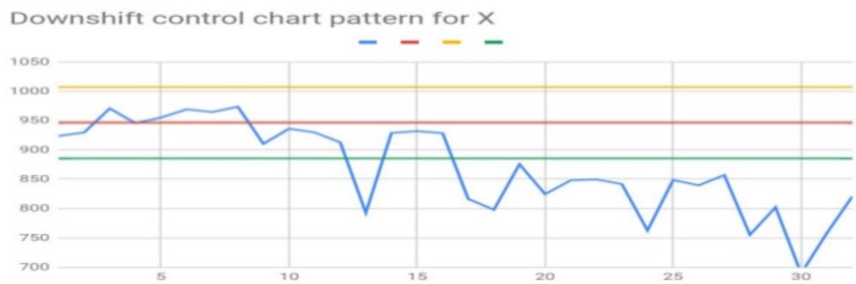


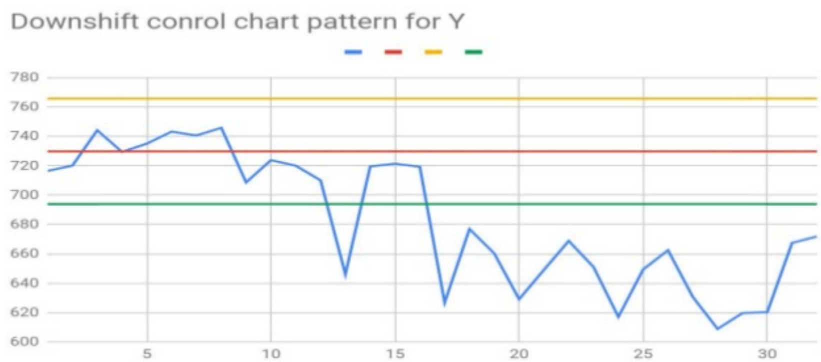
V. Upshift pattern



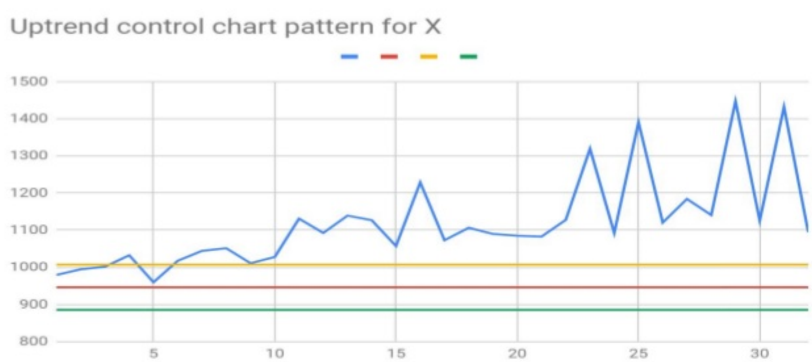


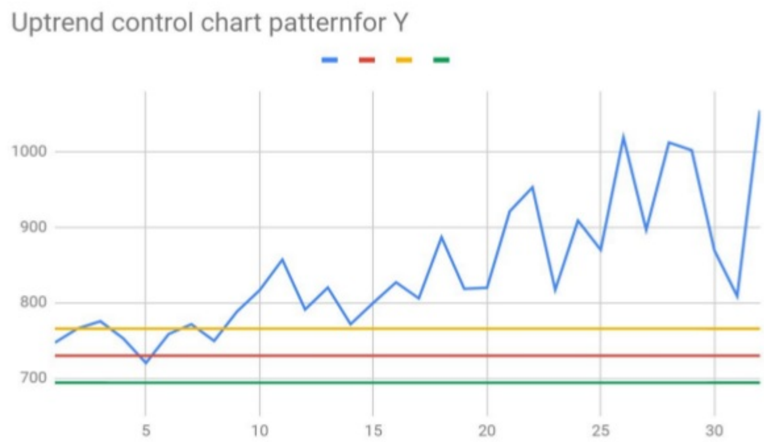
VI. Downshift pattern



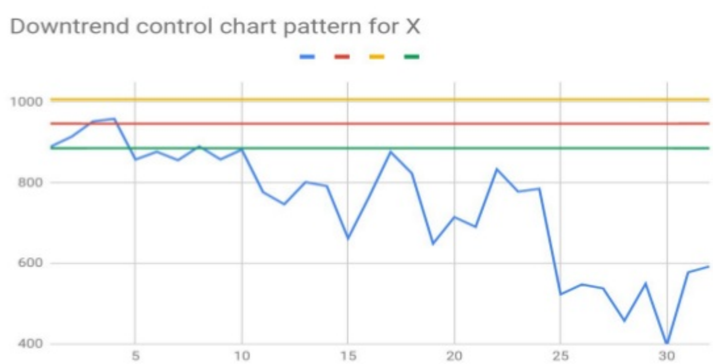


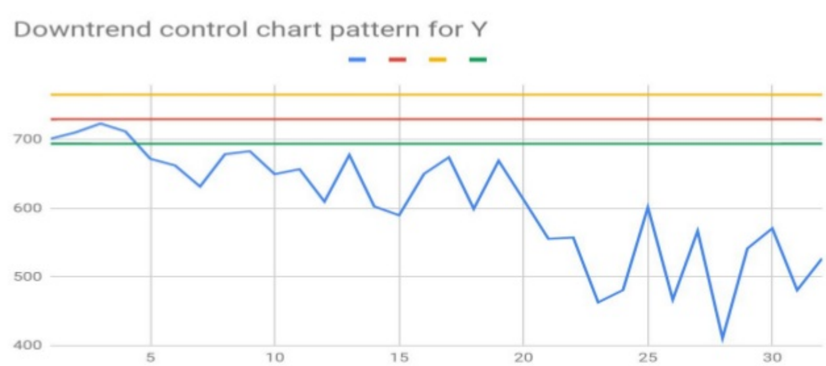
VII. Uptrend pattern





VIII. Downtrend pattern





2) Features extraction using Deep neural Networks

Feature extraction is the second step after data generation for different patterns using monte carlo simulation. We have used various neural networks and 1 dimensional convolutional neural networks to extract the feature from the generated data for different patterns.

How Convolutional neural networks work ?

The structure of CNN can be divided into two parts, The first part is composed of convolutional layers and pooling layers to realize feature extraction, and the second part is composed of fully connected(dense) layers for final classification.

- The convolutional layers: Extract features from the input
- The fully connected(dense) layers: Uses data from convolutional layer to generate output

There are two important processes involved in the training of any neural network:

I. **Forward propagation**: Receive input data, process the information, and generate output
II. **Backward propagation**: Calculate error and update the parameters of the network.

Forward Propagation

A. Forward Propagation: Convolutional layer

Each convolutional layer contains several filters to extract local features from the feature maps of the previous layer, respectively, and followed by an **activation function** to generate the output feature maps. There are various types of activation functions, few of them are sigmoid function, Tanh function, ReLU function, Leaky ReLU, Softmax.

I have used mainly ReLU activation functions on hidden layers and Softmax activation function of output layer.

The main advantage of using ReLU function over other activation functions is that it does not activate all the neurons at the same time. This means that the neurons will only be deactivated if the output of the linear transformation is less than 0.

$$f(x) = max(0, x)$$

The weights of filters to calculate each unit of a feature map are the same, which is called weight sharing. The depth of feature maps is determined by the number of filters. The performance of CNN is affected by the size and number of filters per layer.

The pooling layer is usually set after the convolutional layer, which is used to reduce the size of extracted feature maps. Max pooling and average pooling are two most widely used pooling methods.

Max Pooling- Max pooling is used to reduce the image size by mapping the size of a given window into a single result by taking the maximum value of the elements in the window.

Average Pooling**-** It's the same as max-pooling except that it averages the windows instead of picking the maximum value.

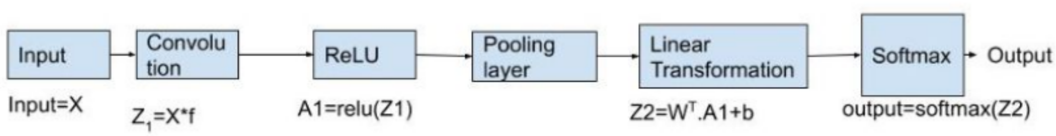


Figure2: Computation Graph for Forward Propagation

Step-1 If we have an input data represented as X and a filter represented with f then our generated data is convolved with the filter and expression would be:

$$Z1 = X * f$$

Step-2 Apply ReLU activation function on extracted local feature maps matrix (Z_1).

$$A1 = ReLU(Z_1)$$

Step-3 Set Pooling Layer (we have used Max pooling layer) after convolutional layer.

B. Forward Propagation: Fully connected layer

Convolutional layer has extracted some valuable features from the data. After step-3, These features are sent to the fully connected layer that generates the final results. The output from the convolutional layer is a 2D matrix then the values generated from the convolutional layer are first converted into a 1D format, once the data is converted into 1D array, it is sent to the fully connected layer. All of these individual values are treated as separated features.

Fully connected layer performs two operations on the incoming data - a linear transformation and a non-linear transformation.

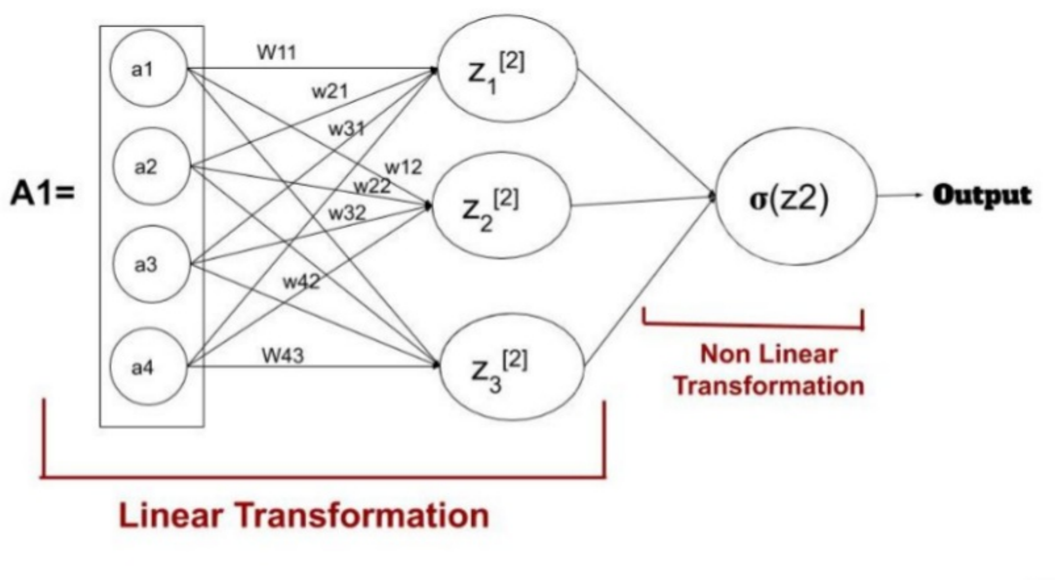


Figure3: Linear transformation and nonlinear transformation in fully connected layer

Step-4 defines (randomly initialize) weight and bias matrix and applies linear transformation on the values

$$A1 = \begin{bmatrix} a1 \\ a2 \\ a3 \\ . \\ . \\ an \end{bmatrix} \qquad W = \begin{bmatrix} W11 & W12 & . & . & . & W1m \\ W21 & W22 & . & . & . & W2m \\ W31 & W32 & . & . & . & W3m \\ W41 & W42 & . & . & . & W4m \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ Wn1 & Wn2 & . & . & . & Wnm \end{bmatrix} \qquad b = \begin{bmatrix} b1 \\ b2 \\ b3 \\ . \\ . \\ bm \end{bmatrix}$$

The equation for linear transformation is:

$$Z2 = W^T . A1 + b$$

Here, A1 is the extracted local feature map obtained from step-3, W is weight, and b(called bias) is a constant.

Step5-Apply softmax activation function on Z_2.

Now there is one final step in the forward propagation process - the non linear transformation.

The linear transformation alone cannot capture complex relationships. Thus, we introduce an additional component in the network which adds non-linearity to the data which is called the activation function. We have used the Softmax activation function in the output layer.

Softmax function is described as a combination of multiple sigmoids. Sigmoid function returns value between 0 and 1, which can be treated as probabilities of a data point belonging to a particular class. Thus sigmoid is widely used binary class problems. The softmax function can be used for multiclass classification problems. This function returns the probability for a data point belonging to each individual class.

$$softmax = \sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \quad \text{for } j = 1 ....., K$$

Applying softmax activation function, This will be our final output

$$O = softmax(z2)$$

Backward Propagation

During the forward propagation process, we randomly initialized the weights, biases and filters. These values are treated as parameters from convolutional neural network algorithms.In the backward propagation process, the model tyries to update the parameters such that the overall predictions are more accurate.

For updating these parameters, we use gradient descent techniques which tries to find the value of parameters at which loss is minimum. The generic equation for updating the parameter values:

new_parameter=old_parameter-(learning_rate*gradient_of_parameter)

The learning rate is a constant that controls the amount of change being made to old value and slope or the gradient to determine whether the values should increase or decrease. So we need to find the gradient, that is, change in error with respect to the parameters in order to update the values. The computational graph of backward propagation is shown in the figure below:

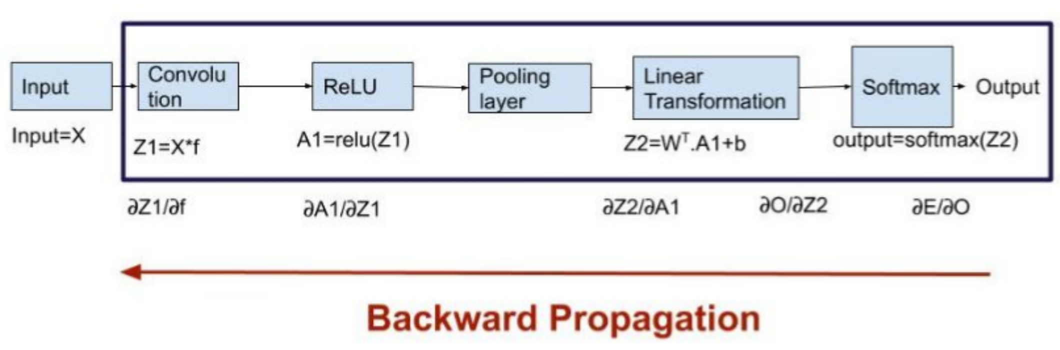


Figure4: Computation graph for Backward Propagation

Backward propagation: Fully Connected Layer

The fully connected layer has two parameters - weight matrix and bias matrix.

$$E/W = E/O \; . \; O/Z_2 \; . \; Z_2/W$$

Where

E/O = change in error with resp[ect to output

O/Z_2 = change in output with respect to Z_2

Z_2/W = change in Z_2 with respect to W(weights)

The shape of E/W will be the same as the weight matrix W. Now we update the weight matrix using following equation:

$$W_{new} = W_{old} - lr * E/W$$

Similarly we will update bias using following equation:

$$b_{new} = b_{old} - lr * E/b$$

Backward Propagation: Convolution layer

For the convolution layer, we had the filter matrix as our parameter. During the forward propagation process, we randomly initialize the filter matrix. We will update these values using the following equation:

new_parameter=old_parameter-(learning_rate*gradient_of_parameter)

To update the filter matrix, we need to find the gradient of the parameter dE/df. Here is the computational graph for backward p[ropagation:

From the above graph we can find the derivative E/f as :

$$E/f = E/O.O/Z_2.Z_2/A_1 .A_1/Z_1.Z_1/f$$

Where

Z_2/A_1 = change in Z_2 with respect to A_1

A_1/Z_1 = change in A_1 with respect to Z_1

Z_1/f = change in Z_1 with respect to f

Now after finding the value of E/f, we will use this value to update the original filter value:

$$f = f - lr * (E/f)$$

In this project we have generated 342 pieces for each pattern using Data Simulation techniques, 300 of which were used for training the 5 different neural network models and 42 for testing the models.

- Training Data- (300*32*2), label-(nor,cyc,sys,str,us,ds,ut,dt)
- Test Data- (42*32*2), label-(nor,cyc,sys,str,us,ds,ut,dt)
- label-(nor,cyc,sys,str,us,ds,ut,dt)-encode-(0,1,2,3,4,5,6,7)

We have used Five different neural networks for recognition of our control chart patterns and applied a keras tuner to find the optimized number of units and filter size and trained each model for around 250 epochs.

1. Artificial neural network
2. 1 layer 1-D CNN
3. 2 layer 1-D CNN
4. 3 layer 1-D CNN
5. Improved 1-D CNN (having inception layer)

The architecture and structure of each neural network used for control chart patterns recognition is shown in the table2 below :

Layer	**ANN**	**1L 1-D CNN**	**2L 1-D CNN**	**3L 1-D CNN**	**Improved 1-D CNN**
Input Layer	32*2	32*2	32*2	32*2	32*2
layer1	Flatten	Conv1D(1*3,112)	Conv1D((1*10,128)	Conv1D((1*3,80)	conv1D (1*10,16),(1*10,32), (1*10,64)
layer2	Dense(448)	Max Pooling (pool_size=2)	Max Pooling (pool_size=2	Max Pooling pool_size=2	Concatenate
layer3	Dense(448)	flatten	(1*10,128)	(1*3,112)	(1*10,32)
layer4	--------------	Dense(80)	Max Pooling (pool_size=2	Max Pooling (pool_size=2)	Max Pooling pool_size=2
layer5	--------------	Dense(8)	flatten	(1*3,64)	(1*10,112)
layer5	--------------	-------------	Dense(80)	Max Pooling (pool_size=2	Max Pooling pool_size=2
layer6	---------------	----------------	Dense(8)	flatten	flatten
layer7	----------------	----------------	------------------	Dense(48)	Dense(80)
layer8	------------------	-----------------	----------------	Dense(8)	Dense(8)

In this project along with ANN and single or multi layer 1 dimensional ANN, we have also used a special type of CNN model called **Improved 1 dimensional CNN** which has a special layer called Inception layer as a layer1 which is a parallel combination of three layers of filter size (1*10) and 16, 32, 62 filters. The main advantages of having an inception layer is It allows the internal layers to pick and choose which filter size will be relevant to learn the required information. The architecture of Improved one dimensional CNN is shown in the figure5 below.

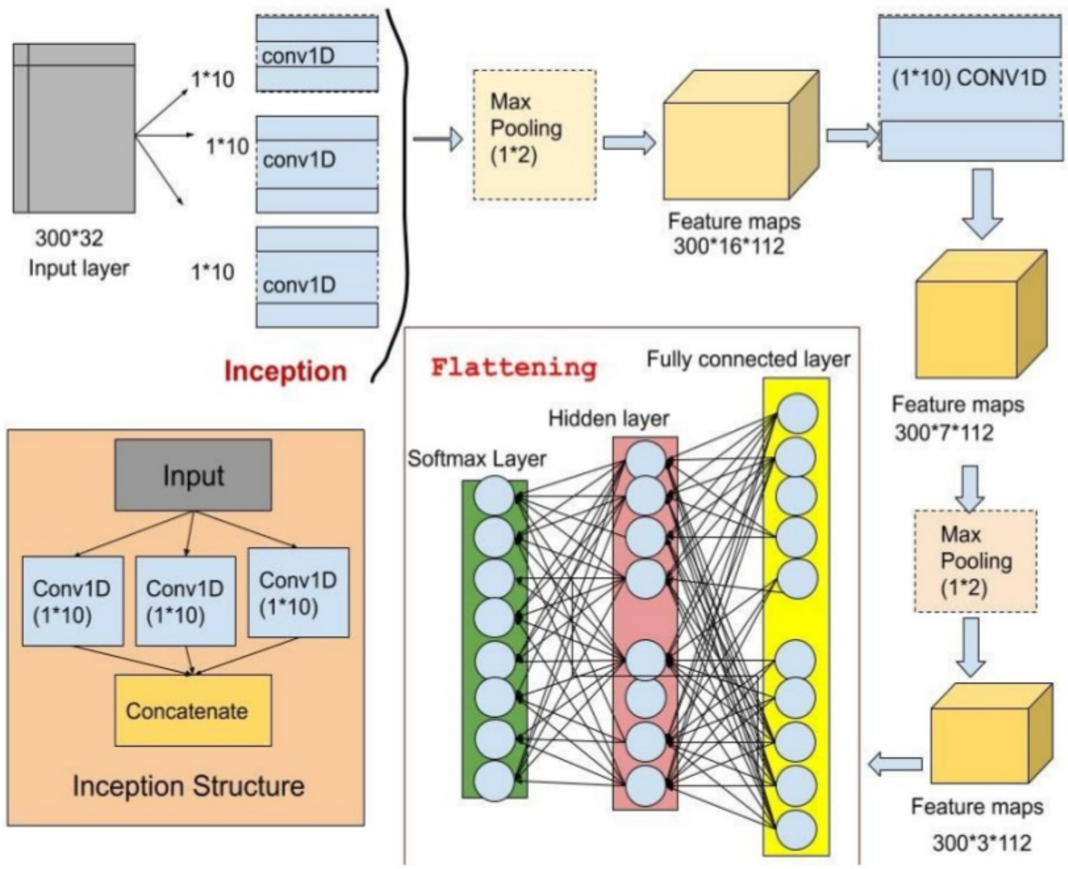
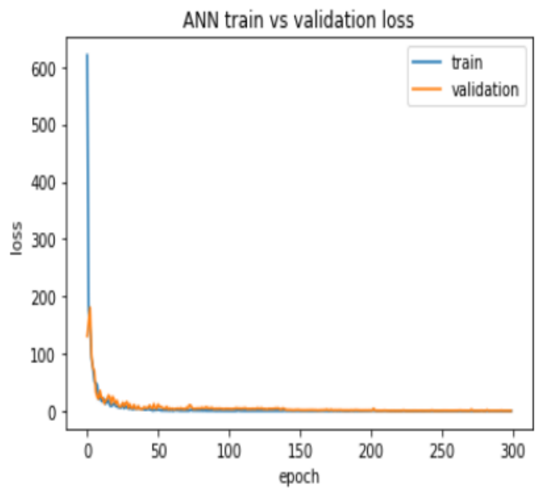


Figure5: Architecture of Improved one dimensional convolutional neural network

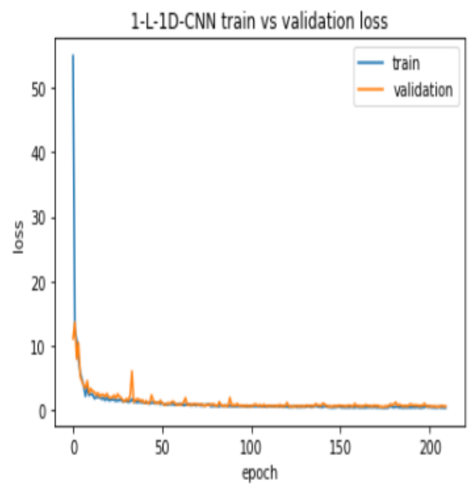
5. Results

After training the model for around 250 epochs, we have tested the test data on the trained model and compare the recognition accuracy, loss, plots and other factors.

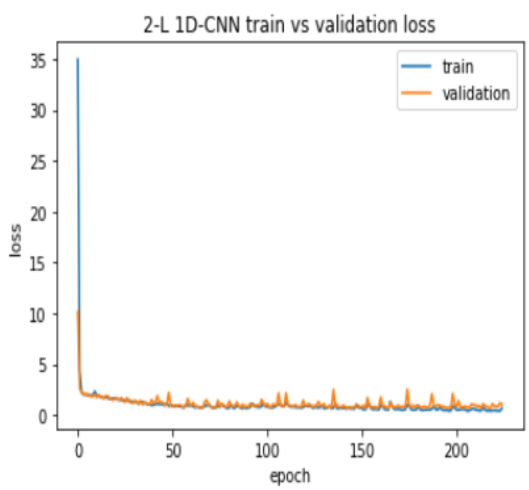
1) **Graph between training and Validation loss of models per epoch**
The following graph shows how the loss is decreasing with the increase in the number of epochs.



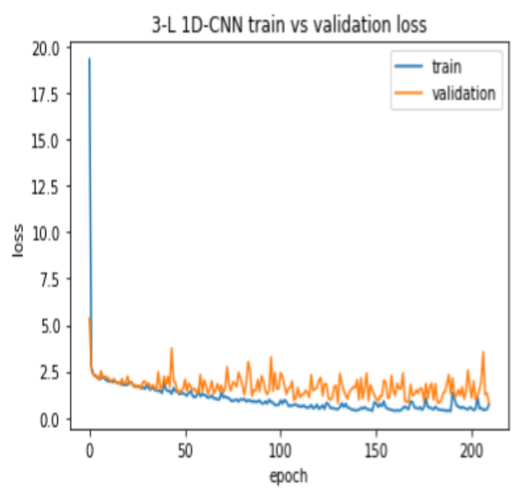
(I) ANN



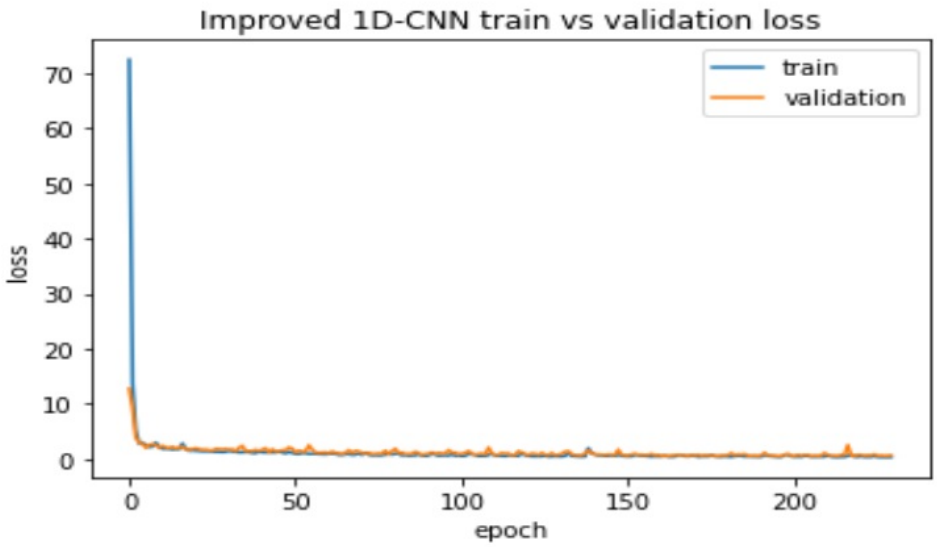
(II) 1layer 1D



(III) 2 layer 1D CNN

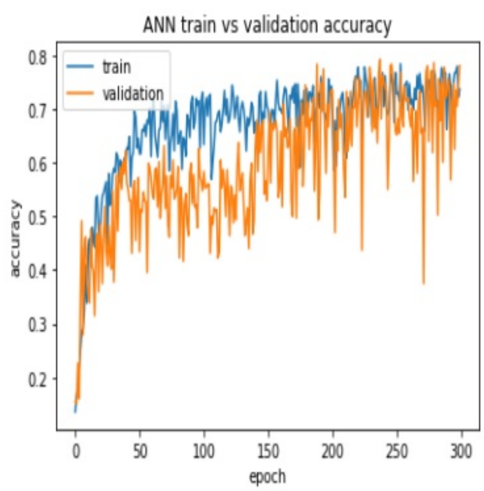


(IV) 3 layer 1D CNN

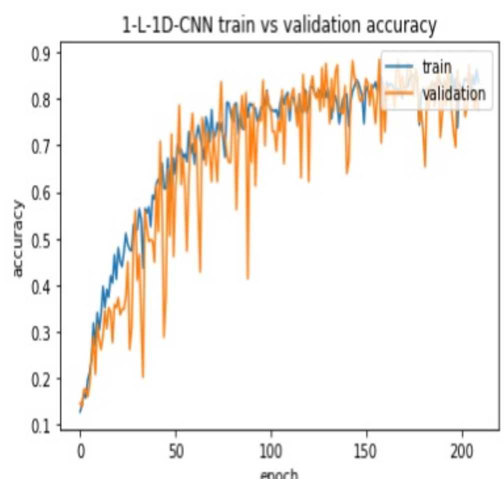


(V) Improved 1D CNN

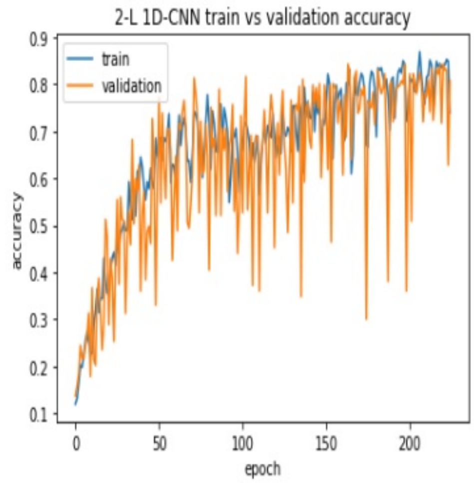
2) **Graph between training and validation accuracy of models per epoch**
The following graphs show how the accuracy of the model increases per epoch during the training process.



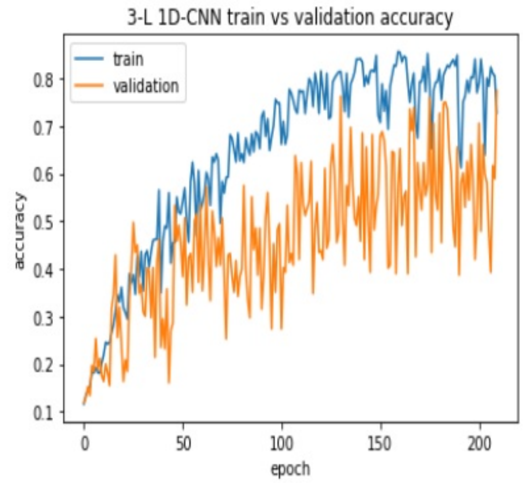
(I) ANN



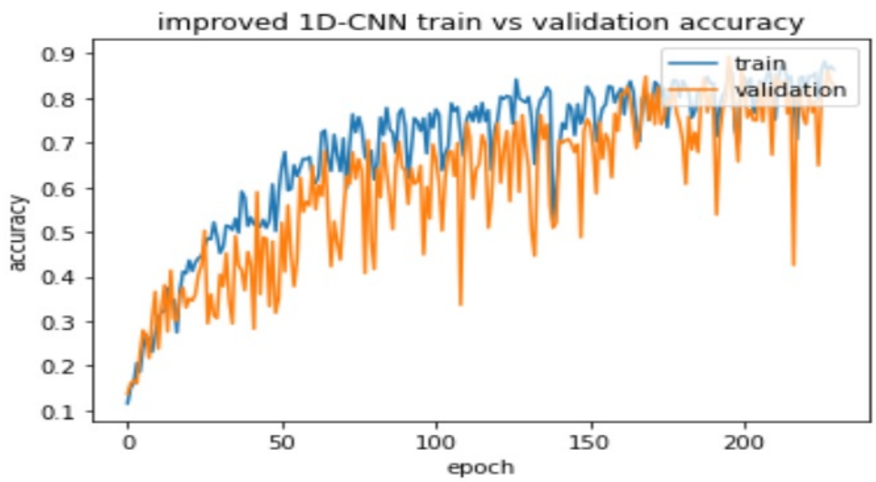
(II)1 layer 1D CNN



(III) 2 layer 1D CNN



(IV) 3 layer 1D CNN

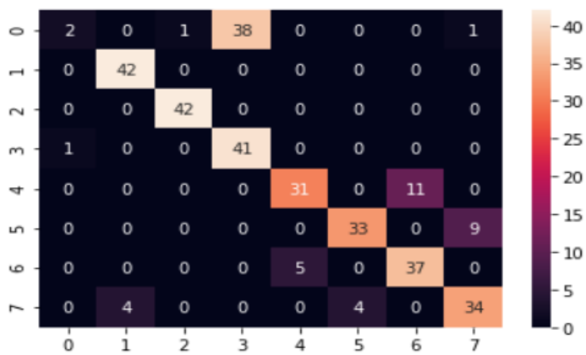


(V) Improved 1D CNN

3) Confusion matrix

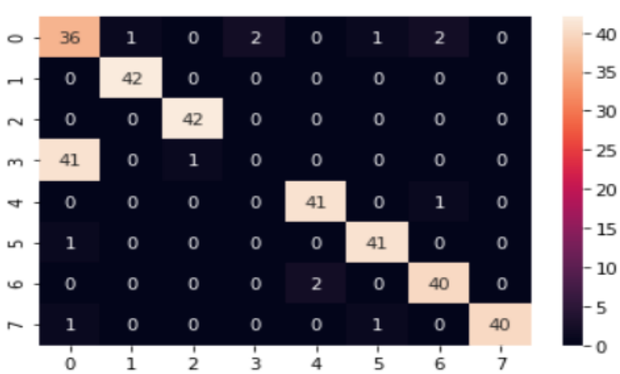
A confusion matrix is used to check the performance of a classification model on a set of test data.Calculating a confusion matrix can give you an idea of where the model is right and what types of errors it is making.

1) ANN



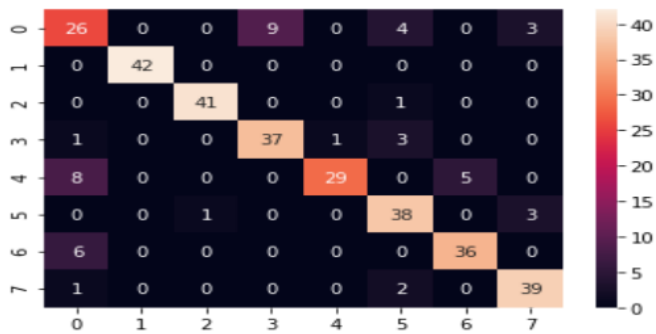
The confusion matrix heatmap for ANN shown in the above figure gives the recognition accuracy of 77.38% which is lowest among all models and misclassification of 22.62% which is highest among all models.

2) 1 layer 1D CNN



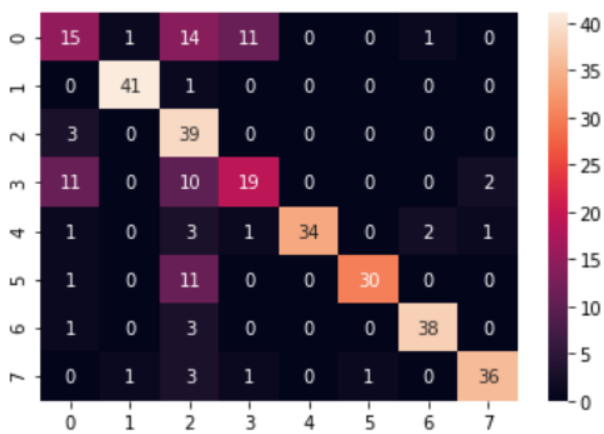
The confusion matrix heatmap for 1 layer 1D CNN shown in the above figure gives the accuracy of 83.9% and misclassification of 16.9%.

3) 2 layer 1D CNN



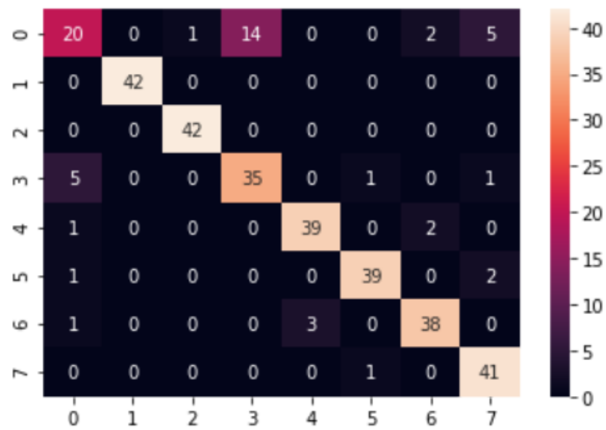
The confusion matrix heatmap shown in the above figure gives the recognition accuracy of 85.7% and has misclassification o0f 14.3%.

4) 3 layer 1D CNN



The confusion matrix heatmap shown in the above figure gives the recognition accuracy of 78.6% which is lowest after artificial neural networks and also has misclassification of 21.4% which is highest after ANN .

5) Improved 1D CNN



Among all CCPs models, Improved 1D CNN has the highest accuracy. Confusion matrix heatmap shown in the above figure gives the recognition accuracy of 88.09% which is highest and has lowest misclassification value of 11.91%.

4) Accuracy

Model	**ANN**	**1 layer 1D CNN**	**2 layer 1D CNN**	**3 layer 1D CNN**	**Improved 1-D CNN**
Accuracy on train data	0.8062	0.84	0.889	0.835	0.90625
Accuracy on test data	0.786	0.839	0.857	0.7738	0.881

5) **Loss**

Model	ANN	1 layer 1D CNN	2 layer 1D CNN	3 layer 1D CNN	Improved 1-D CNN
Loss on train data	0.388	0.30	0.2955	0.33	0.2466
Loss on test data	0.6682	0.336	0.3122	0.69	0.2761

6. Discussion

We have compared the accuracy and loss of five different models for recognition of control charts patterns to detect or identify the unnatural patterns and deviations occurring on control charts during the production process. These five different types of model are Artificial neural network, 1 layer 1D convolutional neural network, 2 layer 1D convolutional neural network, 3 layer 1D convolutional neural network and Improved 1D convolutional neural network. The model which has only one convolutional layer is 1 layer convolutional neural network and if the model has 2 layer of convolutional layer is 2 layer convolutional layer similarly for 3 layer convolutional layer. Improved 1D convolutional neural network has a special type of layer called Inceptional layer. We have trained these models on 200 training datasets for each pattern that are normal pattern, cyclic pattern, systematic pattern, stratification pattern, upshift pattern, downshift pattern, uptrend pattern, downtrend pattern and test the model on 42 test datasets for each pattern. These datasets are generated by applying monte carlo simulation on raw eye tracking datasets. While training the model the model undergoes forward and backward propagation to give the final output. After training each model for around 250 epochs, we fed the validation data and got accuracy and loss for each model. After analyzing the results like accuracy , loss confusion matrix and all the plots of loss and accuracy for training and validation datasets, Improved 1D-CNN has highest recognition accuracy of 90% on train data and 88% on Test data as well as lowest loss of 0.2466 on train datasets and 0.27 on test datasets where as Artificial neural network has minimum recognition accuracy of 80.62% on train data and 77.38% on test data as well as maximum loss 0.388 on train data and 0.69 on test datasets. This is due to the presence of

the inception layer in Improved 1-D CNN which allows the internal layer to pick and choose which filter size will be relevant to learn the required information.
All these feature-based extraction methods help to develop automated recognition systems for control chart patterns recognition and thus when we fed the datasets, the model helps to identify or detect abnormal patterns, deviations and as well as abnormal abruption in the production process. Abnormal patterns exhibited in control charts are associated with various assignable causes adversely affecting the process stability and thus the recognition of these patterns can help us to find those causes and eliminate the potential hazards caused by these factors to make our production process smooth.

7. Conclusion

Feature-based extraction methods like convolutional neural networks are very powerful techniques for the recognition of control chart patterns.The results indicate that feature-based Feature extraction methods like 1D convolutional neural network having inception layer gives more consistent recognition performance and dominant over layer by layer neural network as well as some classical methods like fuzzy inference systems as well as support vector machines. After analyzing the confusion matrix heatmap for all proposed neural network models in our thesis, there is a tendency for stratification patterns to be mostly confused with normal pattern and stratification patterns and similarly shift patterns with trend patterns. But out of all five models used in this thesis Improved 1D convolutional neural network gives highest accuracy and reduces the misclassification between stratification-normal patterns and trend-shift patterns. This indicates that the performance of our recognition model can be improved further by identification of new features that will helpful in discriminating Normal pattern with stratification pattern as well as shift pattern with trend pattern. And thus these efficient automated CCP recognition systems can help to identify eight most common control chart patterns that are normal, stratification, systematic, increasing trend, decreasing trend, upward shift, downward shift and cyclic. After pattern recognition, it can also inform the users about various root assignable causes associated with a particular pattern along with the necessary preemptive actions also reduce the complexity of the production process and help in judging whether the process is normal or abnormal and the recognition of unnatural patterns in control charts provides clue to reveal the potential quality problem in manufacturing process.

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