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PERFORMANCE OF K-NEAREST NEIGHBOR BASED CLASSIFIER FOR CLASSIFICATION OF CARDIOTOCOGRAMS

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Abstract:Fetalheartrate(FHR)anduterinecontractions(UC)aresimultaneouslyrecordedbyCardiotocography(CTG).TheCTG,whichisoneofthemostcommondiagnostictechniquesusedtoevaluatematernalandetalwell-beingduringpregnancyandbeforedelivery.ByobservingtheCardiotocographytracepatternsdoctorscanunderstandthestateofthefetus.Therearesseveralsignalprocessingandcomputerprogrammingbasedtechniquesforinterpretinga typicalCardiotocographydata.Evenfewdecadesaftertheintroductionofcardiotocographyintoclinicalpractice,thepredictivecapacityofthesemethodsremainscontroversialandstillinaccurate.InthisresearchworkIproposeanintegratedmethodologyforCTGanalysisandclassification.Anovelsetoffeatures,derivedfromthetimeandfrequencydomains,is usedto feedthenewtoolforpatternclassification,namedK-Nearestneighbor.WeusedAccuracy,Specificity,NPV,Precision,RecallandROCasthemetrictoevaluatetheperformance.Thearrivedresultsprovethat,eventhoughthetraditionalclusteringmethodscanidentifytheNormalCTGpatterns,theywereincapableofSuspiciousandPathologicpatterns.Itwasfoundthat,theK-NearestneighborbasedclassifierwascapableofidentifyingNormal,SuspiciousandPathologiccondition,fromthenatureof CTGdata.

Keywords— CTG,Datamining,Classification,fetalheartrate,uterine contractionsandK-Nearestneighbor

I. INTRODUCTION

Dataminingreferstoacollection oftechniquesthatprovidethenecessaryactionstoretrieveandgatherknowledgefromanexhaustivecollectionofdataandfacts.Dataisavailableinenormousmagnitude,buttheknowledgethatcanbeinferredfromthe dataisstillnegligible.Dataminingconceptsarefocusedon discoveringknowledge,predictingtrendsanderadicating superfluousdata.Discoveringknowledge inmedicalsystemsandhealthcarescenariosisaherculeanyetcriticaltask.Knowledgediscoverydescribestheprocess ofautomaticallysearchinglargevolumesofdataforpatternsthatcan beconsideredadditionalknowledgeaboutthedata.Theknowledgeobtainedthroughtheprocessmaybecomeadditionaldatathatcanbeusedforfurthermanipulationanddiscovery.Applicationofdataminingconceptstothemedicalarenahasundeniablymaderemarkablestridesinthesphereofmedicalresearchandclinicalpracticesavingtime,moneyandlife.Clinicaldataminingistheapplicationofdataminingtechniquesusingclinicaldata.ClinicalData-Mining(CDM)involvestheconceptualization,extraction,analysis,andinterpretationof availableclinicaldataforpracticalknowledge-building,clinicaldecision-makingandpractitionerreflection.Themainobjectiveofclinicaldataminingistohaulnewandpreviouslyunknownclinicalsolutionsandpatternstoaidthecliniciansindiagnosis,prognosisandtherapy.Moreoverapplicationofsoftwaresolutionstostore patient recordsinanelectronic formisexpectedtomakeminingknowledgefromclinicaldata lessstressful.

A.Cardiotocography(CTG)

Sincethe1960's,obstetriciansareusingtheCardiotocography,anelectronic methodforrecording(graphy)thefetalheartbeat(cardio)anduterinecontractions(toco)duringpregnancy,bymeans ofaCardiotocographoranelectronicfetalmonitor(EFM). Fig.1illustratesatypicalCardiotocogram(CTG).

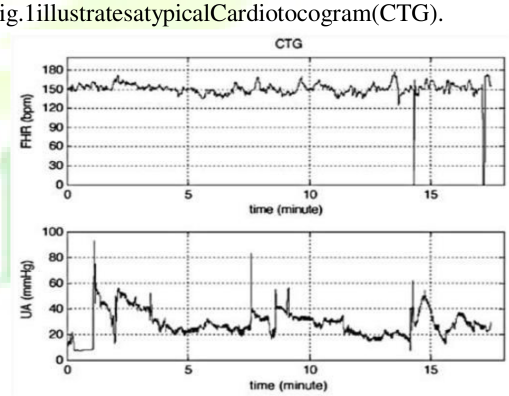

Figure1.AtypicalCTG[4]

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Thecontinuousmonitoringbyusing CTGrequiresqualitativeandquantitativeinterpretationsofseveral parametersdescribedasfollows[3]:

Uterine activity(contractions):

- Frequency:Numberofcontractioninastandard interval.
- Duration:Theamountoftimefromthestartofacontractiontotheendofthesamecontraction.
- Intensity:Ameasureofhowstrongacontractionis.
- Restingtone:Ameasureofhowrelaxedtheuterusis betweencontractions.
- Interval:Theamountoftimebetweentheendofonecontractiontothebeginningofthenextcontraction.

Uterineactivitymaybe definedas:

- Normal-lessthanorequalto5contractionsin10minutes,averagedover a30-minutewindow.
- Tachysystole-morethan5contractionsin10minutes,averagedovera30-minutewindow.

Baselinefetalheartrate(FHR),whichisdeterminedbyapproximatingthemeanFHRroundedtoincrementsoffivebeatsperminuteduringa10-minutewindow,excludingaccelerationsanddecelerationsandperiodsof marked FHRvariability.

- Baseline FHRlessthan110beatsperminuteandsymptomsaretermedasBradycardia.
- BaselineFHRgreaterthan160beatsperminuteandsymptomsaretermedastachycardia.

BaselineFHRvariability,whichisdeterminedina10-minutewindow,excludingaccelerationsanddecelerations.BaselineFHRvariabilityisdefinedasfluctuationsinthebaselineFHRthatareirregularinamplitudeandfrequency.Thefluctuationsarevisuallyquantifiedastheamplitudeofthepeak-to-troughinbpm(beatperminute).

- Absent
- Minimal
- Moderate
- Marked

Presenceofaccelerations:VisuallyapparentabruptincreaseinFHR.Anabruptincreaseisanincreasefromanonsetofaccelerationtothepeakinlessthanorequalto30seconds(tobeconsideredasacceleration, the peakmustbe greaterthanorequal to15bpm).

Periodic orepisodic decelerations

- Periodic:Referstodecelerationsthatareassociatedwithcontractions.
- Episodic:Referstothosenotassociatedwithcontractions

Therearefourtypesofdecelerations:

- Earlydeceleration:ItisrelatedtoagradualdecreaseintheFHRwithanonsetofdecelerationtoanadir(morethan30seconds)wherethenadiroccurswiththepeakof acontraction.
- Latedeceleration:ItisrelatedtoagradualdecreaseintheFHRwithanonsetofdecelerationtoanadir(morethan30seconds).
- Variabledeceleration:ItisrelatedtoanabruptdecreaseintheFHR(morethan15bpm)thatwasmeasuredfromthemostrecentlybaselinewherefromthedeceleration’sonsettonadirislessthan30secondsandthedecelerationlasts(morethan15seconds).
- Prolongeddeceleration:ItispresentwhenthereisavisuallyapparentdecreaseinFHRfromthebaselinethatisgreaterthanorequalto15bpm,lastinggreaterthanorequalto2minutes,butlessthan10minutes.Adecelerationthatlastsgreaterthanorequal to10minutesisa baseline change.Changesortrendsof FHRpatterns overtime.
- CategoryI(Normal):Baselinerate110-160bpm,Moderatevariability,Absenceoflate,orvariabledecelerations,andearlydecelerationsandaccelerationsmayormaynotbepresent.
- CategoryII(Indeterminate):Tracingisnotpredictiveofabnormalfetalacid-basestatus,butevaluationandcontinuedsurveillanceandrevaluationsareindicated.
- CategoryIII(Abnormal):AbsenceofbaselinevariabilitywithrecurrentlateorvariabledecelerationsorBradycardia;orsinusoidal fetal heartrate

II. RELATEDWORK

TheInternationalFederationofObstetricsandGynaecology(FIGO)guidelines[5]wereintroducedasanattempttostandardizetheuseofelectronicmonitoringofFHR.ThefirstworkofautomaticCTGanalysisfollowingFIGOguidelinesconsistsindescribingandextractingtheCTGmorphologicalfeatures[6].Bernades[7]developedSisPorto,asystemforautomaticanalysisof CTGtracings,basedonanimprovementofthemorphological featureextractionintroducedin[6].

ArtificialNeuralNetworks(ANNs)wereusedasaclassifier[8]todetectFHRaccelerationanddecelerationpatternsandtoestimatethe FHRbaselineandvariability.ANNswereusedtoclassifydecelerationpatternsintoepisodicandperiodicdecelerations[9]accordingtoFIGOguidelinesandbasedontherelationshipbetweentheparametersof

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thedecelerationandtheassociateduterinecontraction.ANNswithRadialBasisFunctions(RBF)andMultiLayerPerceptrons(MLP)werethebestperformingclassifiers.

SupportVectorMachines(SVM)havebeenused forFHRsignalanalysis.Georgoulasetal.[10]useddiscrete wavelettransformationtoextractscale-dependentfeaturesoftheFHRsignalandSVMfortheirclassification.Georgoulasetal.[11]usedSVMwithRBFand polynomial kernelstoidentifyfetal andneonatalcompromise,namelymetabolicacidosis[12].TheRBFkernelmachinesoutperformedthepolynomial machinesandbothofthemoutperformedtheconventional methodsofk-nearestneighbor(k-NN),linearandquadraticdiscriminantclassifiers.

Chudáčeketal.[13]usedSVM,naïveBayes,and adecisiontree(C4.5algorithm)withapolynomialkerneltoanalyzeFHRsignalsbasedonlinearfeatures(e.g.DescriptionoftheFHRbaselineusingmean)andnonlinearfeatures(e.g.Fractaldimensionofwaveform).TheyusedthreeFSmethods:PrincipalComponentAnalysis,InformationGain, andGroupofAdaptiveModelsEvolution(GAME).

Krupaetal.[14]proposedanewmethodforFHRsignal analysisbasedonEmpiricalModeDecomposition(EMD)forfeatureextractionandSVMwithRBFforclassificationof FHRrecordings.

Georgoulasetal.[15]proposedaFSmethodbasedonbPSO(binaryParticleSwarmOptimization)forFHR signalanalysisusingSVMandk-NN.

Hybridmethodshavebeenalsoconsideredforautomatedfhrsignalanalysis.Fontenla-Romeroetal.[16]proposedseveralapproachesfortherecognitionofaccelerationanddecelerationpatternsinFHRsignals,includingrule-basedapproach,ANNs,andaneuro-fuzzyapproach.

III. MOTIVATIONANDJUSTIFICATION

Cardiotocography(CTG),consistingoffetalheart rate(FHR)andtocographic(TOCO)measurements,isusedtoevaluatefetalwell-beingduringthedelivery.Since1970,manyresearchershaveworkeddifferentminingmethodsto helpthedoctorsthatinterprettheCTGtracepatternfromthe fieldofsignalprocessingandcomputerprogramming[18].WiththehelpofCTGtracepatternanalysisthedoctorswithinterpretationsinordertoreachasatisfactorylevelofreliability.So,theyactasadecisionsupportsysteminobstetrics.Foreverydaypractice,noneofthemhasbeenadaptedworldwide.Baselineestimationincomputeranalysisofcardiotocographs,whichiscurrentlynoconsensusonthebestmethodology.Morethan30yearsaftertheintroductionofantepartumcardiotocographyintoclinicalpractice,thepredictivecapacityof themethodremainscontroversial.Inareviewoflotofarticlespublishedonthissubject,itwasfoundthatitsreportedsensitivityvariesbetween2and100%,anditsspecificitybetween37and100%[19].So,inthis work,wearegoingtoevaluateK-Nearestneighboralgorithmsforclustering CTGdata.

IV. MATERIALANDMETHODOLOGY

A.*DATASETDESCRIPTION*

TheCardiotocographydatasetusedinthisstudyispubliclyavailableatTheDataMiningRepositoryofUniversityofCaliforniaIrvine(UCI).Byusing21givenattributesdatacanbeclassifiedaccordingtoFHRpatternclassorfetalstateclasscode.Inthisstudy,fetalstateclasscodeisusedastargetattributeinsteadofFHRpatternclasscodeandeachsampleisclassified intooneofthreegroupsNormal,SuspiciousorPathologic. Thedatasetincludesatotalof2126samplesofwhichis1655normal,295suspiciousand176pathologicsampleswhichindicatethe existing of fetaldistress. Attributeinformationisgivenas:LB—FHRbaseline (beatsperminute)AC—#of accelerationspersecondFM—#of fetal movementspersecondUC—#of uterinecontractionspersecondDL—#of light decelerationspersecondDS—#of severe decelerationspersecond DP—#of prolongueddecelerationspersecondASTV—percentage of timewithabnormalshort termvariability MSTV—meanvalue of short term variabilityALTV—percentage of time withabnormal longtermvariability MLTV—meanvalue of longterm variabilityWidth—widthof FHRhistogramMin—minimumof FHRhistogramMax—Maximum of FHRhistogramNmax—#of histogrampeaks Nzeros—#of histogram zerosMode—histogram modeMean—histogram meanMedian—histogrammedianVariance—histogram varianceTendency—histogram tendencyCLASS—FHRpatternclasscode(1to10) NSP—fetalstate classcode(N=normal; S=suspect;P=pathologic)

B. CLASSIFICATION

Classificationprocessmaybeappliedindifferentareasofresearchandpractice,e.g.,farms,military,medicine,Earthremotesensing.Theclassicalclassificationtechniquesusestatisticalapproach,whichtypicallyassumesthenormal multidimensionaldistributionofprobabilityintheexperimentaldataset.Dataclassificationmaybesupervisedand unsupervised. Thesupervisedclassificationmethodrequiresthepresenceoftrainingdatasettypicallydefinedbytheexpert-theteacher.Eachclassofobjectsischaracterisedby thebasicstatisticalparameters

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(meanvaluesvector,covariancematrix),whicharevaluesvector,covariancematrix),whicharecomputedfromthetrainingset.Theseparametersguidethediscriminationprocess.TheBayesianclassifiersaretypicalrepresentatives(Bayesclassifier,Fisher,Waldsequential). Theunsupervisedclassificationisalsoknownasclassificationwithouttheteacher.Thisclassificationuses,inmostcases,themethodsofclusteranalysis.Thedevicethat performsthefunctionofclassificationiscalledclassifier.Theclassifieristhesystemcontainingseveralinputsthataretransportedwithsignalscarryinginformationabouttheobjects.Thesystemgeneratesinformationaboutthecompetenceofobjects intoaparticularclassontheoutput.

C. THEMEDICALBACKGROUNDOFCARDIOTOCOGRAPHY(CTG)

Cardiotocographyisamedicaltestconductedduringpregnancythatrecordsfetalheartrate(FHR)anduterine contractions.Eitherinternalorexternalmethodsthetestsmaybeconducted.Duringtheinternaltesting,theutersplacedbyacatheterafteraspecificamountofdilationhastakenplace.Theexternaltests,apairofsensorynodesareaffixedtothemother'sstomach.TheCTGtracegenerallyshowstwolines.Thefetalheartrateisrecordedbytheupperlineinbeats perminuteandtheuterinecontractionsarerecordingbythe lowerlinefromtheTOCO.

BaselineHeart Rate

Thebaselineheartratehelpstoevaluatethehealthyfunctioningofthe cardiovascularsystem.ThebaselinefetalheartrateisdeterminedbyapproximatingthemeanFHRroundedtoincrementsof5beatsperminute(bpm)duringa10-minutewindow,excludingaccelerationsanddecelerationsandperiodsofmarkedFHRvariability(greaterthan 25bpm.Abnormalbaselineistermedbradycardiaandtachycardia.Thefluctuationsarevisuallyquantitiesastheamplitudeofthepeak-to-troughinbpm.Usingthisdefinition,thebaselineFHRvariabilityiscategorizedbythequantitiesamplitudeas:

Absent-undetectable
Minimal-greaterthanundetectable,butlessthanorequalto 5bpm
Moderate-6bpm-25bpmMarked-greaterthan25bpm

Bradycardia:

Itistherestingheartrateofunder60beatsperminute,thoughitisseldomsymptomaticuntiltheratedropsbelow50beats/min.Itmaycausecardiacarrestinsome patientsTachycardia:Ittypically refers toaheartratethatexceedsthenormalrangeforarestingheartrate(heartrateinaninactiveorsleepingindividual).Dependingonthespeedandtypeofrhythm,itcanbe dangerous.

Type 1(early)

Thisoccursduringthepeakoftheuterinecontraction.TheFHRwithonsetearlyinthecontractionandreturntobaselineattheendofthecontractionwillbeuniform,repetitiveandperiodicslowing.Thereasonsbehindthismaybefetalheadcompression,cordcompressionorearlyhypoxia.Thisoccursinfirstandsecondstagelaborwithdecentofthehead[21].Thisissynchronouswithuterine contraction.

Type 2(late)

Thisoccursafterthepeakoftheuterinecontraction.TheFHRwithonsetmidtoendofthecontractionandnadirmorethan20secondsafterthepeakofthecontractionandendingafterthecontractionwillalsobeuniform,repetitiveandslowing.Ifthelagtimeishighseriousnessisalsohigh.Thisisalsosynchronouswithuterinecontraction.Mx:afetalpH measurementismandatory[21].

Type 3(variable)

Thisisvariable,repetitive,andperiodicslowing ofFHRwithrapidonsetandrecovery.Variableandisolated timerelationshipswithcontractioncyclesmayoccur.Decelerationpatternsintimingandshaperesemblesothertypesinsomecases.Iftheyoccurconsistently,thereisachanceoffetalhypoxia.Thisisunrelatedtouterinecontractions.Mx:checkfetalpHifthepatternpersistsafterturningthepatientonherside(or ifotheradverse featuresare present)[21].

A. D.*K-Nearest neighbor*

Thek-nearest-neighborsareanexampleofaclassificationmethodwith theindependenceoftheparameters.Themethodcanbeclassifiedasbythepointofimplicationassimple,butefficientin manydatasets[11].The k-NNalgorithmisdefinedbythreeterms(S,k,T) whereSrepresentsaresemblancemeasurewhichlinkstoeachpairofdatainanappropriateN-dimensionalspaceat(realorinteger)number,krepresentsthenumberofnearestdatathataretrainedtocarryouttheclassificationandTrepresentsthevectorofMtrainingdataappliedbytheclassifiertoactuallycarryouttheclassification[12].k-NNusesdistancemetricsusuallyEuclideandistance toperformthe similaritymeasure formulatedby

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$$d_E = \sum_{i=1}^{N} \sqrt{x_i^2 - y_i^2}$$

Iftisadatasample,whichclassificationimplementedanditsknearest neighborsturnup,thenthismakesaneighborhoodoft.Whileusingthemethodtoclassifythedatasampleintheneighborhoodaboutt,thedistanceiswhetherconsideredornot.Ofcourse,tousek-NNchoosingtherightvaluefor kiscritical;duetotherateofsuccessofclassificationdirectlyappertaintothisvalue.Thek-NNmethodcanpassforbiasedbyk.Itispossibletochoosethek-valueinsomanydifferentways.Ofcourse,thesmoothandefficientoneisapplying thealgorithmseveraltimeschanging thevalueofktogetthehighestaccuracy.Todecreasethedependencylevelofchoice ofkfork-NNmethod,Wang[13]recommendedcheckingmultiplesetsofnearestneighborsinsteadofonesetofnearestneighbors.

V. EXPERIMENTATIONRESULT

A. PERFORMANCE EVALUATION

Thisisameasurementtooltocalculatetheperformance

$$\text{Accuracy} = \left[\frac{TP+TN}{TP+TN+FP+FN}\right]$$

$$\text{Sensitivity} = \left[\frac{TP}{TP+FN}\right]$$

$$\text{Specificity} = \left[\frac{TN}{TN+FP}\right]$$

$$\text{PositivePredictiveValue}: PPV = \left[\frac{TP}{TP+FP}\right]$$

$$\text{NegativePredictiveValue}: NPV = \left[\frac{TN}{TN+FN}\right]$$

$$\text{ROC} = \frac{sensitivity + speificity}{2}$$

Where

- The*falsenegativerate*(*FN*)is theproportionofpositivescasesthatwereincorrectlyclassifiedasnegative
- The*accuracy*(*AC*)istheproportionofthetotalnumberofpredictionsthatwerecorrect.
- The*SensitivityorRecall*theproportionofactualpositivecaseswhicharecorrectlyidentified.
- The*Specificity*theproportionofactualnegativecaseswhichare correctlyidentified.
- The*PositivePredictive ValueorPrecision*theproportionof positivecasesthatwerecorrectlyidentified.
- The*NegativePredictiveValue*theproportionofnegativecasesthatwerecorrectlyidentified.

TABLE1:PERFORMANCEANALYSISOFK-NEARESTNEIGHBORUSINGCROSSVALIDATION

Performance	**K-NearestN**
Accuracy	97.4230
Sensitivity	96.3320
Specificity	96.6219
PPV	94.7793
NPV	97.5064
ROC	91.9874

VI. CONCLUSION

ThisworkhasevaluatedtheperformanceoftheK-NearestneighbourAlgorithmwithrespectto confusionmatrixandaccuracy.AccordingtothatK-NearestneighbourAlgorithmbasedclassificationapproachprovidedsignificantlypoorperformance.ItwasfoundthattheK-NearestneighbourAlgorithm classifierwascapableofidentifyingNormal,SuspiciousandPathologiccondition,fromthenatureofCTGdatawithcomparativelypooraccuracy.If weconsideronlytheprecisionasametric,thenarrivedresultsproves that,eventhoughthemachinelearningbasedmethodscandistinguishthe NormalCTG

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- The*recall*or*truepositiverate*(*TP*)isthe proportionofpositivecasesthat werecorrectlyidentified
- The*falsepositiverate*(*FP*)istheproportionof negativescasesthatwereincorrectlyclassified aspositive
- The*truenegativerate*(*TN*)isdefinedastheproportionofnegativescasesthat wereclassifiedcorrectly

B. patternsfromtheSuspiciousandPathologicpatternswithrespecttoprecisionandpathologic,but,they wereincapableofdistinguishingSuspicious.Thatiswhywearegettingcomparativelypooraverageperformancewhileclassifyingsuspiciousrecordswithrespecttoprecision.Itisamajorweaknessofthealgorithmswhichshouldbeovercomesinfuturedesign.Onemayaddressthewayto improvethesystemforgettingproperresultswithdifferent

C. classesofCTGpatterns.OnemayconsidermachinelearningbasedmethodtodesigntheCTGdataclassificationsystem.Futureworksmayaddresshybridmodelsusingstatisticalandmachinelearningtechniquesforimprovedclassificationaccuracy.

D.

E. Infuturework,weplantocollaboratewithobstetriccliniciansandphysiciansinordertoassessthe computationalresults.

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