# Performance Analysis of the Machine Learning Algorithms on Heart Condition Predictions

**Geetha.M, Ganesan.R,TallamTharun Sai**

***ABSTRACT---Now-a-daysHealthcaremonitoringwidelyusesInternetofThings(IoT)andbigdatawhichisfurtherintegratedintowearablebiosensors.Thispaperisaboutfindingthebestalgorithmforpredictingtheheartconditionusingdifferentmachinelearningalgorithms.InthiswehavealsoincludedthebasicArtificialNeuralNetworksalgorithmforpredictingtheheartconditionofanindividual.***

***Inthisworkwehadpredictedthepersonsheatconditionsbyknowingsomekeyattributes.Byincreasingtheuseofmachinelearningalgorithms,theaccuracyofeachalgorithmiscalculatedandthequalityandvalueofthehealthservicesincreaseseefficiency.***

***Thisismainlyabouthowdifferentthealgorithmspredictandtheaccuracyofeachalgorithm.HeretheANNhastheheightaccuracywhencomparedtoallothermachinelearningalgorithmslike,SVM-ploy,SVM-RBF,NaïveBayes,Decisiontree,RandomForest,K-NearestNeighbor.***

***Keywords-DecisionTree,K-nearestneighbour,NaiveBayes,Randomforest,SVMPoly,SVMRBF,ANN(ArtificialNeuralNetworksusingmulti-layerPerceptron).***

## I. INTRODUCTION

MachineLearningandanalysisistheextractionofnewinformationbyexaminginlargeamountofdata.Itcanbeusedtotakecertaindecisions,estimateandpredictusingdifferentalgorithms.BysusingmachinelearningalgorithmswithIoTdeviceswecanpredictdifferentdiseaseslikeCardiovascularDiseasesandmanymorebyknowingtheconditionoftheheart.Theseheartconditionscanbepredictedusingdifferentfactorswhichincludesfamilyhistory(genetics),cholesterollevel,diabetes,BloodPressure,heartbeat,age,alcoholicornot,exerciseetc.So,theperson'sdataistakenandanalyzedtopredicthis/herheartcondition.

### A. Back-GroundMotivation

Theheartisveryimportantorganofourbody.So,it'sourdutytotakecareofourheart'scondition.Therateofheartmalfunctionsisincreasingenormouslynow-a-days.Thisisduetothebusylifestylethatpeoplearefacing.Mostlypeopleareeatingjunk,fastfoodanddoingtheirworkfromsittinginoneplacelikesoftwareengineers,bankersandetc.Andpeoplearedoinglessexerciseandarelessactive.Physicalactivitiesarereduced.So,theyarenotatalltakingcareoftheirheartcondition.Thesefactorscausemanypeopletosufferfromheartdiseases.Peoplearebusiertotaketheregularcheck-ups.

### B. Objective

Theobjectiveofthepaperistocollectheartbeatdataandtrainthedatabyatraineddatasetcalled"Cleveland"dataset.Thisdatasetisgivenbyhungarianandswitzerlanddoctorsfromdifferenthospitals.Ithas14attributesand300datarecordsinit.Thisprojectusessupervisedmachinelearningtechniquesforthepredictions.Wewillpredictonlytheseverityoftheheartconditionwhichisrankedfrom0to4.Thiscanbedonebythetakingtherealdatafromthesourceslikefitbit,Googlefitapps,etc.Andaddinganextrafeatureto itthat,theheartcondition.

## II. LITERATURESURVEY

Therearemanypapersonthissolution.Hereonlyfewarediscussed.

Inapapertheprediction saredonebythealgorithmcalledDecisionTree,oneofthebestmachinelearningalgorithms.Bythisalgorithmtheauthorwillcombinedifferentdatasetstoavoidallowingirregulardetailsintothescenario.So,thisisaboutfindingthebestdatafromwhichtheprediction saremadecorrectly.Onlysomefeaturesfromthedatasetsareextractedandusedintheprediction algorithmtogetthebestresults.

Intheotherpapertheimportanceoffeaturescalinganddimensionalityreductionisexplainedclearly.Thisisfinallyshownbytheresultsusingsimplemachinelearningalgorithms

Inotherstudythedatasetisputintothe J48classifierUnprunedtree,Decisiontree,NaïveBayesclassification,NeuralNetworks.Fromwhichtheyaregettingtheaccuracyofabove90%.Thentheyhaveused SensitivityandSpecificityrateforcomparing.Thismodelisdonebyusingthe DataMiningmodelcalledTransthoracicEchocardiographyReportdataset.

Theotherpaper,reflectedthatthecompletestudyofdifferentpaperthathavedonetheheartconditionisusingDataMiningTechniquesandIntelligentFuzzyApproach.Thisanalysisisbasedonthenumberofattributesusedinthedataset,accuracyandsuccessofthemodels.Alltypesofalgorithms,toolsusedetcaretakenintoconsiderationand

broughtintotheversusplatformwhichtellsthebestmodel.

Onfurtheranalysisandresearch,apapershowedhowthedependenciesofthedifferentattributesinthedatasetareresponsiblefortheheartconditionprediction.Inthistheauthorhadtakenthe4different datasetsofsimilarkindofattributes.Thispaperwilltellthatthoseattributesarenotsufficientforpredictingtheheartcondition.

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ThishavebeentestedbymachinelearningalgorithmslikeNaïve Bayes,DecisionTree,SVM,Ada-Boost,LR,MLPetc.Healsofoundabouttheselectionofattributes byIGandGeneticalgorithmsforselectingthemainattributes.

Inotherpaperthecomparativestudyabouttheddifferentmachinelearningalgorithmslike SVM,Logisticregression,Neuralnetworks,RBFs,etc.andhowaccuratetheirpredictionsare.

## III. PROBLEMFORMULATION ANDEXISTINGWORK

[13]Thereareexistingworkslike,comparingtheresultsofdifferentalgorithmsnamely,DecisionTree,NaïveBayes,MultilayerPerceptron,K-NearestNeighbor,SingleConjunctiveRuleLearner,RadialBasisFunctionandSupportVectorMachine.Hereensemblepredictionsofclassifiers,whichincludesbagging,stacking,boosting,areappliedtothedataset.

Therearework slikeunderstandingofdifferentdatasetspredictions.Inthese,relationshipsbetweentheinputandoutputattributeshadbeenconcentratedmore.

[4]Intheotherpapertheheartconditionwaspredictedbytheneuralnetworksandneuro-fuzzysystem.TheyhaveusedCRIP-DMmethodologytotheClevelanddatasetforpredictions.Thisisdonebyestablishingtherelationships,patternsconnectedwithheartdiseases.Bywhichtheyaregettinganaccuracyof75.93%.

Therearemanyexistingworkssuchasthebestalgorithms,thehighlydependedattributes,dimensionalityreducedmodels,featurescalingimportanceonceetc.Butthisprojectisdifferentbecausebytheusageofmachinelearningalgorithmswhicharefeaturescaled,andalsodimensionalityreducedone.

## IV. PROPOSEDWORK

Inthisproposedworkthedifferentmachinelearningalgorithmslike Decisiontree,Randomforest,NaiveBayes,SVMkernel(RBFandploy),K-nearestneighbourareapplieddirectlytothedataset.Andthenappliedafterdimensionalityreductiontechniquetothedatasetbyapplying PCA(PrincipleComponentanalysis)algorithmwhichtakesthehighestvariantattributesandthenpredict.Thisprojectalsoshowshowthedataisdistributedgraphicallybyplottingthegraphtaking2attributestoplotlinearly.

Theproposedworkistotakethereal-timedatabyusingECGandBPMsensorsandpredictthatdatausingdifferentalgorithmslikeDecisiontree,Randomforest,NaiveBayes,SVMkernel(RBFandploy),K-nearestneighbourandfordimensionalityReductionPCA(PrincipleComponentanalysis)isused.Thisisusefultofindthepatientswhosehasheartdiseaseinaneasyway.Andwearegoingtocomparethesealgorithmsandfindoutthebestalgorithmbyitsaccuracyvalue.

## V. TOOLS/HARDWARE/SOFTWAREREQUIREMENT

TheThehardwareandsoftwarerequirementsusedforthisproposedworkareWearableMedicalSystem,ECGandBPMsensors, SpyderIde-Pythonanaconda,JupiterNotebook.

## VI. IMPLEMENTATIONSTRATEGY

### A. AlgorithmsusedforPredictions:

ThesearethealgorithmsusedforpredictionoftheHeartCondition.Theseareallmachinelearningalgorithms.Forgivingthebest resultsPCA(PrincipleComponentAnalysis).

#### 1. DecisionTree:

DecisionTreeAlgorithmisanensemblelearningofmethodslikeclassification,regressionandothertasks.Thisisbasedonthecl assificationoftheattributesbasedontheirInfoandgain.Theheightgainattributeissplitintoitsrespectivevalues.Thenewsplitdatais setintonewdatasetsandtheappliedasnewdecisiontree.Thisisrepeateduntilwegetpuresubsets.Thisisoneofthebestalgorithmsforlinearlydistributeddatasets.[14]Treemodelswithadiscretesetofvaluesthatthetargetvariablecantakearecalledclassificationtrees;Inthesetreestructures,leavesrepresentclasslabelsandbranchesrepresentcombinationoffeaturesthatleadtoclasslabels.

#### 2. RandomForestAlgorithm:

*RandomForestalgorithmorRandomforestsarethesamealgorithms*Theseare*ensemblesof*methodsforclassification,regressionandothertasks.Theseworkonthebasisofconstructionofmultipledecisiontrees.Thiswillbebetterthandecisiontreebecauseherewareusingmultipletreestopredicttheresults,astherearemoretreestopredicttheaccurateresults.Randomdecisionforestscorrecttheflawofdecisiontreealgorithm'shabitofoverfittingtotheirtrainingset.

Randomforestalgorithmismoreadaptableandeasiertousemachinelearningalgorithmthatpredictsandproduces,evenwithout hyper-parametertuning.Itismostlyusedalgorithmbecauseofitssimplicity.

#### NaïveBayes:

NaïveBayesclassifierisamere"probabilisticclassifier"withinthefamily.Thisisbasedonapplyingthetheoremof Bayeswithstrongindependentassumptionsamongthefeaturesoftheattributes.NaïveBayesclassifiersareexceptionallyadaptable,requiringdifferentparametersintheamountoffactorsinalearningproblem. Byevaluatingiterativeapproxthemostextremeprobabilitytraining canbeperformed.

$$p(C_k \mid \mathbf{x}) = \frac{p(C_k)\, p(\mathbf{x} \mid C_k)}{p(\mathbf{x})}$$

ThroughthisNaiveBayesformula,thepredictionsaremade.

#### 4. SVMKernel(RBFandPOLY):

InMachineLearning,kernelmethodsareaclassofalgorithmsforpatternanalysisthe*SupportVectorMachine(SVM)beingthebest-knownmember.Thepatternanalysistaskistostudyandfindthegeneralrelationshipsinclusters,rankings,inanygivendatasets.*

RadialBasisFunctionkernel,orRBFkernel,iswidelyusedinvariouslearningalgorithms.Inprecise,itisordinarilyusedinSupportVectorMachineClassification.

Thepolynomialkernelisakernelfunctionwidelyusedwithsupportvectormachines(SVMs)andotherkernelizedmodels,thatexemplifiesthesimilarityofvectors(trainingsamples)inafeaturespaceoverpolynomialsoftheoriginalvariables,allowinglearning ofnon-linearmodels.

*K-NearestNeighbour:*


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OneofthesimplestofallMachinelearningalgorithmsisthek-NNalgorithm.Thealgorithmk-nearestneighbourisamethodusedtoclassifyandregress.Inbothcases,theinputconsistsinthefeaturespaceofthekclosesttrainingexamples.Theoutputdependsonwhetherclassificationorregressionk-NNisused

K-NNisalazylearningmethodinwhichthefunctionisonlylocallyapproximatedandthecomputationispostponeduntilfinalclassification.

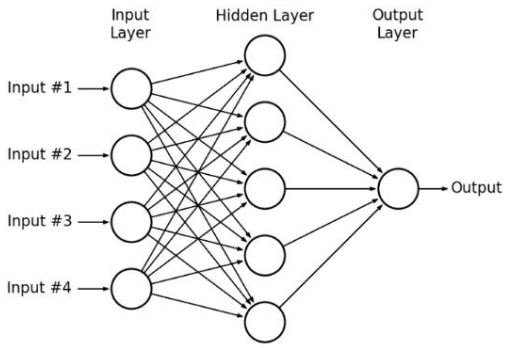
*ArtificialNeuralNetworks:*

ArtificialNeuralNetworksareinspiredbythebiologicalneuralnetworksandarethemimicofthehumanneuralnetworks.Thisisnotitselfanalgorithm,itisframeworkofmanydifferentmachinelearningalgorithms.Thereareacollectionorgroupofconnectednodescalled ArtificialNeurons.Eachneuronisconnectedlikebrainsynapsesusedtotransmitthesignalfromneurontoneuron.

Itreceives,processesthensendsthesignalstotheotherartificialneuronsinwhichtheyareconnected.Eachneuronalconnectionis calledEdges.

ThereisaweightinArtificialNeuronsandEdgesthatadjustsaslearningprogresses.Theweightsareadjustedtoreflectthestrengthofthesignalataconnection.Artificialneuronsaretypicallyassembledintolayers.

Differentlayerscantransformtheirinputsindifferentways.Signalstravelfromthefirstlayer(theinputlayer)tothelastlayer(theoutputlayer)aftermultiplecrossingsofthelayers.




***B. FordimensionalityReduction:***

Forthebetteraccuracydimensionalityisreducedsothatonlytheattributesthatareresponsibleforthepredictionoftheheartconditionpredictionistakenintoconsiderationandtherestwhichdoesnotaffectthechangeintheclasslabelisdiscardedfromthedataset.Thentheaccuracyofthemodelwillbechangedappropriately.

*1. PCA(PrincipalComponentanalysis):*

PrimaryComponentAnalysis(PCA)isastatisticalprocedure usinganorthogonaltransformationtoconvertasetofobservationsofpotentiallycorrelatedvariablesintoasetofvaluesoflinearlyuncorrelatedvariablescalledmaincomponents.Ifvariablesareobserved,thenumberofseparatemaincomponentsismin(n-1,p).Thistransformationisdefinedinsuchawaythatthefirstmaincomponenthasthegreatestpossiblevarianceand,inturn,eachsuccessorcomponenthasthehighestpossiblevarianceunderthecontraintthatitisorthogonaltothepreviouscomponents.Theresultingvectorisanorthogonalbasesetthatisuncorrelated.PCAissensitivetotheoriginalvariables'relativescaling.

## VII. METHODOLOGY

*A. Thedatasetusedis*

- ThedatasetisaHungarianhospital'sdataof400persons.
- Inthisthereare14attributes.
- With400datarecordsofdifferentpersonsinHungary.
- Hereweareusingallsupervisedlearningalgorithmsforprediction.

*B. TheAttributesare:*

TheseattributesaretakenfromtheUCImachinelearningrepositorywheretheattributesdescriptionisgivenandexplainedclearly.[16]

1. Age-ageinyears
2. sex-sex(1=male;0=female)
3. Cp-chestpaintype(1=typicalangina;2=atypicalangina;3=non-anginalpain;4=asymptomatic)
4. trestbps-restingbloodpressure(inmmHgonadmissiontothehospital)
5. chol-serumcholesterolinmg/dl
6. fbs-fastingbloodsugar>120mg/dl(1=true;0=false)
7. Restecg-restingelectrocardiographicresults(0=normal;1=having ST-T;2=hypertrophy)
8. Thalach-maximumheartrateachieved
9. Exang-exerciseinducedangina(1=yes;0=no)
10. Oldpeak-STdepressioninducedbyexerciserelativetorest
11. Slope-theslopeofthepeakexerciseSTsegment(1=upsloping;2=flat;3=downsloping)
12. ca-numberofmajorvessels(0-3)colouredbyfluoroscopy
13. Thal-3=normal;6=fixeddefect;7=reversabledefect
14. Num-thepredictedattribute-diagnosisofheartdisease(angiographicdiseasestatus)(Value0=<50%diameternarrowing;Value1=>50%diameternarrowing)

*C. Methodofapplyingthealgorithm:*

Firstimportingthelibraries
Readingthedataset,splittingthedatasetintotrainingandtestof80%and20%
ApplyingFeatureScaling
SettingtheClassifierforalltheMLalgorithmsoneatatime
Predicatingtheresults
FindingtheaccuracybyusingConfusionMatrix
ApplyingthePCAalgorithmandtakingthenewtrainingandtestdatasets.
SettingtheClassifierforalltheMLalgorithmsoneatatime
Predicatingtheresults
FindingtheaccuracybyusingConfusionMatrix
Comparingtheresults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## VIII. ACCURACYOFEACHALGORITHM

DifferenttypesofalgorithmslikeDecisiontr.ee,Randomforest,NaiveBayes,SVMKernel(RBFandpoly),K-nearestneighbourareusedtopredictthedataoftheheartpatientsandfordimensionalityReduction,PCA(PrincipleComponentanalysis)isusedusingPythonanacondasoftware.

*1. DecisionTree*

- Accuracywith14attributes:
- 44.73%

```
In [4]: cm
Out[4]:
array([[28,  8,  0,  3,  1],
       [ 3,  3,  0,  3,  1],
       [ 1,  5,  1,  1,  1],
       [ 1,  4,  1,  2,  4],
       [ 0,  4,  0,  1,  0]], dtype=int64)
```

- AccuracyafterPCAdimensionalityreduction:
- 52.63%

```
In [8]: cm
Out[8]:
array([[31,  6,  2,  1,  0],
       [ 8,  1,  1,  0,  0],
       [ 2,  3,  4,  0,  0],
       [ 3,  1,  3,  4,  1],
       [ 1,  0,  2,  2,  0]], dtype=int64)
```

*2. K-Nearestneighbour*

- Accuracywith14attributes:
- 52.63%

```
In [10]: cm
Out[10]:
array([[37,  3,  0,  0,  0],
       [ 6,  3,  0,  0,  1],
       [ 2,  7,  0,  0,  0],
       [ 3,  6,  3,  0,  0],
       [ 0,  4,  1,  0,  0]], dtype=int64)
```

- AccuracyafterPCAdimensionalityreduction:
- 53.94%

```
In [25]: cm
Out[25]:
array([[37,  1,  1,  1,  0],
       [ 7,  2,  1,  0,  0],
       [ 1,  7,  0,  1,  0],
       [ 2,  3,  5,  2,  0],
       [ 0,  1,  3,  1,  0]], dtype=int64)
```

*3. NaiveBayes*

- Accuracywith14attributes:
- 42.10%

```
In [5]: cm
Out[5]:
array([[26,  0,  0,  1, 13],
       [ 2,  1,  1,  0,  6],
       [ 0,  2,  0,  0,  7],
       [ 0,  0,  1,  1, 10],
       [ 0,  0,  0,  1,  4]], dtype=int64)
```

- AccuracyafterPCAdimensionalityreduction:
- 59.21%

```
In [7]: cm
Out[7]:
array([[38,  2,  0,  0,  0],
       [ 6,  2,  2,  0,  0],
       [ 2,  5,  2,  0,  0],
       [ 1,  3,  5,  3,  0],
       [ 0,  2,  2,  1,  0]], dtype=int64)
```

*4. Randomforest*

- Accuracywith14attributes:
- 53.94%

```
In [3]: cm
Out[3]:
array([[37,  1,  1,  1,  0],
       [ 7,  1,  1,  0,  1],
       [ 3,  3,  1,  2,  0],
       [ 3,  3,  4,  2,  0],
       [ 1,  4,  0,  0,  0]], dtype=int64)
```

- AccuracyafterPCAdimensionalityreduction:
- 57.89%

```
In [5]: cm
Out[5]:
array([[35,  2,  2,  1,  0],
       [ 6,  3,  1,  0,  0],
       [ 3,  1,  3,  2,  0],
       [ 3,  2,  4,  3,  0],
       [ 1,  2,  1,  1,  0]], dtype=int64)
```

*5. SVMPoly*

- Accuracywith14attributes:
- 51.31%

```
In [4]: cm
Out[4]:
array([[38,  1,  0,  1,  0],
       [ 8,  0,  2,  0,  0],
       [ 8,  1,  0,  0,  0],
       [ 4,  3,  3,  1,  1],
       [ 1,  3,  0,  1,  0]], dtype=int64)
```

- AccuracyafterPCAdimensionalityreduction:
- 59.21%


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```
In [6]: cm
Out[6]:
array([[40,  0,  0,  0,  0],
       [ 8,  1,  1,  0,  0],
       [ 7,  0,  2,  0,  0],
       [ 4,  2,  4,  2,  0],
       [ 2,  2,  1,  0,  0]], dtype=int64)
```

*6. SVMRBF*

- Accuracywith14attributes:
- 48.68%

```
In [4]: cm
Out[4]:
array([[36,  3,  1,  0,  0],
       [ 7,  1,  2,  0,  0],
       [ 2,  7,  0,  0,  0],
       [ 5,  3,  4,  0,  0],
       [ 1,  3,  0,  1,  0]], dtype=int64)
```

- AccuracyafterPCAdimensionalityreduction:
- 57.89%

```
In [6]: cm
Out[6]:
array([[38,  2,  0,  0,  0],
       [ 6,  3,  1,  0,  0],
       [ 4,  3,  2,  0,  0],
       [ 3,  3,  5,  1,  0],
       [ 0,  3,  2,  0,  0]], dtype=int64)
```

*7. ArtificialNeuralNetworks:*

- Accuracy–58.53%

```
Epoch 100/100
217/217 [==============================] - 0s 142us/step - loss: -6.0687 - acc: 0.5853
24/24 [==============================] - 0s 10ms/step
```

- AfterPCA:-

```
Epoch 100/100
217/217 [==============================] - 0s 234us/step - loss: -5.5517 - acc: 0.5530
24/24 [==============================] - 0s 11ms/step
```

## IX. RESULTSANDGRAPHS

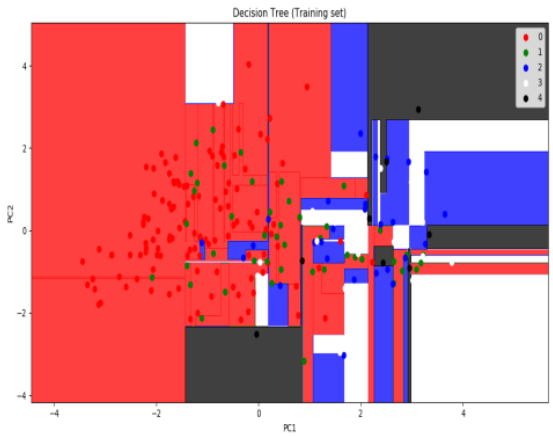


**Fig-4.1**
**DecisionTree(Trainingset)**

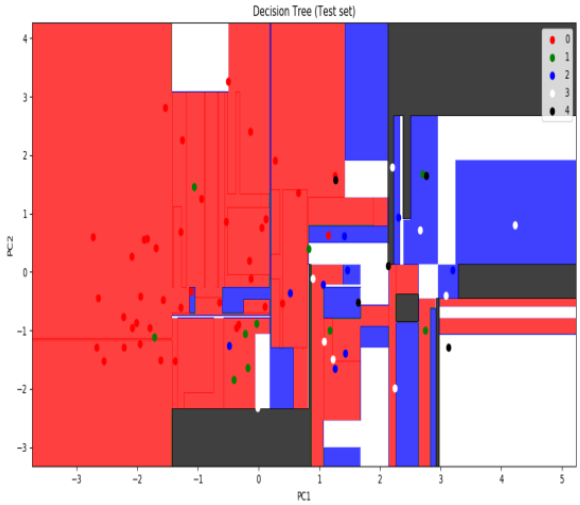


**Fig-4.2**
**DecisionTree(Testset)**

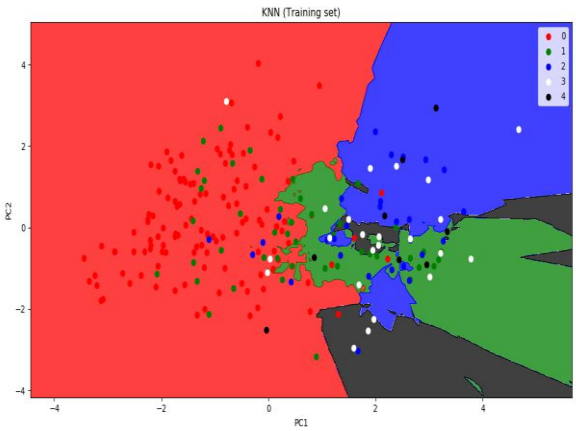


**Fig-5.1**
**Nearestneighbour(Trainingset)**

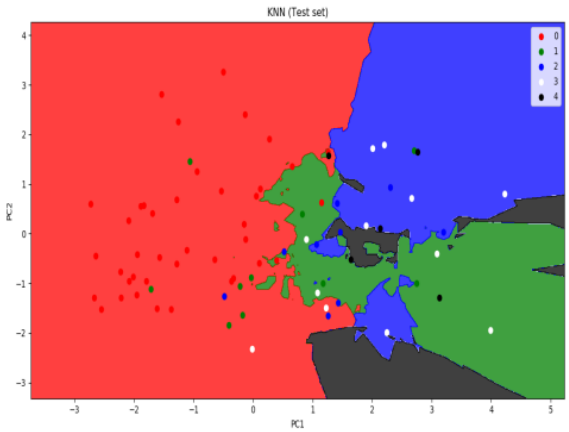


**Fig-5.2**
**K-Nearestneighbour(Testset)**


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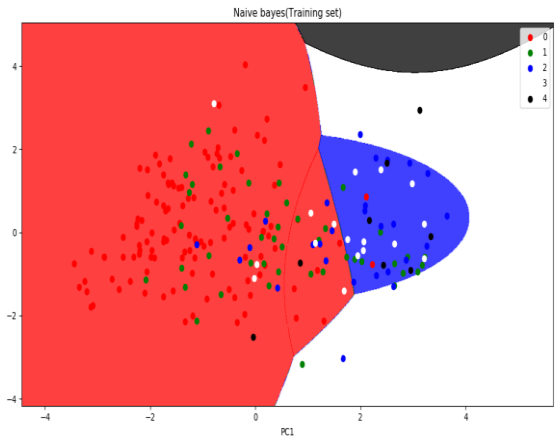


**Fig-6.1**
**NaiveBayes(Trainingset)**

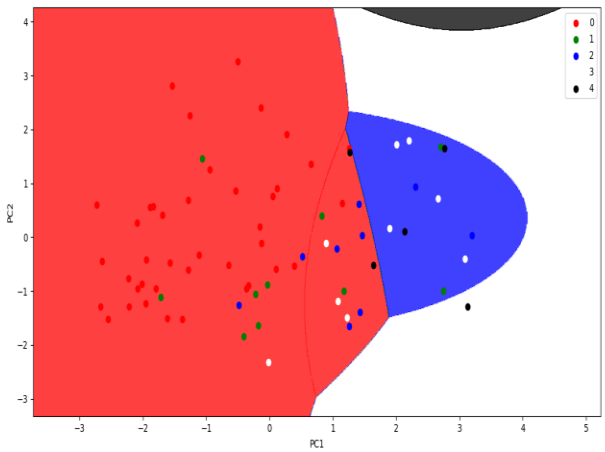


**Fig-6.2**
**NaiveBayes(Testset)**

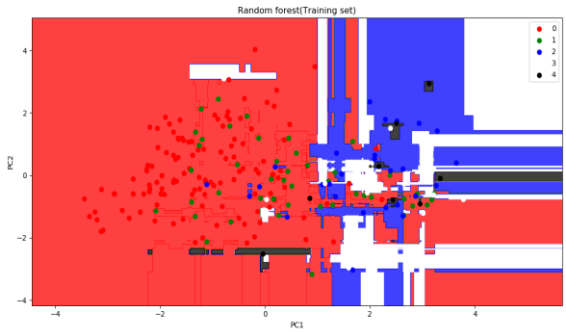


**Fig-7.1**
**RandomForest(Trainingset)**

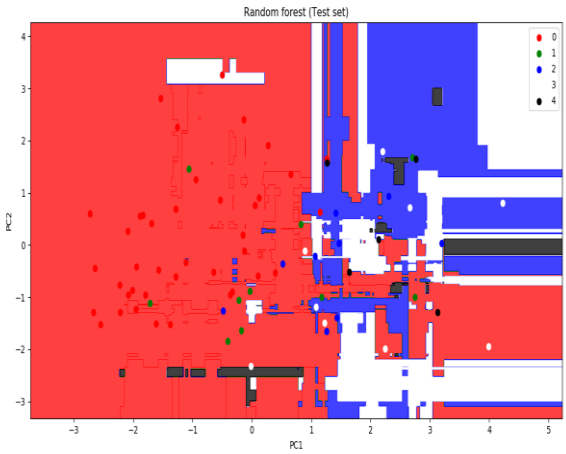


**Fig-7.2**
**RandomForest(Testset)**

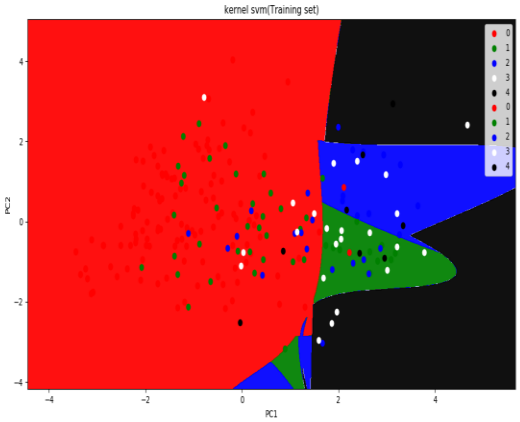


**Fig-8.1**
**SVMPoly(Trainingset)**

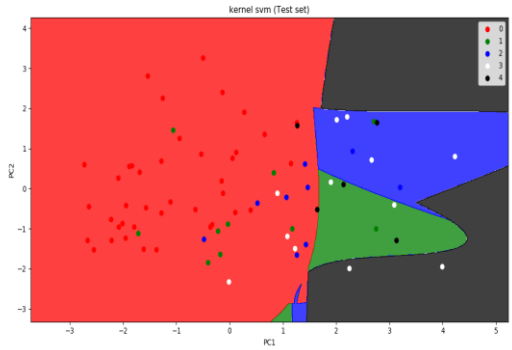


**Fig-8.2**
**SVMPoly(Testset)**

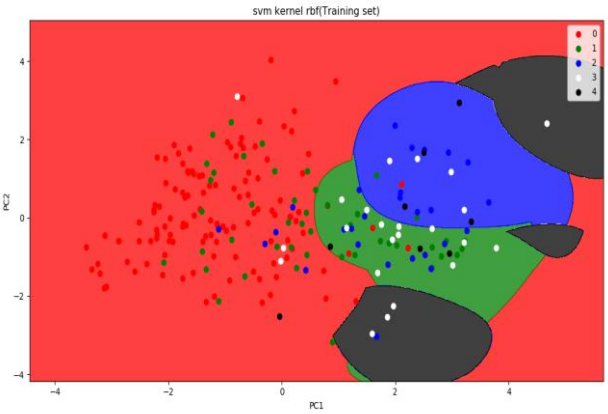


**Fig-9.1**
**SVMRBF(Trainingset)**

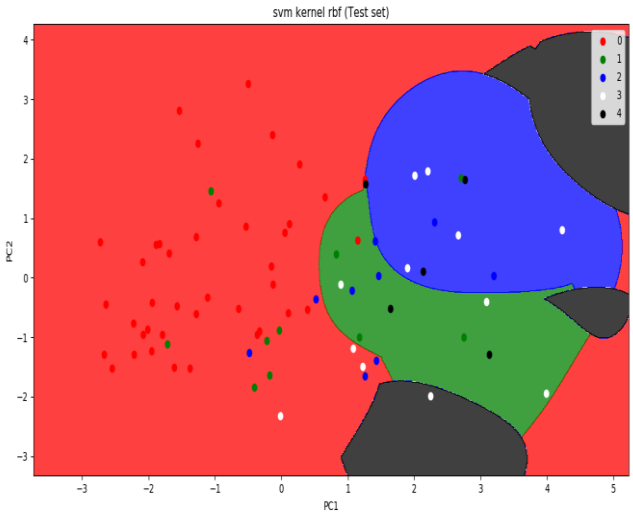


**Fig-9.2**
**SVMRBF(Testset)**

## X. CONCLUSION

Theconclusionofthispaperistheneuralnetworksisthebestalgorithmforthepredictionoftheheartconditionamongtheotheralgorithmslike KNN, SVM, RandomForest, NaïveBayes, andDecisiontree. Theneuralnetworksresultsaredirectlyproportionaltothenoofinputstheyaregiven. So, themoretheinputsforthemthemoretheaccuracytheyshow.

## REFERENCES

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