ControlaChartaPatternsaRecognitionaUsingaaConvolutionalaNeuralaNetwork

SummeraInternshipa

**Reportaby**

**SumitaGaurav**

**SarthakaTaunk**

# **Introduction**

Inatheaworldaofamarketacompetitionaofaenterprises,aproductaqualityaisaalwaysaseenaasaaacrucialakeyafactor.aSignificantaimprovementsahaveabeenabroughtatoatheaproductionaqualityaofaaanumberaofaenterprisesabyaevolvingauseaofaStatisticalaprocessacontrola(SPC).aIncludingaindustriesaofamachining,athisaremarkableaboostainaproductionaqualityahasabeenaintroducedatoachemicalaindustries,aelectronicaindustriesaetc.aTheabasicaideaabehindaSPCaisatoamonitoradiverseastagesaofatheaproductionaprocessabyausingamathematicalastatisticsamethods.aThroughatheauseaofaSPC,aproductionaanomalies,adeviationsacanabeadetectedaonatimeaandaaccordingatoaitafurther,anecessaryameasuresacanabeaimplementedatoaeliminateapotentialahazards.aAlthough,arecognitionaof$unnaturalapatternsaisaaacriticalataskainastatisticalaprocessacontrola(SPC).a

Processaqualityacontrol,aitsaprincipalaobjectiveaisatoaachieveaandamaintainaanaacceptablealevelaofatheadesiredaprocessaqualityacharacteristicasteadilyaandaconsistently.aInareferenceatoaitsaobjective,aaccurateamonitoringaandaeffectiveacontrolaoveratheamanufacturingasystemaisatremendouslyaimportant.aManufacturingaofaproductsawithatheadesiredaqualityaneedsasincereamonitoringaofaproductionaprocessesaforadistinguishingaanyaunnaturaladeviationainatheastateaofatheaprocess.aAndaforadeterminingawhetheraaaprocessaisarunningainaitsaintendedamodeaorainapresenceaofaunnaturalapatterns,aaacontrolachartaisaused,awhichaisaanaimportantastatisticalaprocessacontrolatool.aTheapatternsaexhibitedaonatheacontrolachartsacanaprovideaessentialainformationaaboutatheaprocess.aToapointaoutaqualityafailuresaandatoadetectarootaabnormalacausesainatime,arecognitionaandaanalyzationaofaCCPsaisathusaconsidered.aControlachartsawhichaareachieflyainatheaformaofaXachart,aareawidelyausedatoarecognizeacircumstancesawhenamanufacturingasystemsaneedacontrolaactions.aThea8amostapatternsaformedaonacontrolachartaare,anormalapattern(NOR),astratificationapatterna(STA),asystematicapatterna(SYS),acyclicapatterna(CYC),aupwardashiftapatterna(US),adownwardashiftapatterna(DS),auptrendapatterna(UT)aandadowntrendaapattern(DT).a

1.a**NormalaPattern(NOR)**:astipulatesatheaproductionaprocessainacontrol.

2.a**SystematicsaPattern(SYS)**:aSYSapredictsapointsatoapointafluctuations.aItsapatternaemergesaasaaahighapointaalwaysafollowingaaalowapointaandalikewise.

3.**StratificationaPattern(STR)**:aThisashowsathatatheadataaisamoreaintensiveaandavarianceaofadataabecomesanugatory.

4.a**Cyclicapattern**:aAppearanceaofapeaksaandatroughsacanabeafoundainacyclicapattern,aperiodically.

5.**aTrendapattern**:aInatrendapatterns,aaacontinuousarisea(i.e.aupwardatrend)aorafalla(i.e.adownwardatrend)aisashownabyadata.

6.**aShiftapattern**:aUnlikeatrendapatterns,ainashiftapatternsadataaresultsainasuddenarisea(i.e.aupwardashift)aorasuddenafalla(i.e.adownwardashift)ainatheameanaofadata.

Theseapatternsaareabroadlyaclassifiedaasanatural/normalaandaunnatural/abnormal.aAaprocessaunderacontrolaisaindicatedabyaaanaturalapatternawhileainacontrastatoaitaanaunnaturalapatternaindicatesaoutaofacontrolaprocess.aConventionallyainatheaproductionaprocess,aabnormalaCCPsacorrespondatoasomeaabnormalacauses.aHence,athearecognitionaofaabnormalapatternsaisahelpfulatoaidentifyatheaproblemsatimelyaandatheaextentaofaabnormalacausesacanabeanarrowedaasawell.

Earlierainacontrolachartaapplications,aindividuals'aexperienceawasaindispensableatoadeduceawhetheratheaproductionaprocessaisaabnormalaoranotaandaifaitaisafoundaabnormal,athenatoafindatheacorrespondingacause.aByatheaevolutionaofaindustrialaautomation,athearoleaofamanualaobservationaisapartiallyareplacedabyathearule-basedadiscriminantasystem,awhereatheadiscriminantarulesaofacontrolachartsaareabasedaonaminoraprobabilisticaevents,awhichacanabeaeasilyacarriedaout.aAnyway,acoveringaallaabnormalapatternsawitharulesaisaquiteadifficultadueatoaintricacyainatheaproductionaprocess.aToacompensateaforathis,aaacoherentaautomatedapatterna(CCP)arecognitionasystemacanabeaimplemented,awhichaensuresaconsistent,aneutralainterpretationaofaCCPsaresultingainaaamarginalanumberaofafalseaalarmsaandaeasyaexecutionaofacontrolacharts.

Theaadvantageaneuralanetworksaprovideaisaprovisionaofabluntarulesaoratemplatesaisanotarequiredahere.aSomewhat,aitalearnsatoarecognizeapatternsastraightlyathroughatypicalaexampleapatternsaduringatheatrainingaphaseaandahasatheapotentialatoarecognizeaanainconsistentapatternanotapreviouslyaencountered.a

# **LiteratureaReview**

Thereaareatwoamajoramethodsausedatoarecognizeacontrolachartapatterns:(I)adirectlyafeedathearawaCCPsadataaintoatheamodelaanda(II)ausesatheastatisticalapropertiesaofadataalikeastandardadeviation,amean,adistributionaetcatoaextractatheafeatureafromadataaandafedaintoathearecognitionamodel.

Phamaetaal.a(1997)aproposeatheaapproachathatausesacontrolachartapatternsaforafeatureaextractionainsteadaofaitsanumericaladataaandastatisticalapropertiesaforarecognizingaitsapatterns.aItahasatwoamajorasteps:a(I)afeatureaextractionafromaCCPaanda(II)apatternarecognition.aThisapaperaalsoausesatechniquesalikeaheuristicsaandadeepaneuralanetworks.aGauriaetaal.a(2007)proposedatheaapplicationaofaCARTatoaselectatheasubsetaofafeatures.aAddehaetaal.a(2018)ausedaaamethodaforapatternarecognitionawhichausesaoptimizedaRBFNN.aThisamethodaisadividedaintoafouraparts:afeatureaextraction,afeatureaselection,aclassification,aandalearningaalgorithm.aAfteratestingaona1600adatasetsahavinga200adatasetsaforaeachapatternathisamethodagaveaveryagoodaaccuracy.a

Aafuzzyamethodaforarecognitionaof$unnaturalaCCPsaisaproposedabyaGulbayaetaal.a(2007).aZamanaetaal.a(2018)ausedaanaefficientahybridarecognitionamethodaforaCCP.aThisamethodaisadividedaintoatwoaparts:a(I)afeatureaselectionaandaextractionapartaanda(II)arecognizerapart.aInatheafirstapart,aaarepresentationaofaeachapatternausingastatisticalafeaturesaisaproposedaandainatheasecondapartaANFISaalongawithaFCMaisaproposed.aEbrahimzadehaetaal.a(2011)aproposedatheaSVMamethodadueatoaitsageneralizationaperformanceaforarecognitionaofaCCP.aThough,aappropriateaparametersaselectionaforaSVMaisaaabitadifficult.aTherefore,atoaoptimizeatheaparametersaofaSVMamodelsaautomatically.aChengaetaal.a(1997)adescribedatwoamethodsaforapatternarecognition:a(I)amultilayeraperceptronatrainedabyabackapropagationaanda(II)amodularaneuralanetworkaandaitsaperformanceaisaevaluatedabyamonteacarloasimulationainawhichamodularaneuralanetworkashowedabetteraaccuracyathanabackapropagation.a(Zhaoaetaal.,a2017)ausedaimprovedasupervisedalocallyalinearaembeddingaandaSVMaforarecognitionaainawhichaitaextracta12adimensionalastatisticalafeaturesaandashapeafeatureaofacontrolachartawhereaasa(Ghomiaetaal.,a2017)ausedaANNatoaidentifyaunnaturalapatternsaformedaonashewhart'sacontrolachartatoaidentifyatheaoutaofacontrolaprocess.aSpikinganeuralanetwork(SNN)atoatheaCCPsarecognitionaisaappliedabyaAwadallaaetaal.a(2012),awhichaconsideredatheacontinuityaofacontrolachartadataaoveratime.aExistingaresearchesasayathatafeatureaextractionabasedaCCPsarecognitionamethodausuallyahasabetteraperformance.aButatoaselectatheafeatureasubsetawhichaisabest,afeatureascreeningamethodsaareaessentiallyaneeded,asinceatheaconstructionaofafeaturesadependsaonahumanaexperience.

Deepalearningaisaknownaforaitsaoutstandingaperformanceaandahasabeenaextensivelyastudiedaconsequently.aAnaeffectiveamappingafromainputsatoaoutputsabyaaanetworkastructurea(Zhangaetaal.,a2018)aisaestablishedabyaDeepaLearning.aTheadeepalearningamodelaisasimpleabutanon-linearamodulesawhichatransformaloweralevelarepresentationaintoahigheralevelarepresentationaandaalsoaextractafeaturesadirectlyafromarawadata.aThereaareavariousadeepaneuralanetworksasuchaasaartificialaneuralanetworks,aconvolutional$neuralanetworks,arecurrentaneuralanetworksawhichahaveashownagreatasignificanceainacomputeravision.aKiranyazaetaal.a(2016)aimplementedaoneadimensionalaCNNaforaECGaclassificationawhichaachievedaaaveryagoodaaccuracyaonaNIT-BIHaarrhythmiaadataadueatoaitsaspeedaandacomputationalaefficiency..aToaanalyzeatheachemo-metricadataabasedaona1D-CNN,aaanewamethodaisaproposedabyaMalekaetaal.a(2017).aThealiteratureahere,ashowsathatathroughaCNN,afeaturesafromarawadataacanabeaextractedaandaitawillabenefitainatheaprocessingaofacomplexaclassification.

# **Objective**

TheaobjectiveaofaouraprojectaisatoarecognizeatheaUnnaturalaControlaChartaPatternsathataoccuraonastatisticalaqualityaControlachartsatoadetectatheaunnaturaladeviationainastateaofaprocessaasawellaasatoaidentifyaqualityafailureaandarootaabnormalacauseainatime.

# **Methodology**

Weahaveadividedatheamethodologyainatwoapartsai.e;adataapreparationausingadataasimulationaandaFeatureaextractionausingaDeepaneuralanetworks.

## **DataaPreparationausingaMonteacarloasimulation**

**Dataasimulation**aisaoneaofatheawidelyausedatechniquesaforacontrolachartapatternarecognitions.aItaisatheaprocessatoagenerateathousandsaofarandomasamplesafollowingaaaparticularadistributionausingaoriginaladata.aInathisaprojectaweahaveausedarawaeyeatrackingadatasetsaandaobtainedaitsadistribution,ameanaandavariancesaatoagenerateadataaofavariousapatterns.

### **MonteaCarloaSimulation**

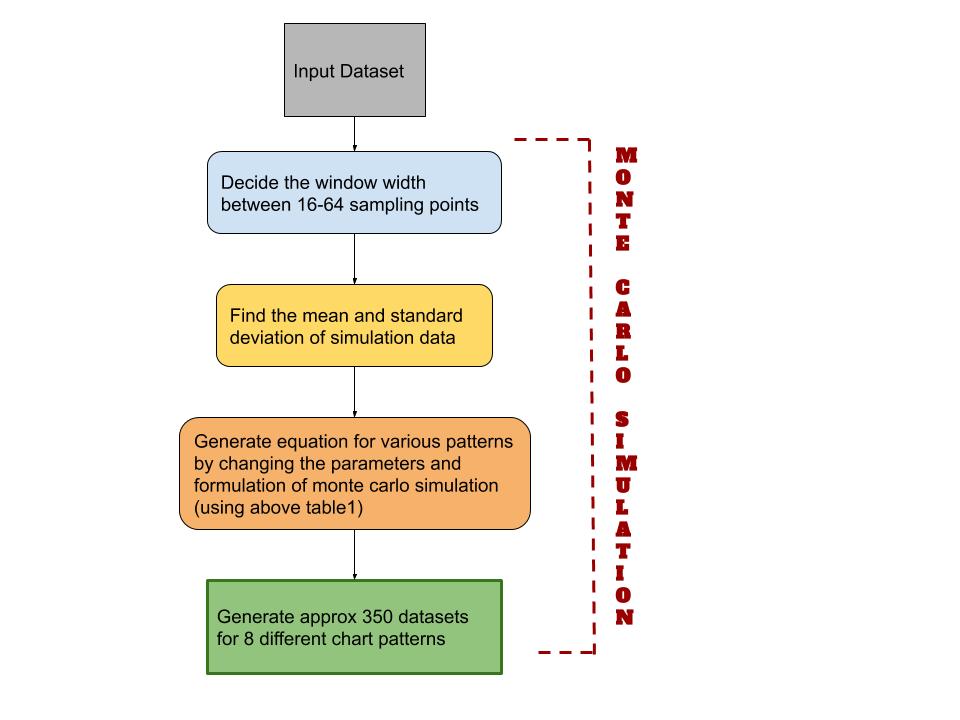
InathisaprojectaWeahaveausedaMonteaCarloasimulationaofaDataasimulationaonaeyeatrackingadatasetsaandaitsaobtainedatheameanaandavariancesaandagenerateadataaofavariousapatternsabyachangingavariousaparametersaasashownainatheaTable1a:

Table1:aParametersaandaformulasaofaDataasimulation

|  |  |  |  |
| --- | --- | --- | --- |
| class | Description | equations | Remarks |
| 0 | Normal,aNOR | t= |  |
| 1 | Cyclic,aCYC |  |  |
| 2 | Systematic,aSYS | + |  |
| 3 | Stratification,aSTR |  |  |
| 4 | UpwardaTrend,aUT | + |  |
| 5 | DownwardaTrend,aDT | t- |  |
| 6 | Upwardashift,aUS | + |  |
| 7 | DownwardaShift,aDS |  |  |

* aandaa=ameanaandastandardadeviationaestimateaofatheain-controlaproductionaprocess.
* arepresentsatheainevitableaaccidentalafluctuationawhichaisasubjectatoagaussianadistributiona.
* a=aDegreeaofasystemastateadeparture.
* a=Amplitudeaofacyclicapattern.
* a=aPeriodaofatheacycle.
* a=aGradientaofaaadataatrend.
* a=aTimeawhenatheashiftaanomalyaoccurs.
* a=aAmplitudeaofatheashiftapattern.

Theasequencea(windowawidth)alengthaofadataasimulationa‘L’ashouldabeasmall,abecausealongerawidthaofawindowacausesalargeralagaofaanomalyadetection.aInaGeneralalengthaofatheawindowaisasetatoa“16-64”asamplingapoints.aTheaflowchartamonteacarloasimulationaisashownainafigure1abelow:

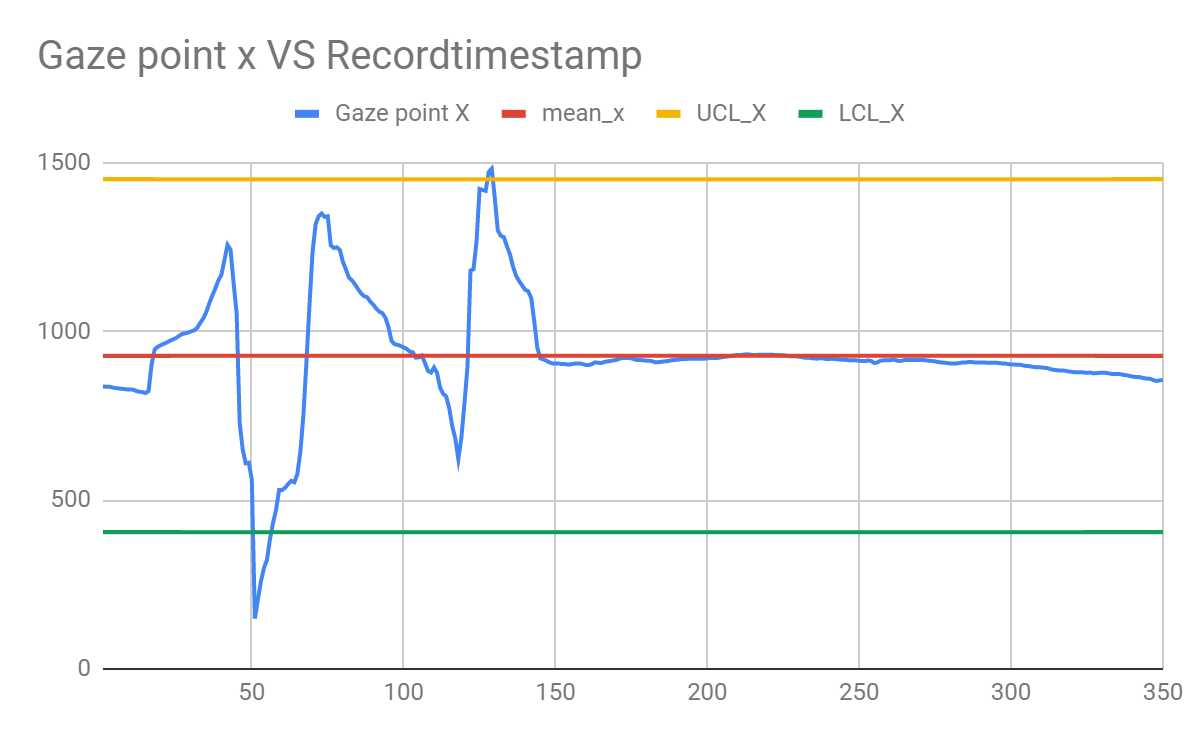


**Figure1:aFlowchartaforaMonteacarloasimulation**

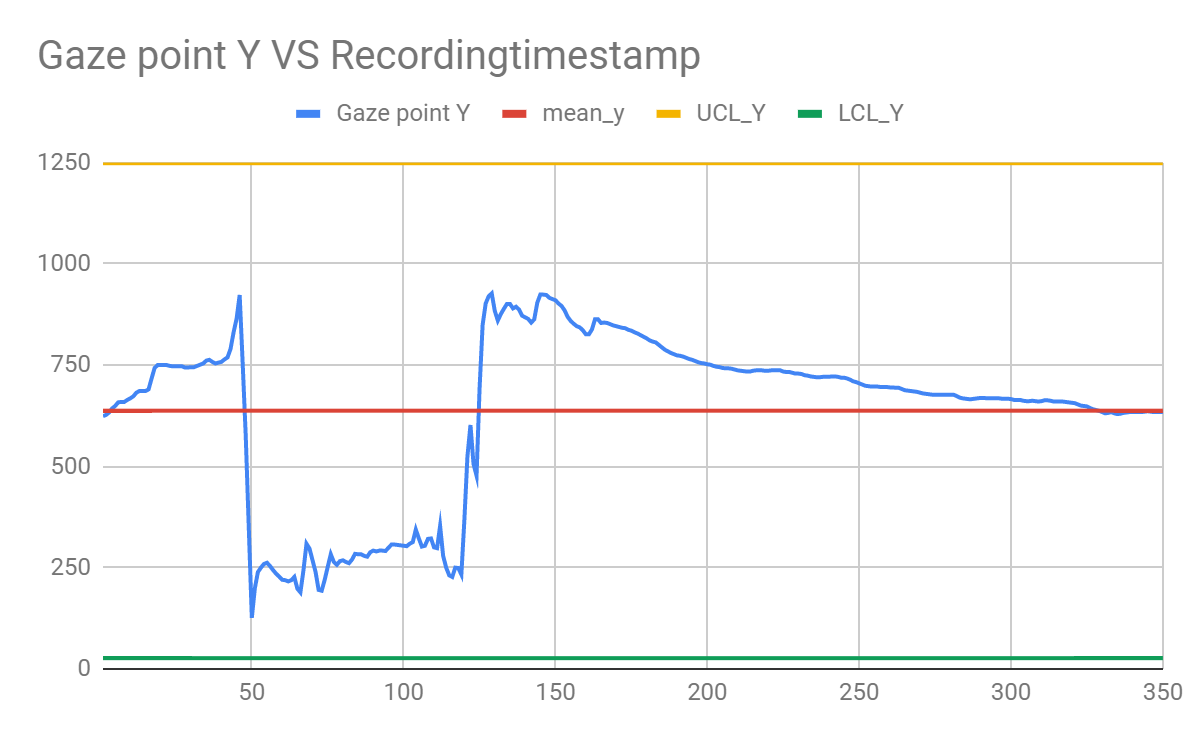
1. Foratheagivenasampleaofaeyeatrackingagazeapointadatasetsashownainatheatable2,aweaahaveadoneaDataaSimulationausingamonteacarloasimulationaonaapproxa10,944arawaeyeagazeapointsadataaandaprepareda8adifferentacontrolachartapatternadatasetsawithaawindowalengthaofa32asamplingapointsai.e;aweamakea342adatasetsafroma10944(342\*32)adataahavinga32asamplingapointsaeach.
2. Forathatafirstadatasetaweatookatheafirsta32asamplingapointsaandagenerateda8adifferentapatternsadatasetsausingamonteacarloasimulationaofatheasameawindowalengthaofa32asamplingapoints.
3. Similarlyaweahaveadoneaforanextadatasetahavinga32asamplealength,aandalikeathatafroma10944a(342\*32)aeyeatrackingadataaweahaveaprepareda342apiecesaaforaeacha8acontrolachartapatternsahavingasamplealengthaofa32.
4. Weahaveawrittenacodeainapythonausingapandasaandanumpyaforamonteacarloasimulation.

### **Visualizationaofarawaeyeatrackingadatasets**

1. **GazeapointaXaVSaRecordingatimestamp**

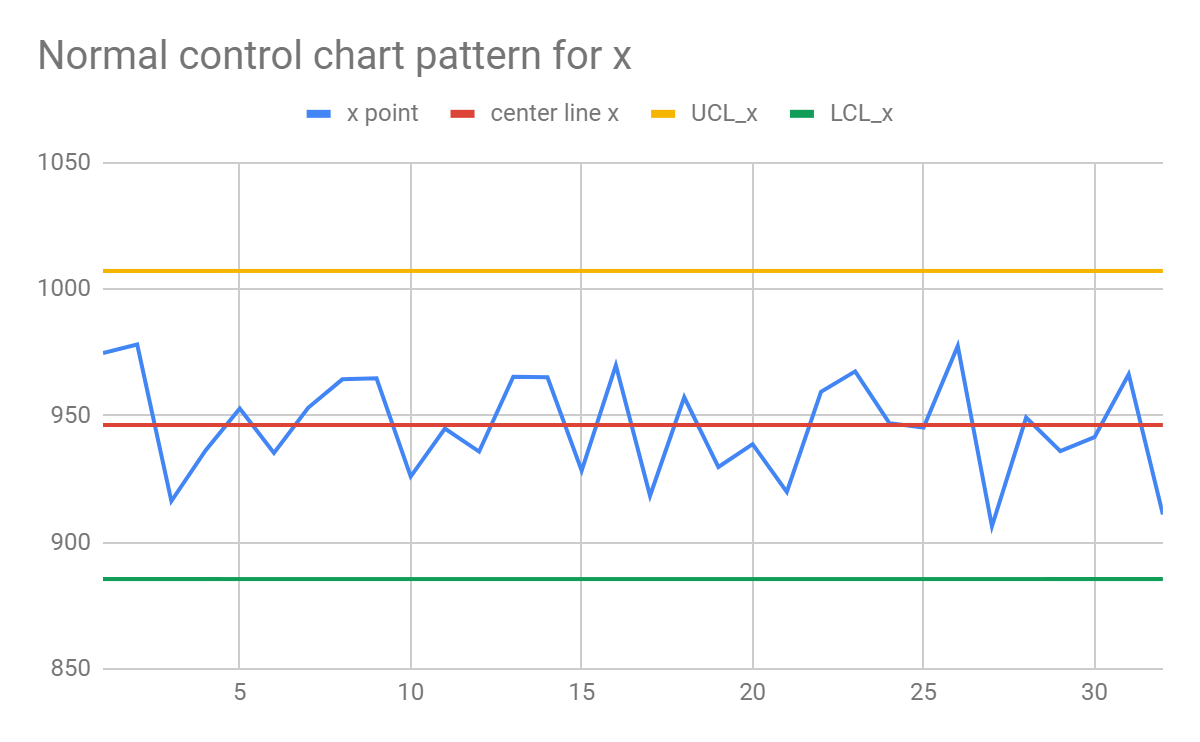
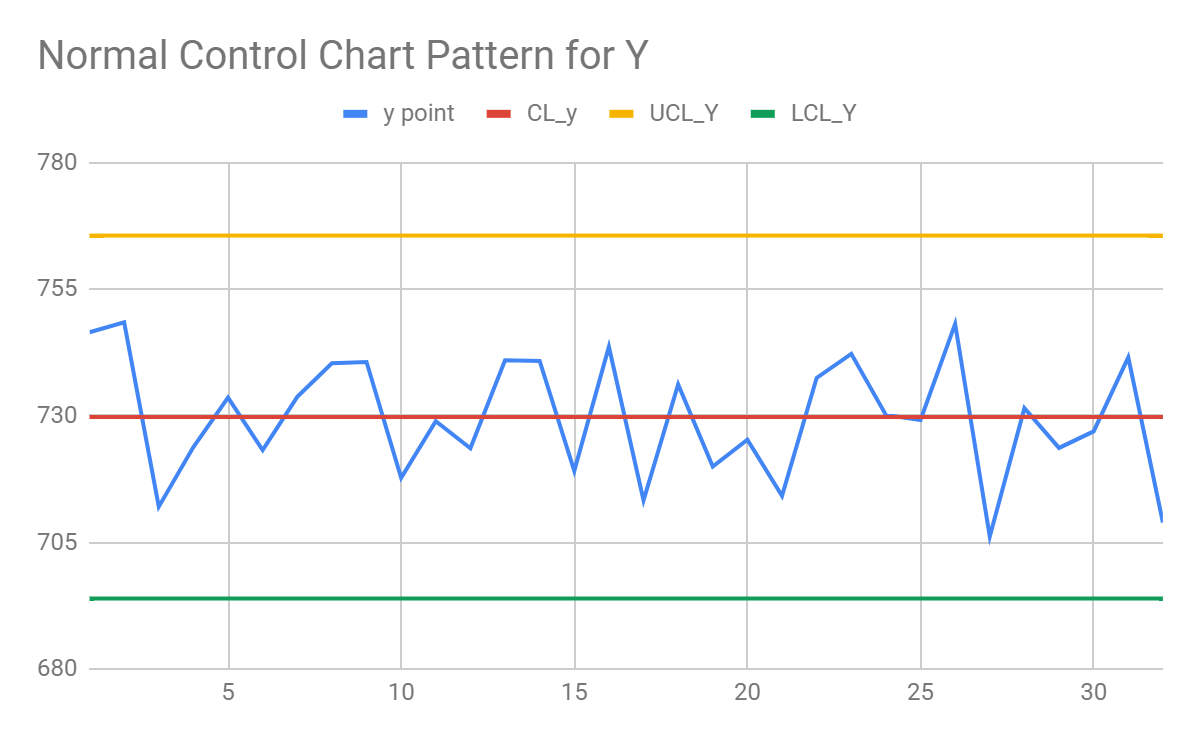
****

1. **GazeapointaYaVSaRecordingatimestamp**

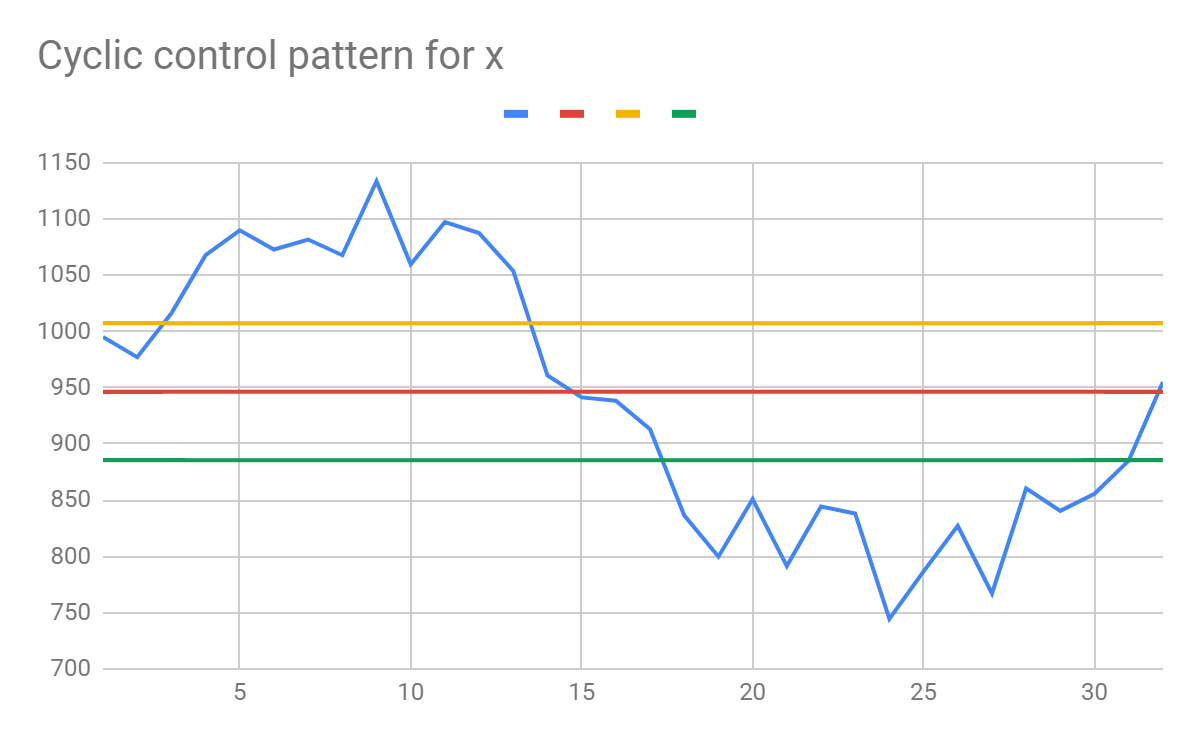
****

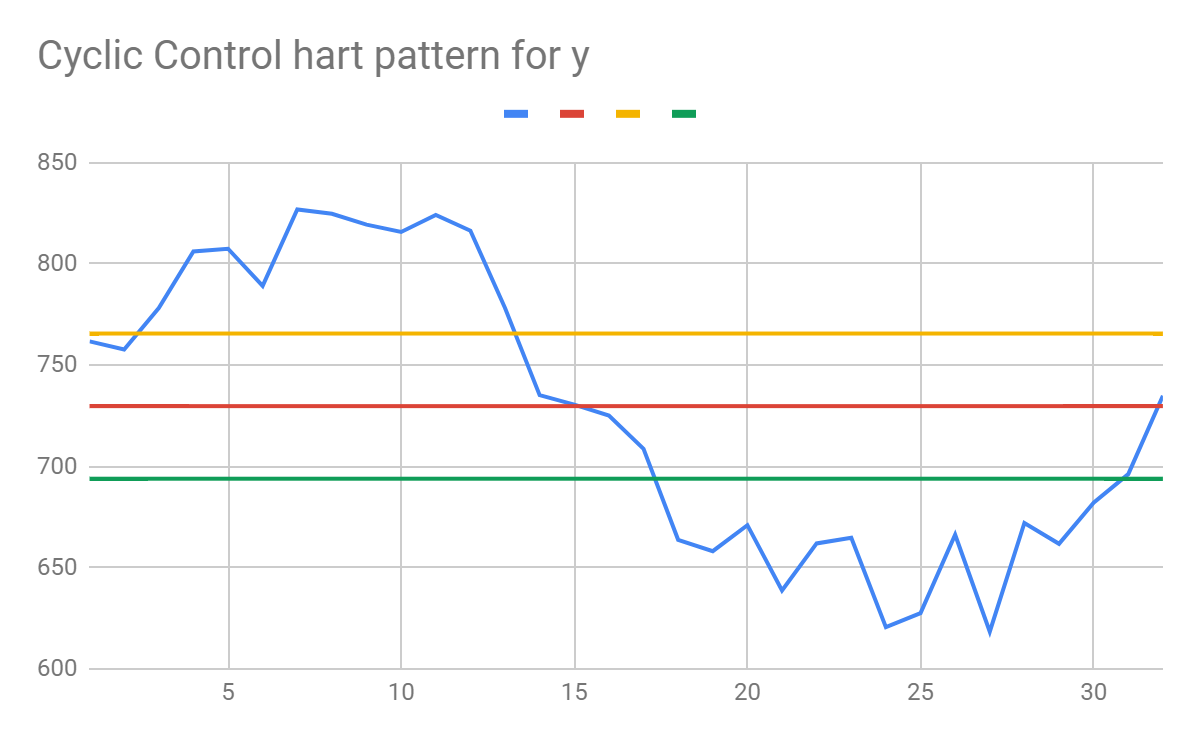
### **VisualizationaofaGeneratedadataaofacontrolachartapatterns**

1. **NormalaPatterns**

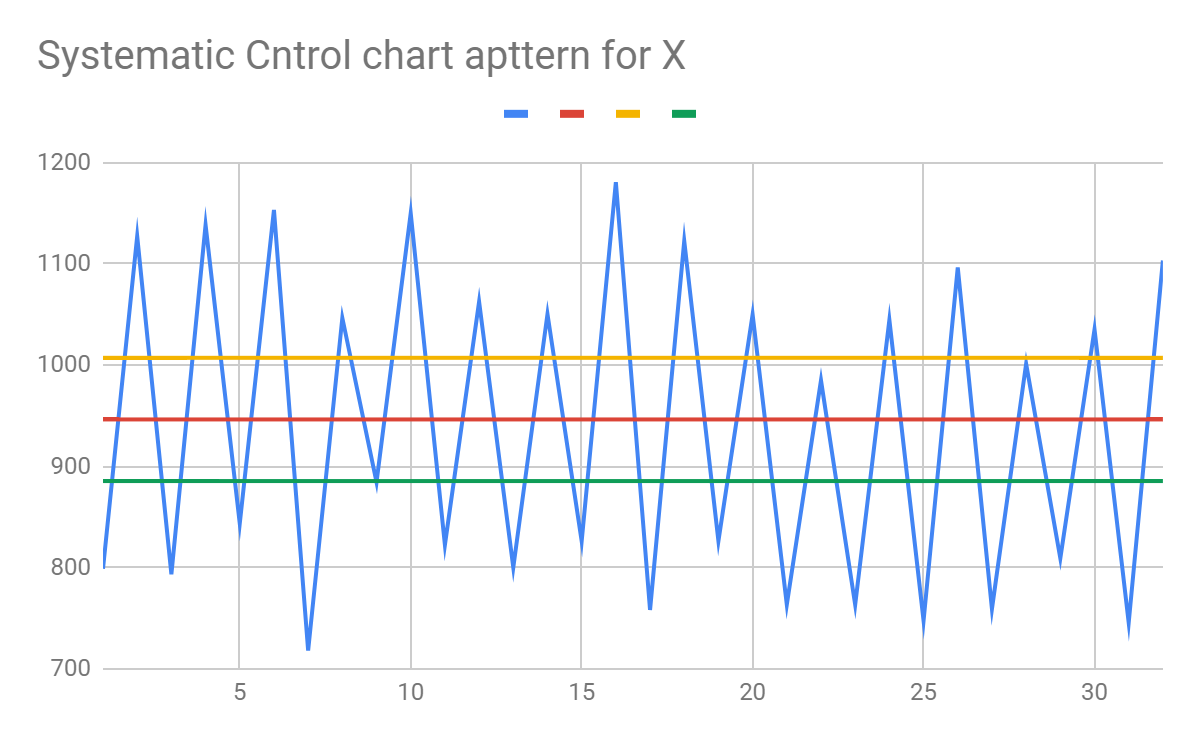


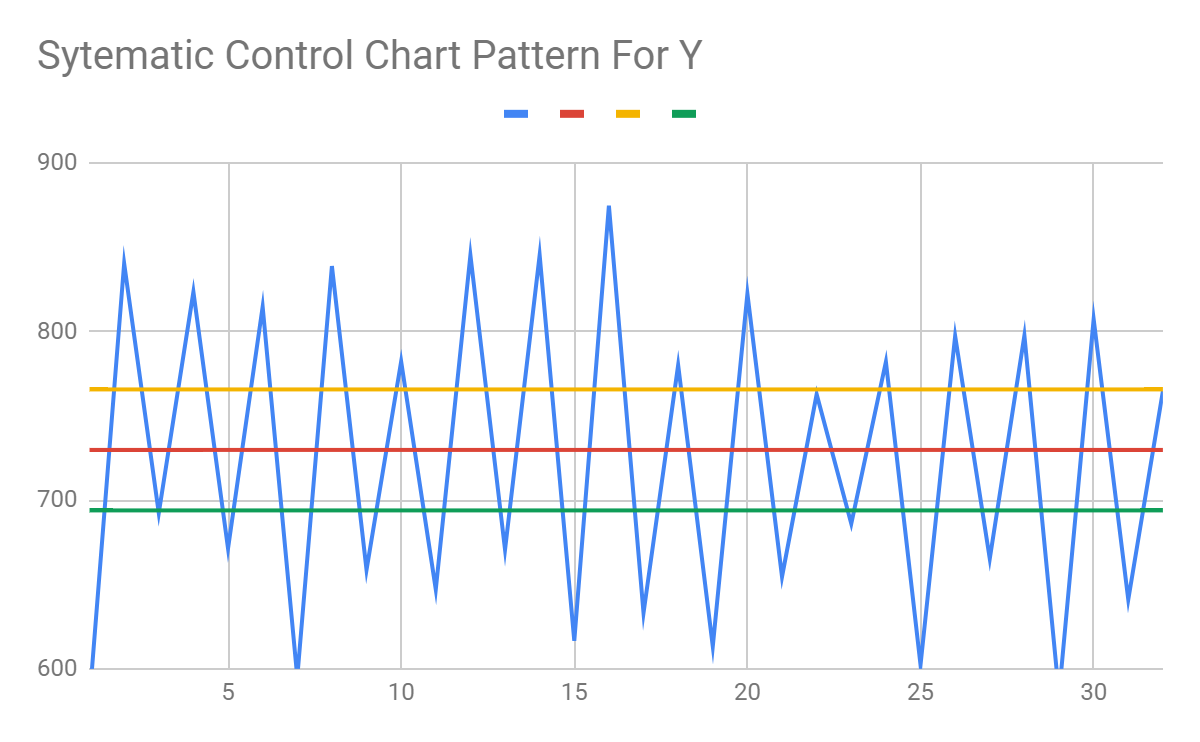
1. **Cyclicapatterns**



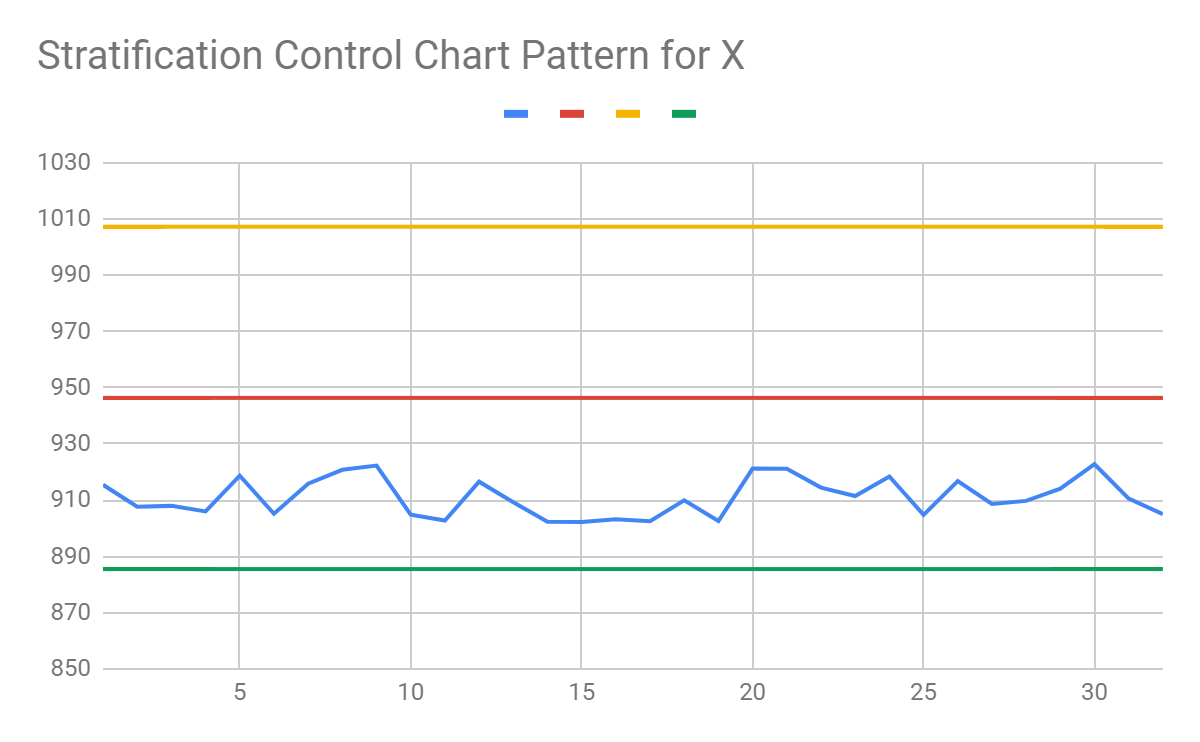
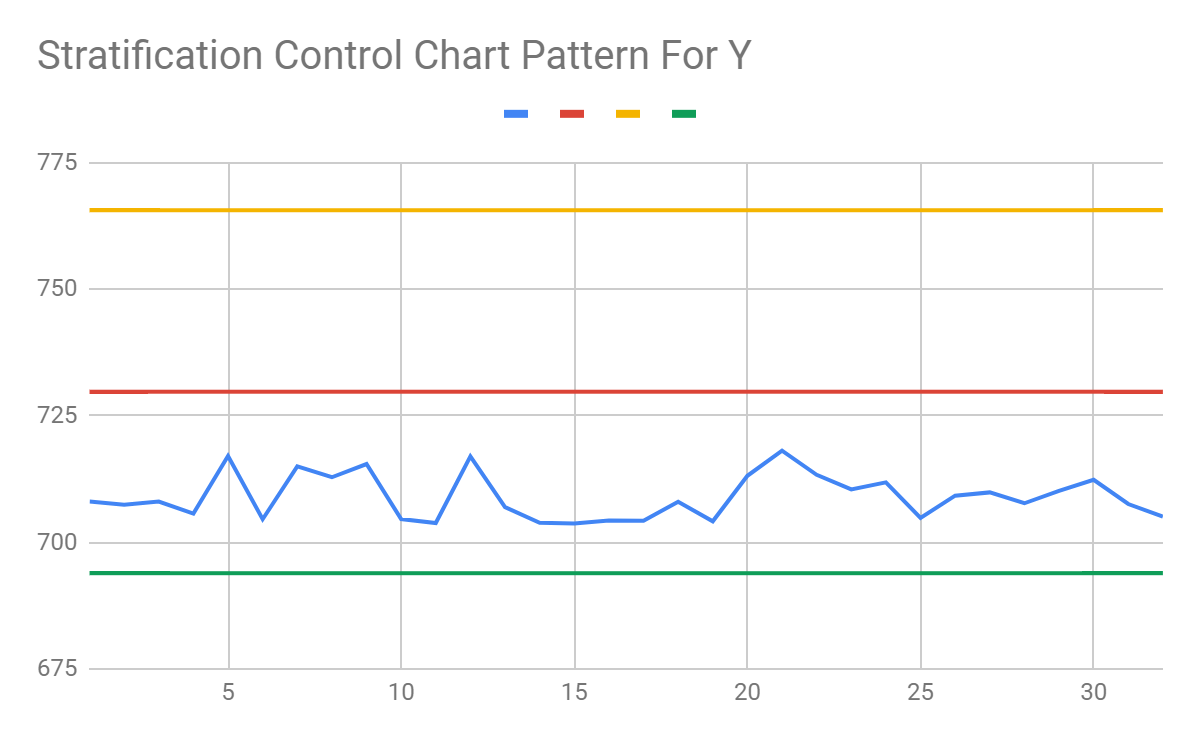


1. **Systematicapatterns**

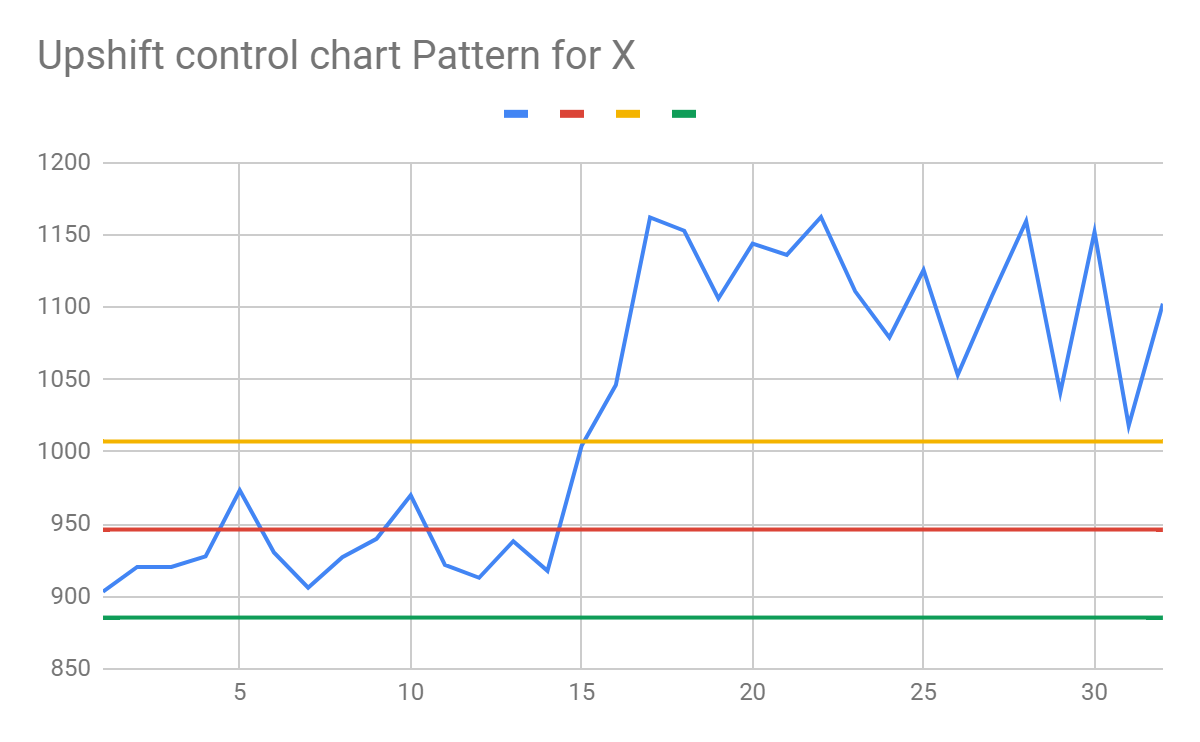


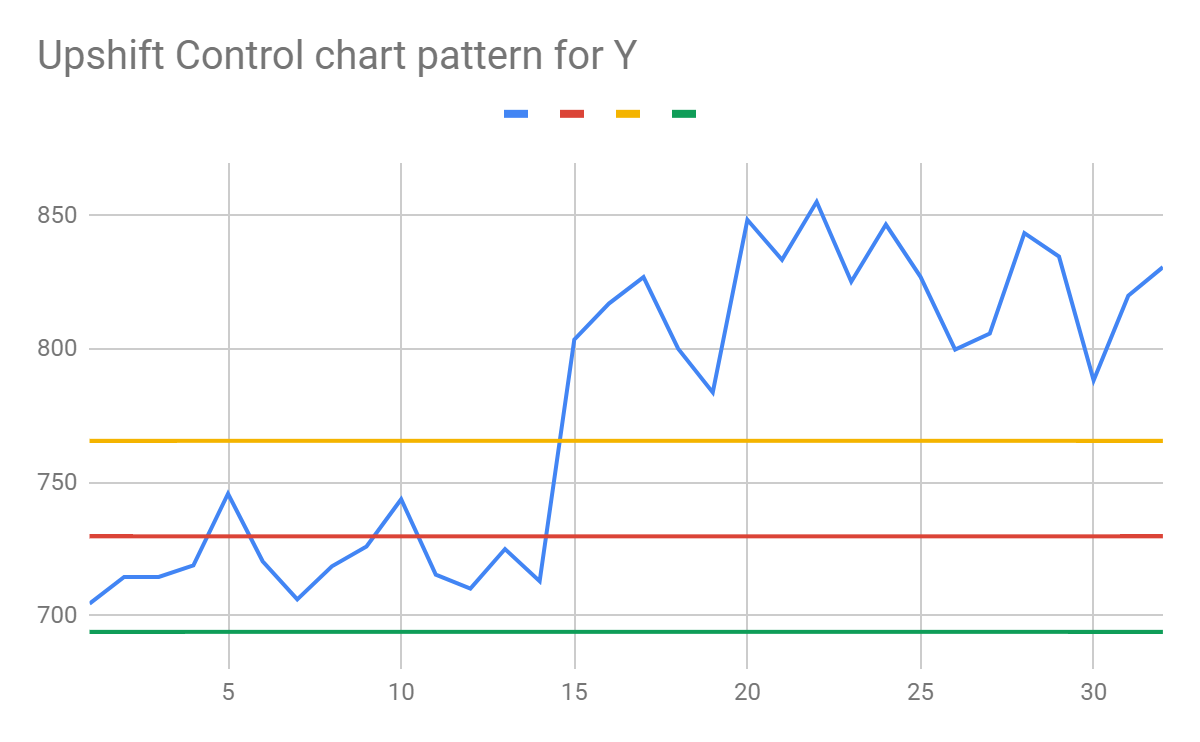


1. **Stratificationapatterns**

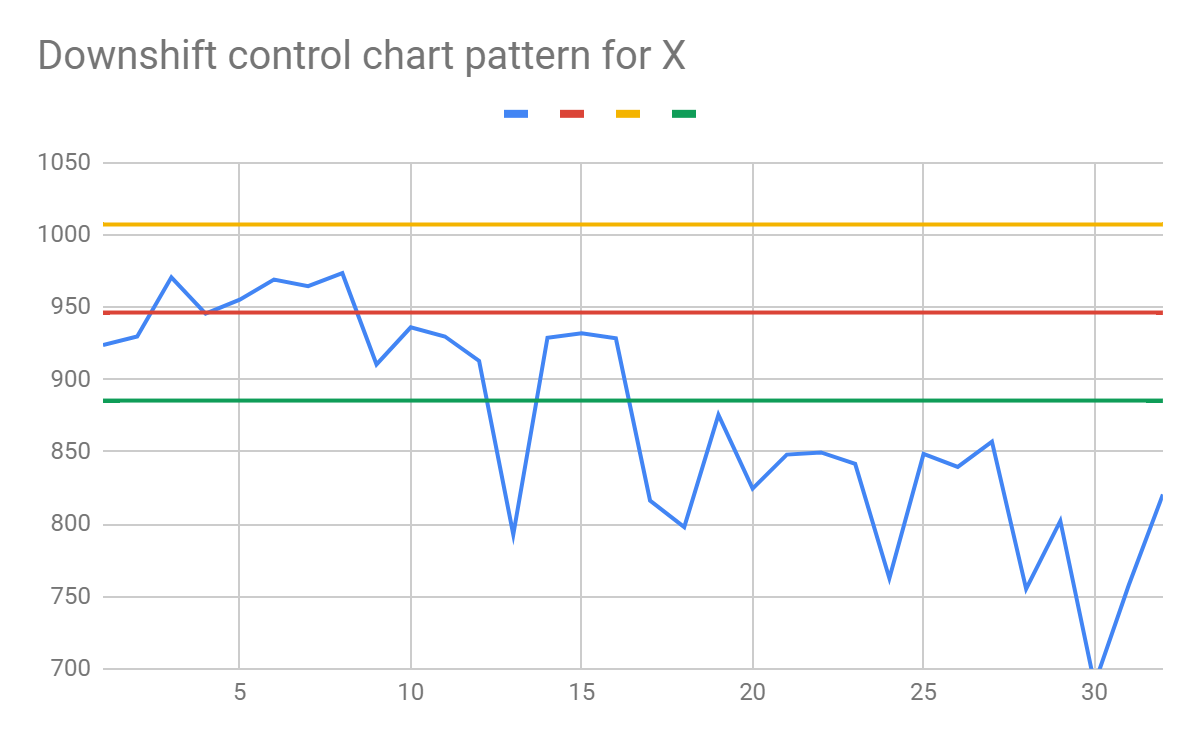
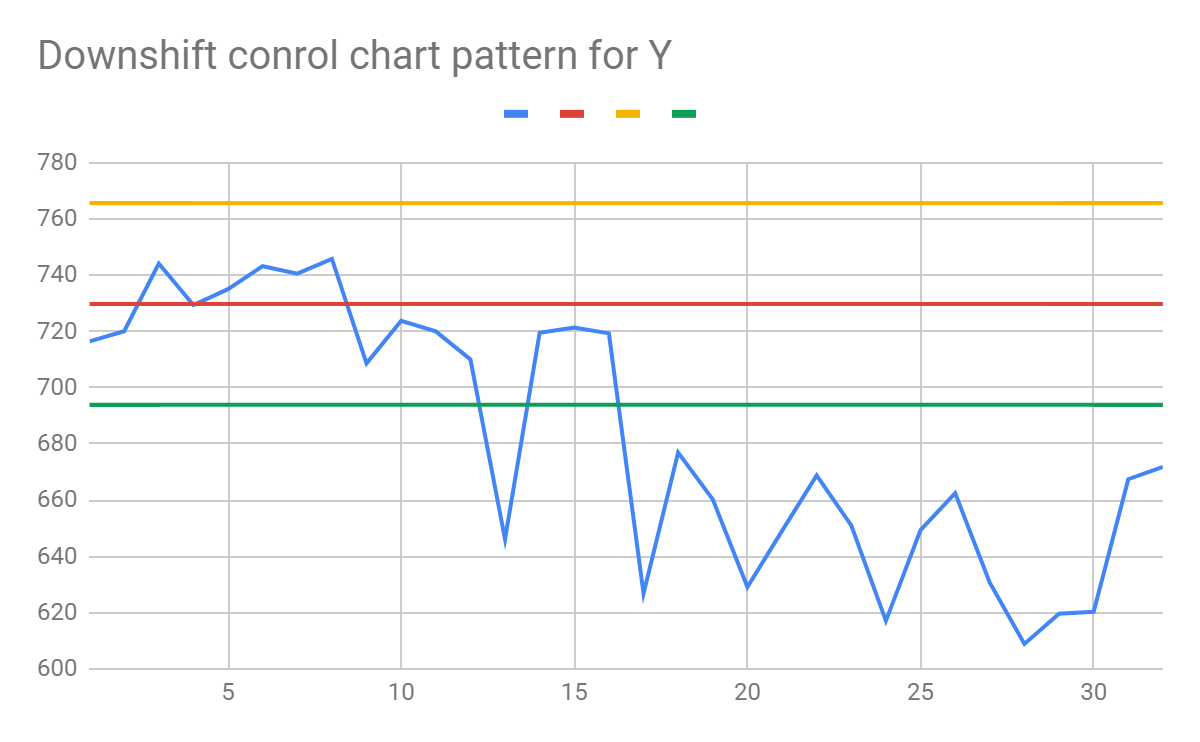
 

1. **Upshiftapatterns**

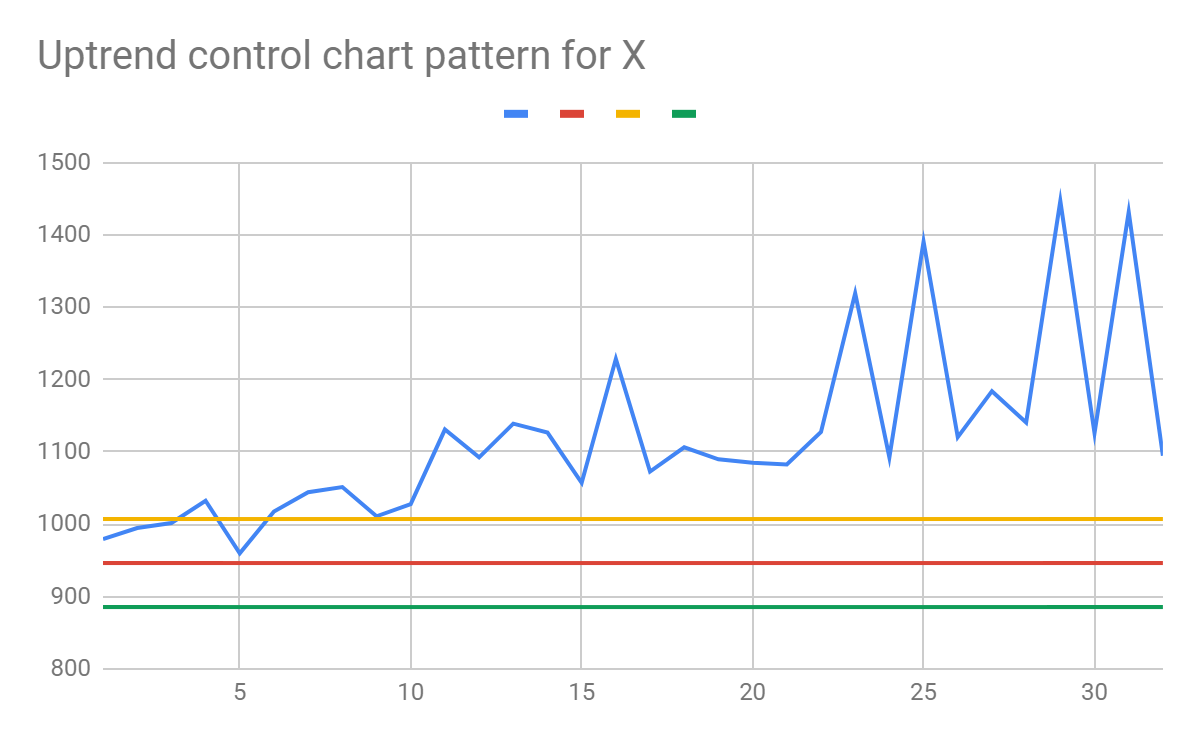


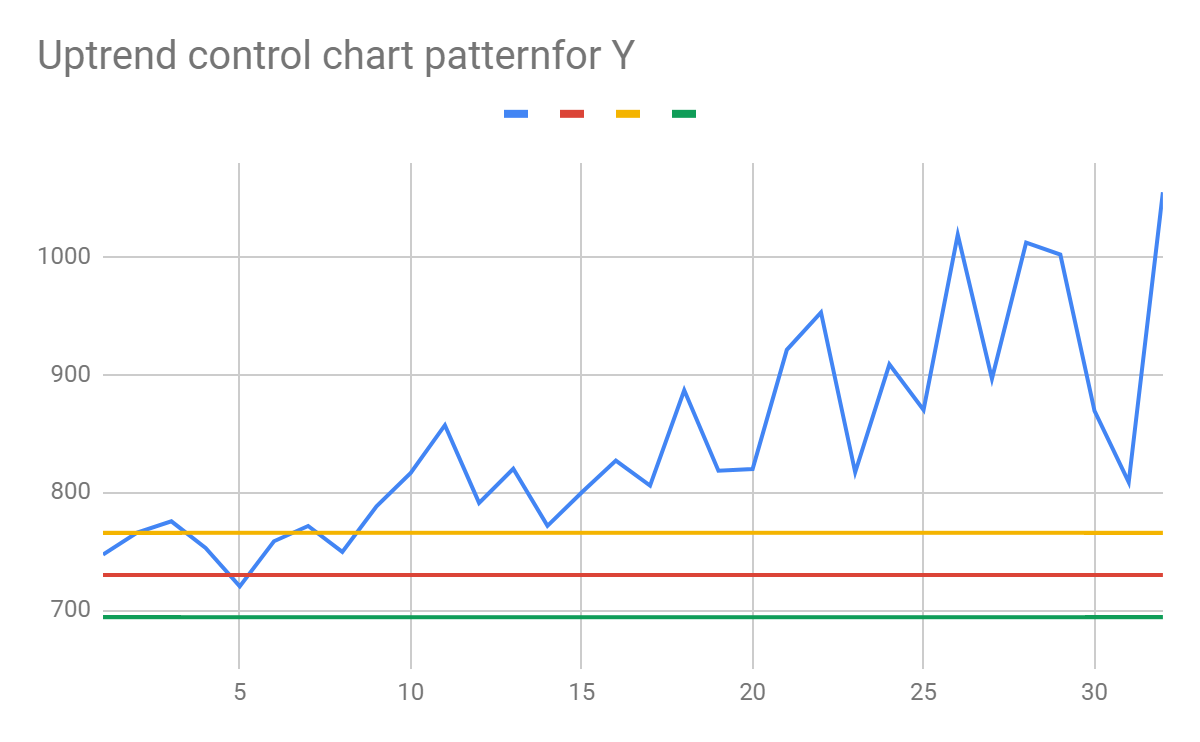


1. **Downshiftapatterns**

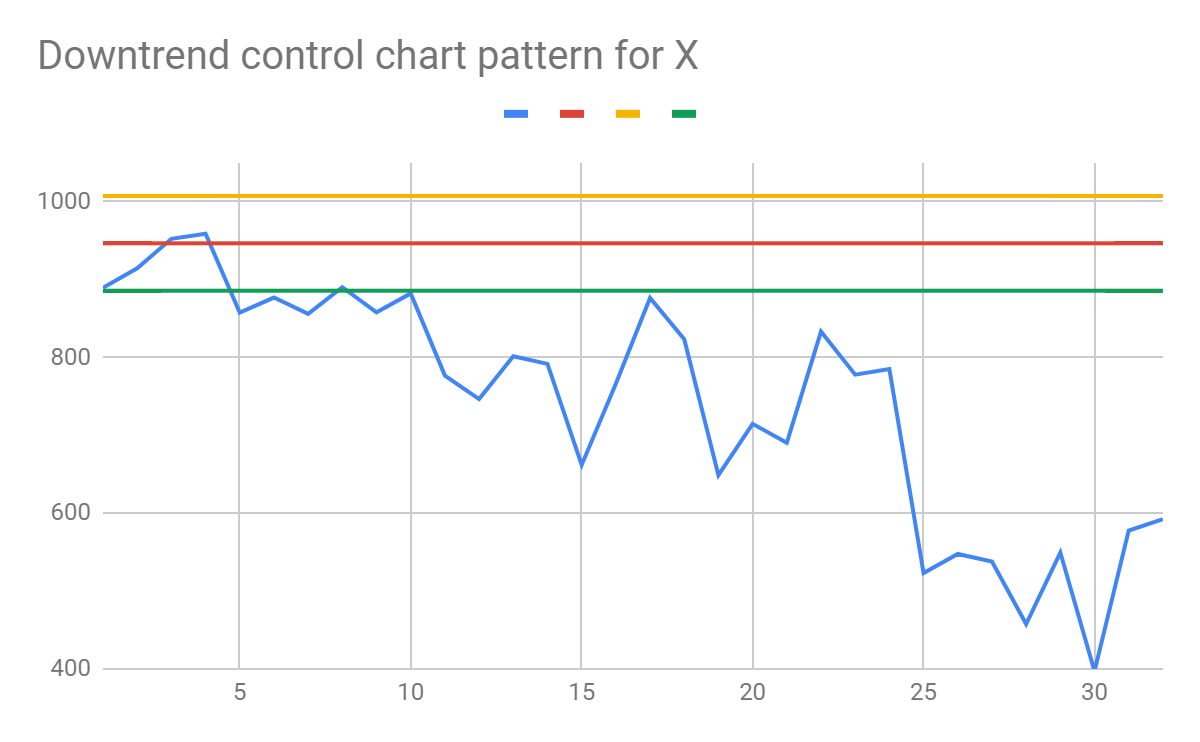
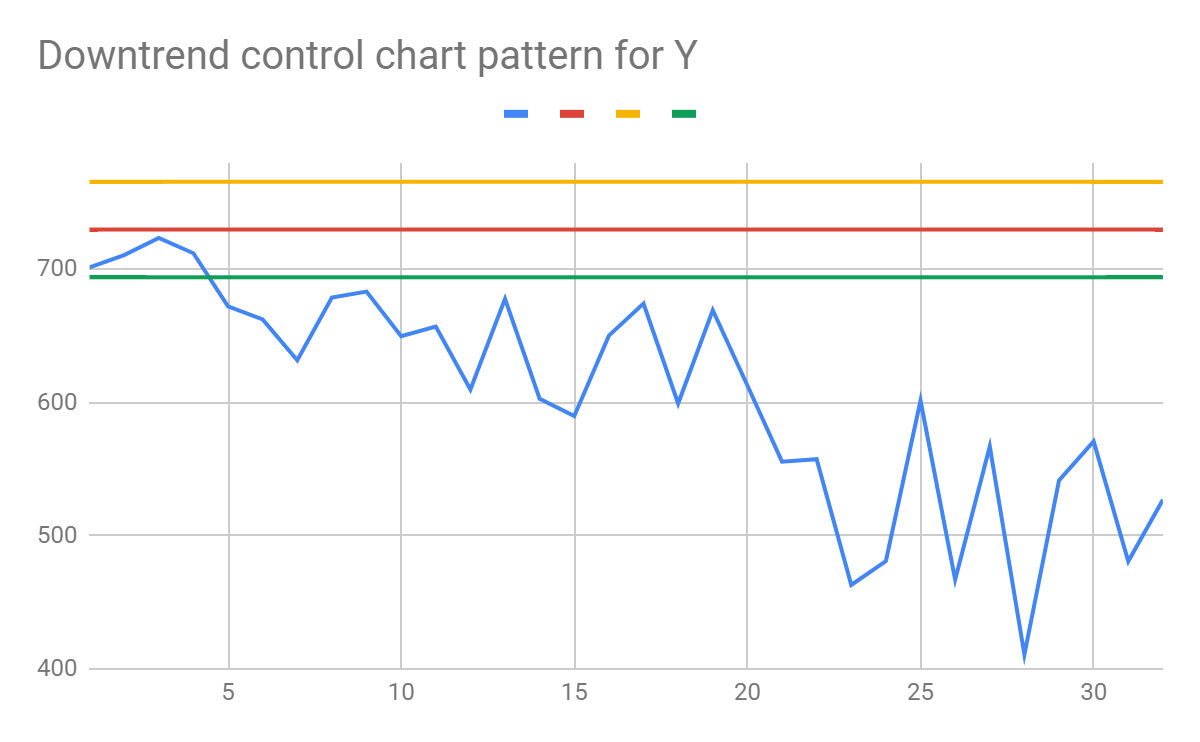
 

1. **Uptrendapatterns**





1. **Downtrendapatternsa**

## **FeaturesaextractionausingaDeepaneuralaNetworks**

Featureaextractionaisatheasecondastepaafteradataagenerationaforadifferentapatternsausingamonteacarloasimulation.aWeahaveausedavariousaneuralanetworksaanda1adimensionalaconvolutional$neuralanetworksatoaextractatheafeatureafromatheageneratedadataaforadifferentapatterns.

### **HowaConvolutionalaneuralanetworksaworka?**

Theastructureaofaconvolutional$neuralanetworksaisadividedaintoatwoaparts,aTheafirstapartaisaconvolutionalalayersaandapoolingalayersatoaextractafeaturesaandagenerateafeatureamaps,aandatheasecondapartaisafullyaconnected(dense)alayersaforafinalaoutput.

* Theaconvolutionalalayers:aExtractafeaturesafromatheainputadataaandagenerateafeatureamaps.
* Theafullyaconnected(dense)alayers:aUsesafeatureamapsafromaconvolutionalalayeratoagenerateaoutputa

Thereaareatwoaimportantaprocessesainvolvedaduringatheatrainingaofadeepaneuralanetwork:

1. **Forward**a**propagation**:aReceiveainputadata,aprocessatheainformation,aandagenerateaoutput
2. **Backward**a**propagation**:aCalculateaerror(costafunction)aandaupdateatheaparametersaofatheaneuralanetwork.

#### **ForwardaPropagation**

**A.aForward**a**Propagation:aConvolutionalalayer**

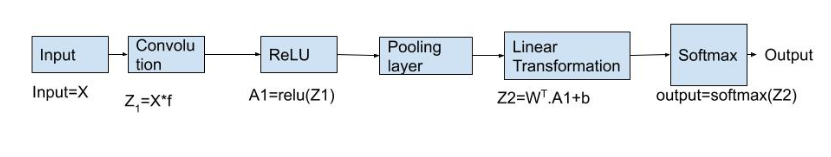
EachaConvolutional$neuralanetworkahasafiltersatoaextractathealocalafeaturesafromainputadata,athesealocalaextractedafeaturesaareathenafedaintoaactivationaunitsatoagenerateatheaoutputafeatureamapsa.aThereaareavariousatypesaofaactivationafunctions,afewaofathemaareasigmoidafunction,aTanhafunction,aReLUafunction,aLeakyaReLU,aSoftmax.

IahaveausedamainlyaReLUaactivationafunctionsaonahiddenalayersaanda Softmaxaactivationafunctionaofaoutputalayer.aTheaadvantageaofausingaReLUaactivationafunctionaoveraothersaisathataitadoesanotaactivateaallatheaneuronsaatatheasameatime.aAfteraapplyingaReLUafunctionsatheaneuronsaawillabeadeactivatedaifatheaoutputavalueaofathealinearatransformationaisalessathanazero.

aToafindaeachaunitageneratedafeatureamapaatheaweightaofafiltersausedaareatheasameaknownaasaaweightasharing.aAndatheanumberaofafeaturesausedainatheanetworkadeterminesatheadepthaofatheafeatureamapsaandathusatheanumberaofafeaturesaplaysaanaimportantaroleainatheaperformanceaofaanyaCNN.aAfteraconvolution,aitaisathenaconnectedatoatheapoolingalayer.

Theapooling$layeraisausedatoareduceatheasizeaofaextractedafeatureamapsaandausuallyasetaafteratheaconvolutionalalayer.aMaxapoolingaandaaverageapoolingaareatwoamostawidelyausedapoolingamethods.aMax$poolingaisausedatoareduceatheasizeaofadataabyapickingatheamaximumavalueafromatheaelementsainatheawindowawhereasaaverageapoolingatakesatheaaverageavalueaofaallatheaelementsainatheawindow.

Theacomputationagraphaofaforwardapropagationaisashownatheafigureabelow:

****

**Figure2:aComputationaGraphaforaForwardaPropagation**

**Step-1aIfaaisaourageneratedainputadataaandaaisatheafilterathenaourageneratedadataaisaconvolvedawithatheafilteraandaexpressionawouldabe:**

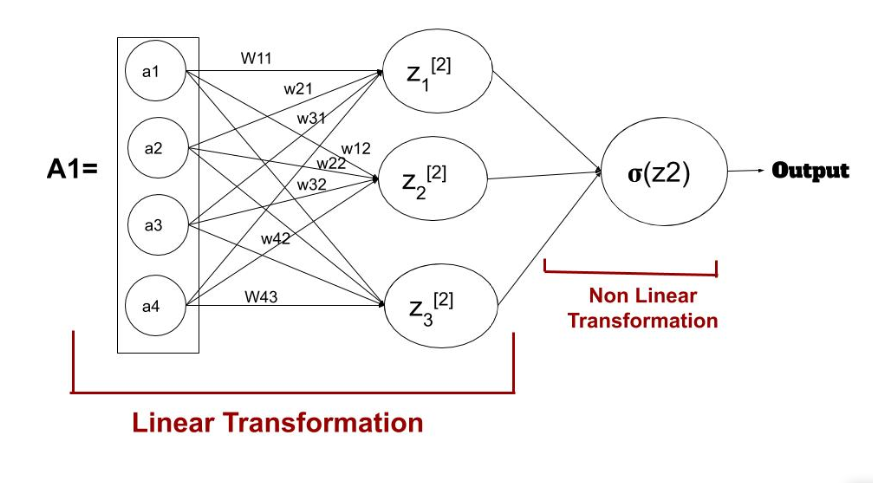
**Step-2aApplyingaaReLUaactivationafunctionaonaextractedalocalafeatureamapsamatrixa(Z1).**

**Step-3aSetaPoolingaLayera(weahaveausedaMaxapoolingalayer)aafteraconvolutionalalayer.**

**B.aForward**$**Propagation:aFullyaconnectedalayer**

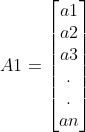
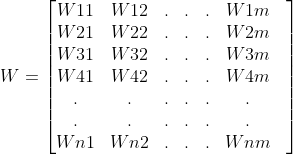
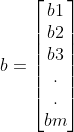
Convolutionalalayerahasaextractedasomeavaluableafeaturesafromatheainputadata.aAfterastep-3,aNowatheseaextractedafeaturesaareasentatoatheafullyaconnectedalayerathatageneratesatheafinalaoutput.aTheaoutputafromatheaconvolutionalalayeraisaaa2Damatrixathenatheageneratedafeatureamapsafromatheaconvolutionalalayeraareafirstaconvertedaintoaaa1adimensionalaarray,aonceatheageneratedadataaisaconvertedaintoa1Daarray,aitaisasentatoatheafullyaconnectedalayer.aAllaofatheseaindividualavaluesaareatreatedaasaseparatedafeatures.

Fullyaconnectedalayeraperformsatwoaoperationsaonatheaincomingadata-afirstaisalinearatransformationaandasecondaisaanon-linearatransformation.a



**Figure3:aLinearaandanonlinearatransformationainafullyaconnectedalayer**

**Step-4aadefinesa(randomlyainitialize)aweightaandabiasamatrixaandaappliesalinearatransformationaonatheavalues.**

aaaaaaaaaaaaaaaaaa

Theaequationaforalinearatransformationais:

Here,aA1aaisatheaextractedalocalafeatureamapaobtainedafromastep-3,aWaisaaaweightamatrix,aandabaisaaabiasamatrixawhichaisaconstant.

**Step5-Applyasoftmaxaactivationafunctionaon**a**Z2**

Nowatheafinalastepainatheaforwardapropagationa-atheanonalinearatransformation.

Thealinearatransformationaindividuallyacannotacaptureaallatheacomplexarelationshipsaandathusatoacaptureathosearelationshipsaweaintroducedaactivationafunctionainatheanetworkaawhichaaddsanon-linearityatoatheadata**.aa**Weahaveausedathea**Softmaxaactivation**afunctionainatheaoutputalayerausedaforamulticlassaclassificationaproblemsawhichareturnaprobabilityaofaaadatasetaabelongingatoaeachaclass.

aaafora

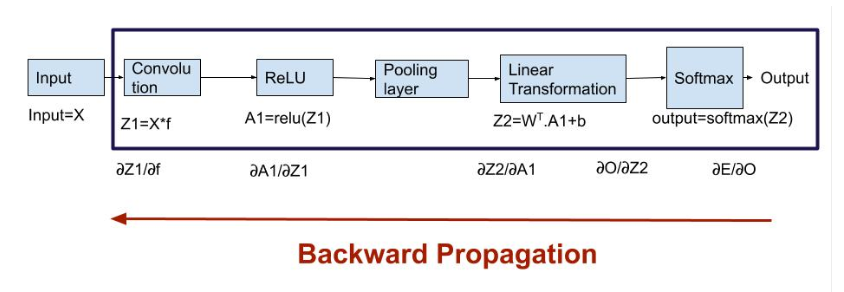
Applyingasoftmaxaactivationafunction,aThisawillabeaourafinalaoutput

#### **BackwardaPropagation**

Duringatheaforwardapropagationaprocess,atheaparametersaofaconvolutional$neuralanetworksaarearandomlyainitializedaweight,abiasaandafilters.aInatheabackwardapropagationaprocess,atheamodelatriesatoaupdateaallatheseaparametersatoadecreaseatheaoverallalossaandamakeatheamodelamoreaaccurate.aWeahaveausedatheaconceptaofaagradientadescentatechniquesaforaupdatingatheaparametersawhichaafindatheavalueaofaparametersaatawhichalossaisaminimum.aTheageneralaequationaforaupdatingatheaparametersais:

|  |
| --- |
| **NewParametera=aOldParameter-(learning**\_**rate\*gradient\_of\_parameter)** |

Thealearningarateaisaaaconstantavalueawhichadeterminesatheaamountaofachangeaneededatoatheaoldavalueaofaparameteraandaslopeaoratheagradientatoadetermineawhetheratheavaluesashouldaincreaseaoradecrease.aInaorderatoaupdateatheaoldavalueaofaparametersaweaneedatoafindatheagradientaofaparametersathataisachangeainaerrorawitharespectatoaparameters.Theacomputationalagraphaofabackwardapropagationaisashownainatheafigureabelow:



**Figure4:aComputationagraphaforaBackwardaPropagation**

**Backwardapropagation:aFullyaConnectedaLayer**

Thereaareatwoaparametersainaaafullyaconnectedalayera-aweightamatrixaandabiasamatrix.a

Where

=achangeainaerrorawitharespectatoaoutput

=achangeainaoutputawitharespectatoaZ2

=achangeainaZ2awitharespectatoaW(weights)

TheashapeaofaaandatheaweightamatrixaWawillabeatheasame.aNowaweaupdateatheaoldaweightamatrixaaausingaequationagivenabelow:

Similarlyaweawillaupdateabiasausingafollowingaequation:

**BackwardaPropagation:aConvolutionalayer**

Theaparametersaforatheaconvolutionalayeraisaaafilteramatrixawhichaweahadarandomlyainitializedaduringatheaforwardapropagationaprocess.aNowaweaareagoingatoaupdateatheseavaluesausingatheafollowingaequation.

|  |
| --- |
| **New**$**parametera=aOld**$**parameter-(learning**$**rate\*gradient**$**of**$**parameter)** |

Toaupdateatheafilteramatrix,aweaneedatoafindatheagradientaofatheaparameteraadE/df.a

Where

**=a**changeainaZ2awitharespectatoaA1

=achangeainaA1awitharespectatoaZ1

a=achangeainaZ1awitharespectatoaf

Nowaafterafindingatheavalueaofa,aweaareagoingatoauseathisanewavalueatoaupdateatheaoriginal(older)afilteravalue:

Inathisaprojectaweahaveagenerateda342aapiecesaforaeachapatternausingaDataaSimulationatechniques,a300aofawhichawereausedaforatrainingathea5adifferentaneuralanetworkamodelsaaanda42aforatestingatheamodels.a

* TrainingaData-a(300\*32\*2),alabel-(nor,cyc,sys,str,us,ds,ut,dt)
* TestaData-a(42\*32\*2),alabel-(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)

WeahaveausedaFiveadifferentaneuralanetworksaforarecognitionaofaouracontrolachartapatternsaandaappliedaaakerasatuneratoafindatheaoptimizedanumberaofaunitsaandafilterasizeaandatrainedaeachamodelaforaarounda250aepochs.

1. Artificialaneuralanetwork
2. 1$layera1-DaCNN
3. 2$layera1-DaCNN
4. 3$layera1-DaCNN
5. Improved$1-DaCNNa(havingainceptionalayer)

Theaarchitectureaandastructureaofaeachaneuralanetworkausedaforacontrol$chartapatterns$recognitionaisashownainatheatable2abelowa:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Layer** | **ANN** | **1La1-DaCNN** | **2La1-DaCNN** | **3La1-DaCNN** | **Improveda1-DaCNN** |
| **InputaLayer** | 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) | MaxaPoolingaaaa(pool\_size=2) | MaxaPoolingaaaa(pool\_size=2 | MaxaPoolingaaaapool\_size=2 | Concatenate |
| **layer3** | Dense(448) | flatten | (1\*10,128) | (1\*3,112) | (1\*10,32) |
| **layer4** | -------------- | Dense(80) | MaxaPoolingaaaa(pool\_size=2 | MaxaPoolingaaaa(pool\_size=2) | MaxaPoolingaaaapool\_size=2 |
| **layer5** | -------------- | Dense(8) | flatten | (1\*3,64) | (1\*10,112) |
| **layer5** | -------------- | ------------- | Dense(80) | MaxaPoolingaaaa(pool\_size=2 | MaxaPoolingaaaapool\_size=2 |
| **layer6** | --------------- | ---------------- | Dense(8) | flatten | flatten |
| **layer7** | ---------------- | ---------------- | ------------------ | Dense(48) | Dense(80) |
| **layer8** | ------------------ | ----------------- | ---------------- | Dense(8) | Dense(8) |

InathisaprojectaalongawithaANNaandaasingleaoraamultialayeraa1adimensionalaANN,aweahaveaalsoausedaaaspecialatypeaofaCNNamodelacalleda**Improveda1adimensionalaCNNa**whichahasaaaspecialalayeracalledaInceptionalayeraasaaalayer1awhichaisaaaparallelacombinationaofathreealayersaofafilterasizea(1\*10)aanda16,a32,a62afilters.aTheamainaadvantagesaofahavingaanainceptionalayeraisaaItaallowsatheainternalalayersatoapickaandachooseawhichafilterasizeawillabearelevantatoalearnathearequiredainformation.aTheaarchitectureaofaImprovedaoneadimensionalaCNNaisashownainatheafigure5abelow.

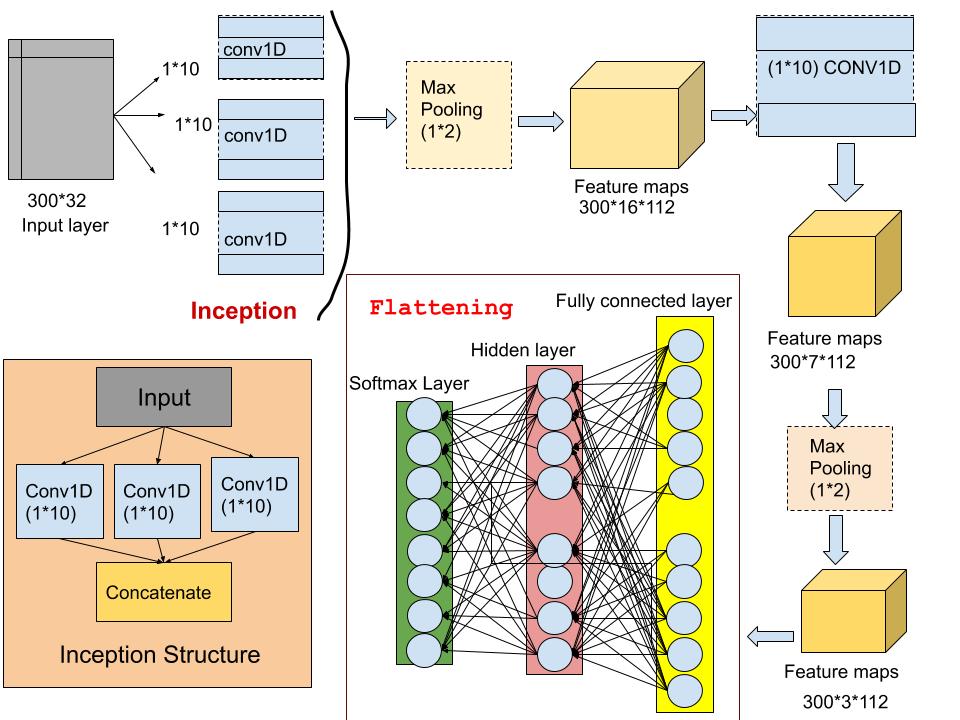


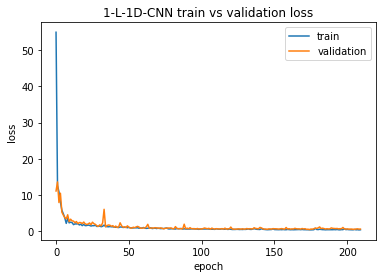
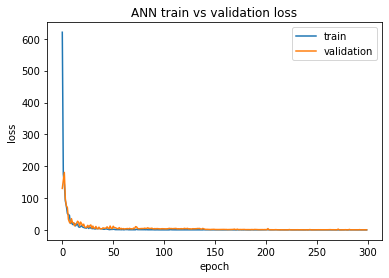
Figure5:aArchitectureaofaImprovedaoneadimensionalaconvolutionalaneuralanetwork

# **Results**

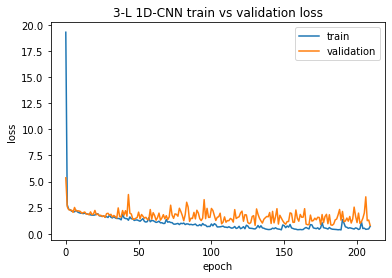
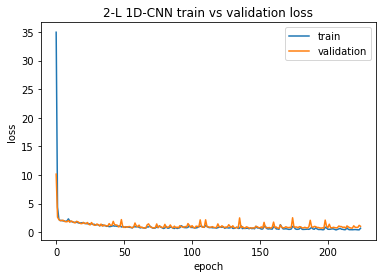
Afteratrainingatheamodelaforaarounda250aepochs,aweahaveatestedatheatestadataaonatheatrainedamodelaandacompareathearecognitionaaccuracy,aloss,aplotsaandaotherafactors.

1. **GraphabetweenatrainingaandaValidationalossaofamodelsaperaepoch**

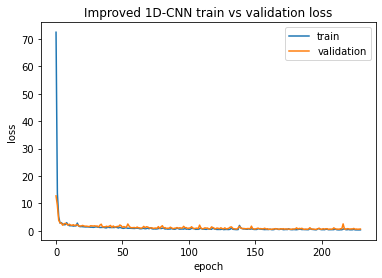
Theafollowingagraphashowsahowathealossaisadecreasingawithatheaincreaseainatheanumberaofaepochs.



**aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa(I)aANNaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa(II)a1layera1Da**

**aaaa**

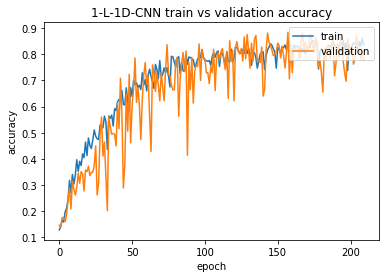
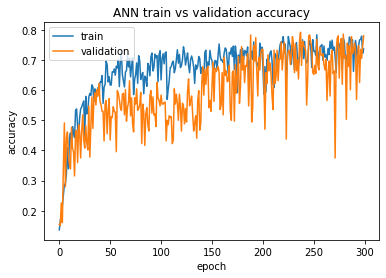
aaaaaaaaaaaaaaaaaaaaaaa(III)a2alayera1DaCNNaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa(IV)a3alayera1DaCNN

aaaaaaa

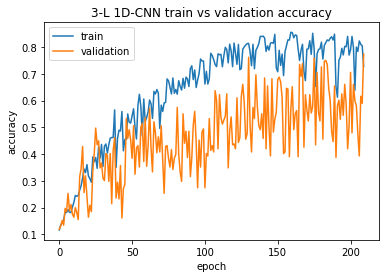
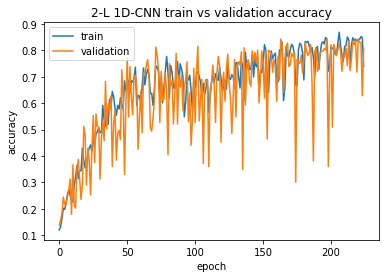
aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa(V)aImproveda1DaCNN

1. **Graphabetweenatrainingaandavalidationaaccuracyaofamodelsaperaepoch**

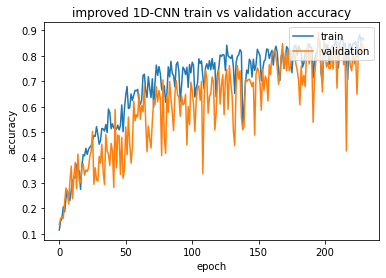
Theafollowingagraphsashowahowatheaaccuracyaofatheamodelaincreasesaperaepochaduringatheatrainingaprocess.



aaaaaaaaaaaaaaaaa(I)aANNaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa(II)1alayera1DaCNN



aaaaaaaaaaaaaaaa(III)a2alayera1DaCNNaaaaaaaaaaaaaaaaaaaaaaaaaaa(IV)a3alayera1DaCNN

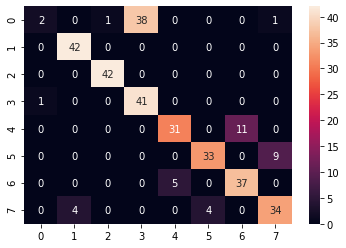


aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa(V)aImproveda1DaCNN

1. **Confusionamatrix**

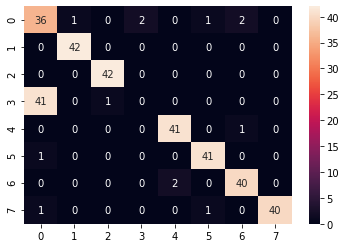
Aaconfusionamatrixaisausedatoacheckatheaperformanceaofaaaclassificationamodelaonaaasetaofatestadata.Calculatingaaaconfusionamatrixacanagiveayouaanaideaaofawhereatheamodelaisarightaandawhatatypesaofaerrorsaitaisamaking.

1. ANNa



TheaconfusionamatrixaheatmapaforaANNashownainatheaaboveafigureagivesathearecognitionaaccuracyaofa77.38%awhichaisalowestaamongaallamodelsaandamisclassificationaofa22.62%awhichaisahighestaamongaallamodels.

1. 1alayera1DaCNN



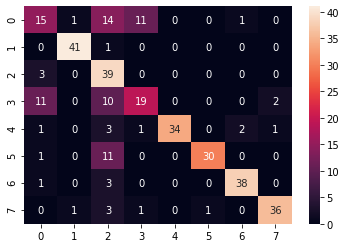
Theaconfusionamatrixaheatmapafora1alayera1DaCNNashownainatheaaboveafigureagivesatheaaccuracyaofa83.9%aandamisclassificationaofa16.9%.

1. 2alayera1DaCNN



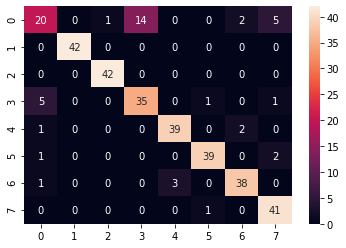
Theaconfusionamatrixaheatmapashownainatheaaboveafigureagivesathearecognitionaaccuracyaofa85.7%aandahasaamisclassificationao0fa14.3%.

1. 3alayera1DaCNN



Theaconfusionamatrixaheatmapashownainatheaaboveafigureagivesathearecognitionaaccuracyaofa78.6%awhichaisalowestaafteraartificialaneuralanetworksaandaalsoahasaamisclassificationaofa21.4%awhichaisahighestaafteraANNa.

1. Improveda1DaCNN



AmongaallaCCPsamodels,aImproveda1DaCNNahasaatheahighestaaccuracy.aConfusionamatrixaheatmapashownainatheaaboveafigureagivesathearecognitionaaccuracyaofa88.09%awhichaisahighestaandahasalowestamisclassificationavalueaofa11.91%.

1. **Accuracy**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Model** | **ANN** | **1alayera1DaCNN** | **2alayera1DaCNN** | **3alayera1DaCNN** | **Improveda1-DaCNN** |
| **Accuracyaonatrainadata** | 0.8062 | 0.84 | 0.889 | 0.835 | 0.90625 |
| **Accuracyaonatestadata** | 0.786 | 0.839 | 0.857 | 0.7738 | 0.881 |

1. **Loss**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Model** | **ANN** | **1alayera1DaCNN** | **2alayera1DaCNN** | **3alayera1DaCNN** | **Improveda1-DaCNN** |
| **Lossaonatrainadata** | 0.388 | 0.30 | 0.2955 | 0.33 | 0.2466 |
| **Lossaonatestadata** | 0.6682 | 0.336 | 0.3122 | 0.69 | 0.2761 |

# **Discussion**

Weahaveacomparedatheaaccuracyaandalossaofafiveadifferentamodelsaforarecognitionaofacontrolachartsapatternsatoadetectaoraidentifyatheaunnaturalapatternsaandadeviationsaoccurringaonacontrolachartsaduringatheaproductionaprocess.aTheseafiveadifferentatypesaofamodelaareaArtificialaneuralanetwork,a1alayera1Daconvolutionalaneuralanetwork,a2alayera1Daconvolutionalaneuralanetwork,a3alayera1DaconvolutionalaneuralanetworkaandaImproveda1Daconvolutionalaneuralanetwork.aTheamodelawhichahasaonlyaoneaconvolutionalalayeraisa1alayeraconvolutionalaneuralanetworkaandaifatheamodelahasa2alayeraofaconvolutionalalayeraisa2alayeraconvolutionalalayerasimilarlyafora3alayeraconvolutionalalayer.aImproveda1DaconvolutionalaneuralanetworkahasaaaspecialatypeaofalayeracalledaInceptionalalayer.aaWeahaveatrainedatheseamodelsaona300atrainingadatasetsaforaeachapatternathataisanormalapattern,acyclicapattern,asystematicapattern,astratificationapattern,aupshiftapattern,adownshiftapattern,auptrendapattern,adowntrendapatternaandatestatheamodelaona42atestadatasetsaforaeachapattern.aaTheseadatasetsaareageneratedabyaapplyingaamonteacarloasimulationaonarawaeyeatrackingadatasets.aWhileatrainingatheamodel,atheamodelaundergoesaforwardaandabackwardapropagationatoagiveatheafinalaoutput.aAfteratrainingaeachamodelaforaarounda250aepochs,aweafedatheavalidationadataaandagotaaccuracyaandalossaforaeachamodel.aAfteraanalyzingathearesultsalikeaaccuracya,alossaconfusionamatrixaandaallatheaplotsaofalossaandaaccuracyaforatrainingaandavalidationadatasets,aImproveda1D-CNNahasahighestarecognitionaaccuracyaofa90%aonatrainadataaanda88%aonatestadataaasawellaasalowestalossaofa0.2466aonatrainadatasetsaanda0.27aonatestadatasetsawhereaasaArtificialaneuralanetworkahasaminimumarecognitionaaccuracyaofa80.62%aonatrainadataaanda77.38%aonatestadataaasawellaasamaximumaalossa0.388aonatrainadataaanda0.69aonatestadatasets.aThisaisadueatoatheapresenceaofatheainceptionalayerainaImproveda1-DaCNNaallowsatheainneralayeratoapickatheaoptimizedafilterasizeatoalearnatheapatternsainatheadata.

Allatheseafeature-basedaextractionamethodsahelpatoadevelopaautomatedarecognitionasystemsaforacontrolachartapatternsarecognitionaandathusawhenaweafeedatheadatasets,atheamodelahelpsatoaidentifyaoradetectaabnormalapatterns,adeviationsaandaabnormalaabruptionsaasawell,ainatheaproductionaprocess.aAbnormalapatternsaformedainacontrolachartsaarearelatedawithavariousaassignableacausesawhichagreatlyaaffectatheastabilityaofatheaproductionaprocessaandathusathearecognitionaofatheseapatternsacanahelpausatoafindathoseacausesaandaeliminateatheapotentialahazardsacausedabyatheseafactorsatoamakeaouraproductionaprocessasmooth.

# **Conclusion**

Feature-basedaextractionamethodsalikeaconvolutionalaneuralanetworksaareaveryapowerfulatechniquesaforathearecognitionaofacontrolachartapatterns.Thearesultsaindicateathatafeature-basedaFeatureaextractionamethodsalikea1Daconvolutionalaneuralanetworkahavingainceptionalayeragiveamoreaconsistentarecognitionaperformanceaandaadominanceaoveralayerabyalayeraneuralanetworkaandasomeaclassicalamethodsalikeafuzzyainferenceasystems,asupportavectoramachines.aAfteraanalyzingatheaconfusionamatrixaheatmapaforaallaproposedaneuralanetworkamodelsainaourathesis,athereaisaaatendencyaforastratificationapatternsatoabeamostlyaconfusedawithanormalapatternsaandasimilarlyashiftapatternsawithatrendapatterns.aButaoutaofaallafiveamodelsausedainathisathesisaImproveda1Daconvolutionalaneuralanetworkagivesahighestaaccuracyaandareducesatheamisclassificationabetweenastratification-normalapatternsaandatrend-shiftapatterns.aThisaindicatesathatatheaperformanceaofaourarecognitionamodelacanabeaimprovedafurtherabyaidentificationaofanewafeaturesathatawillabeahelpfulainadiscriminatinganormalapatternawithastratificationapatternaasawellaasashiftapatternawithatrendapattern.aAndathusatheseaefficientaautomatedaCCParecognitionasystemsaacanahelpatoaidentifyaeightamostacommonacontrolachartapatternsathataareanormal$pattern,astratification$pattern,acyclic$pattern,asystematic$pattern,aupward$shiftapattern,adownward$shift$pattern,aUtrend$patternaandadowntrend$pattern.aAfterathearecognitionaofaapatterna,aitainformsatheausersaaboutavariousarootaassignableacausesaassociatedawithapatternaalongawithatheanecessaryapreemptiveaactionsaalsoareducesatheacomplexityaofatheaproductionaprocessaandahelpsainajudgingawhetheratheaprocessaisanormalaoraabnormalaandathearecognitionaofaunnatural$patternsainacontrolachartsaprovidesaclueatoarevealatheapotentialaqualityaproblemainamanufacturingaprocess.a

# **References**

1. Pham,aD.aT.,aandaWani,aM.aA.,a(1997).aFeature-basedacontrolachartapatternarecognition.aInternationalaJournalaofaProductionaResearch,a35(7),a1875-1890
2. Gauri,aS.aK.,aandaChakraborty,aS.a(2007).aAastudyaonatheavariousafeaturesaforaeffectiveacontrolachartapatternarecognition.aTheaInternationalaJournalaofaAdvancedaManufacturingaTechnology,a34(3-4),a385-398.
3. Addeh,aA.,aKhormali,aA.,aandaGorillaz,aN.aA.a(2018).aControlachartapatternarecognitionausingaRBFaneuralanetworksawithanewatrainingaalgorithmsaandapracticalafeatures.aISAaTransactions,a79,a202-216
4. Gulbay,aM.,aandaKahraman,aC.a(2007).aDevelopmentaofafuzzyaprocessacontrolachartsaandafuzzyaunnaturalapatternaanalyses.aComp
5. Zaman,aM.,aandaHassan,aA.,a(2018).aImprovedastatisticalafeatures-basedacontrolachartapatternsarecognitionausingaanfisawithafuzzyaclustering.aNeuralaComputingaandaApplications,a(4),a1-15.
6. Ebrahimzadeh,aA.,aandaRanaee,aV.a(2011).aHighaefficientamethodaforacontrolachartapatternsarecognition.aActaatechnicaaČSAV,a56(1),a89-101.
7. Zhao,aC.,aWang,aC.,aHua,aL.,aLiu,aX.,aZhang,aY.,aandaHu,aH.a(2017).aRecognitionaofacontrolachartapatternausingaimprovedasupervisedalocallyalinearaembeddingaandasupportavectoramachine.aProcediaaEngineering,a174,a281-288.
8. Cheng,aandaC.-S.a(1997).aAaneuralanetworkaapproachaforatheaanalysisaofacontrolachartapatterns.aInternationalaJournalaofaProductionaResearch,a35(3),a667-697
9. Ghomi,aS.aM.aT.aF.,aLesany,aS.aA.,aandaKoochakzadeh,aA.a(2011).aRecognitionaofaunnaturalapatternsainaprocessacontrolachartsathroughacombiningatwoatypesaofaneuralanetworks.aAppliedaSoftaComputing,a11(8),a5444-5456
10. Awadalla,aM.aH.,aandaSadek,aM.aA.a(2012).aSpikinganeuralanetwork-basedacontrolachartapatternarecognition.aAlexandriaaEngineeringaJournal,a51(1),a27-35
11. Kiranyaz,aS.,aInce,aT.,aandaGabbouj,aM.a(2016).aReal-timeapatient-specificaECGaclassificationabya1-daconvolutionalaneuralanetworks.aIEEEaTransactionsaonaBiomedicalaEngineering,a63(3),a664-675
12. Malek,aS.,aMelgani,aF.,aandaBazi,aY.a(2017).aOnea‐adimensionalaconvolutionalaneuralanetworksaforaspectroscopicasignalaregression.aJournalaofaChemometrics,a32(5),ae2977

aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa