ACCELERATED PLETHYSMOGRAPHYBASED

ENHANCED PITTACLASSIFICATION

A Dissertation submitted in fulfillment of the requirements for theDegree
of

MASTER OFENGINEERING
in
Electronics Instrumentation & ControlEngineering

Submittedby

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Under the Guidanceof
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DECLARATION

I hereby certify that the work which is presented in dissertation entitled, "**Accelerated Plethysmography based Enhanced Pitta Detection**" in partial fulfillment of the requirements for the award of the degree of **Master of Engineering** in **Electronics (Instrumentation & Control)**, submitted to Electrical & Instrumentation Engineering Department of Thapar University, Patiala is as authentic record of my own work carried under the supervision of **Mr. Mooninder Singh**, Assistant Professor, Electrical and Instrumentation Engineering Department, Thapar University, Patiala, Punjab. It refers others researcher's work which are duly listed in the reference section. The matter contained in this dissertation has not been submitted, neither in part nor in full to any other degree to any other university or institute except as reported in text and references.

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It is certified that the above statement made by the student is correct to the best of my knowledge and belief.

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LIST OFABBREVIATIONS

ANN-Artificial NeuralNetwork

APG-AcceleratedPlethysmography

FDR-Fisher DiscriminantRatio

FP-FalsePositive

FN-FalseNegative

LED-Light EmittingDiode

MR-MagneticResonance

PPG-Photoplethysmography

PTT-Pulse TransitTime

RWTT-Reflected Wave TransitTime

SDFAP-Second derivative of Finger Arterial PressureWaveform

SDNN-Standard Deviation of Duration of heartbeats

SDPPG-Second Derivative ofPhotoplethysmograph

TP-TruePositive

TN-TrueNegative

ABSTRACT

TheAcceleratedPlethysmography(APG)isanon-invasiveopticaltechniquedevelopedforits experimental usage in cardio vascular diseases. The existing traditional cardiovascular diagnostics tools might be replaced by this technique. It uses the second derivativeof Photoplethysmography(PPG)waveformtoevenoutthebaselineandtoisolatethecomponents more visibly as compared to the first derivative. The purpose of this research is to design aHigh Pitta Classifier and to find the features that may relate to the intensified pittalevel.

Our focus of research is to analyze Accelerated Plethysmography and optimally selectthose featuresthatmaygivehighaccuracyofenhancedPittalevel.Forthisfisherlineardiscriminant analysisandcorrelationhasbeenemployed.Thefeaturesselectedareclassifiedusingdifferent classificationtechniques.Aclassifierachievinganaccuracyof75%forComparativeGroup1, 75% for Comparative Group 2 and 68.75% for Comparative Group 3 has beendeveloped effectively usingLIBSVM.

Artificial Neural Network approach has been used to verify the result further.Comparative Group 1 classifies high Pitta on the basis of effect of Mid-day only. 81.30% accuracy isachieved usingArtificialNeuralNetworkhaving2neuronsinthehiddenlayer.ComparativeGroup2 classifiesonthebasisofmid-dayaswellasdigestionfollowingtheconsumptionofmeals. 87.5%accuracyisachievedusingArtificialNeuralNetworkhaving2neuronsinthehidden layer. This indicates that the consumption of meals also have some role in the enhancedpitta level.ComparativeGroup3classifiesonthebasisofdigestionfollowingtheconsumptionof meals.75% accuracy is achieved using Artificial Neural Network having 6 neurons in thehidden layer.Fromthisstudyitisconcludedthat(i)PittadetectionusingPhotoplethysmographyis feasible (ii) Effect of mid-day is prominent (iii) Effect of consumption of meals is also there(iii) Effect of mid-day is more as compared to consumption ofmeals.

CHAPTER1

INTRODUCTION

1.1 Overview

AccordingtoAyurveda,healthisaperpetualandaparticipatoryprocessthatincludeallaspectsof life i.e. physical, spiritual, emotional, mental, social, behavioral, familial and universal.Attaining harmony among all these aspects is the correct determination of vibrant health [1].Every biomedicalengineerresearcheraimsatdevelopingageneraltoolfordiagnosingalltypesof diseases.Accordingtotheancientmedicalsystemdiagnosisofpulseissuchatool.Physiciansuse thepulsefordeterminingtheheartrateandtofeelthepatternsofpulsationsthatindicatethe metabolicprocessesinthehumanbodyataparticulartime.Thethreedifferentpulsescouldbe locatedinasinglearteryonboththewrists,correspondingtothethreedoshas.32differentqualities can be detected by a skilled pulse-taker. Regardless of its inclusive foundation, Ayurveda hasnot obtained scientific recognition in the twenty-first century. This might be due to absence ofa quantitative beginning in its experimental research. Since the need for a well-organized andnon-invasivesubstitutetotheadvancedmedicalsystemisincreasingdaybyday,researchinAyurvedic science and traditional medical sciences has experienced a new drift [2]. PulsePlethysmography is a widely used non-invasive technique that has been used to detect the AyurvedicDoshas.This well-established optical technique detects variations in the volume of blood in themicrovascular bed of tissue. The features extracted from the finger pulse waveform can be analyzed forvarious studies.InourstudyweanalyzedthesefeaturestodetecttheAyurvedicconstituentPittaand classified the optimized features to design a High PittaClassifier.

1.2 Ayurveda- The Science ofLife

Ayurveda means ‘The Science of Life’ or living sensibly on the basis of knowledge. Itrepresents acomplextraditionalsystemofnaturalhealingwhichoriginatedinIndiaaroundthousandsof yearsago.ThetheoryofAyurvedaevolvedfromthedeepunderstandingofcreationandis composedoftwoSanskritwords‘Ayur’meaninglifeand‘Veda’meaningScience.Ayurvedaisa precioustreasureofpracticalandtheoreticalknowledgewhichhelpsinimprovingthelivingof humanbeings.RecognizedandexpandedfarbeyondIndia,Ayurvedaofferedwithtimethe practicalandtheoreticalfoundationtobuildfurthertraditionalhealingsystems,todaywell-known as numerous branches of alternative medicine[3].

1.3 Constituents of the HumanBody

Human health is dependent on three body constituents known as doshas namely: Vata, Pittaand Kapha.Thesebiologicalenergieshaveaphysical,mentalandspiritualimpactonthehumanbody. Aslongasthesethreeconstituentsareinharmony,thehumanishealthy.Increaseinanyone constituent at the cost of others results in disease [4]. Every cell in the body comprises of allthe three constituents [5]. These doshas are the dynamic energies that vary continually in responseto our actions, emotions, the seasons, the foods we consume, and other sensory inputs that feedour bodyandmind.Figure1.1representstheconstituentsofthehumanbodyinreferencetoAyurveda.

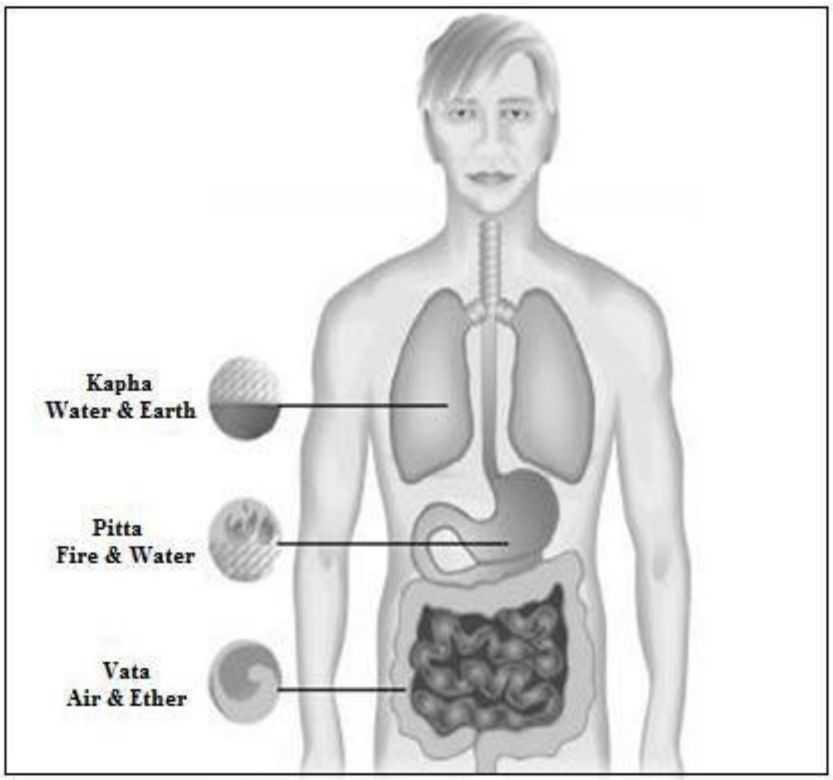

Figure 1.1: Constituents of the human body[6]

1.3.1 Vata Type

The Vatadosha is derived from the components of air and space. It is an energy of themovement andgovernsallthebiologicalactivities.Itisoftencalledasthe“KingoftheDoshas”,sinceit administersbody’sgreaterlifeforceandprovidesmotiontoPittadoshaandKaphadosha.Aperson withapredominantVatadoshawillhavementalandphysicalcharacteristicsthatimitatethe fundamental characteristics of Air and Space. Vata type individuals are mainly thin, movesfast and thinkquickly.

1.3.2 Pitta Type

Pittadoshaisderivedfromthecomponentsoffireandwater.Itisanenergyofmetabolismand digestioninthebodywhichoperatesthroughcarriersubstancessuchasenzymes,bile,organic acids and hormones. While the Pitta dosha is closely related to the component of fire, theliquid nature of these substances accounts for the component of water. The characteristics of Pittatype areacidic,moving,sharp,hot,lightandliquid.Pittatypeindividualwillexhibitmentaland physical characteristics that indicate these qualities in both balanced and imbalancedstate.

1.3.3 Kapha Type

Kaphadoshaisderivedfromthecomponentsofearthandwater.It isanenergyoflubricationand building that provides body with structure, physical form and smooth functioning of all itsparts. ThecharacteristicsofKaphadoshaaredull,heavy,sticky,static,soft,moistandcold.Kaphatype individualswillhaveacalmtemperatureandsolidbodilyframe,indicatingthefundamental components of Earth andWater.

1.4 The Three DoshicStates

An individual will have a vibrant health if the amount of doshas in the existing state is close toits birthcomposition.Adeviationbetweenthesestatesindicatesastateofdisharmony.Primarily there are three doshicstates:

- BalancedState
- IncreasedState
- DecreasedState

Abalancedstateiswhenallthreedoshasarepresentintheirnormalproportions.Whenadoshais present in a greater proportion than normal it is known as the increased state and when thedosha is present in lesser amount than normal it is known as the decreased state[1].

1.5 Outline of theDissertation

This dissertation consists of 8 chapters which have been introduced as follows to get anoverview of the study carriedout.

Chapter 1 is Introduction. In this chapter the concept of Ayurveda has been discussed. Thethree constituents of human body namely: Vata type, Pitta type and Kapha type have beenintroduced anddiscussedindetail.Thentheoutlineofthedissertationisgivensoastogetanoverviewofthis study.

Chapter 2 is Accelerated Plethysmography. Our study is based on AcceleratedPlethysmography which is obtained by differentiating Photoplethysmography signal twice. In thischapter Plethysmography and its various types have been discussed. Photoplethysmograpy, itsclinical applications and its various types have been discussed in detail. Analysis ofAccelerated Plethysmography has also beendiscussed.

Chapter3isLiteratureSurvey.Inthischaptertheresearchesthathavebeendonebyvarious researchers have been discussed. The contributions that have been made by different studieshave beenmentioned.

Chapter4isProblemDefinition.Inthischapterthe aimofthisstudyhasbeenmentionedindetail.

Chapter 5 is Proposed Solution. In this chapter the methodology proposed to conduct thisstudy has beendiscussed.

Chapter 6 is Methodology. This chapter explains the methodology used to carry out thisstudy. The data which have been used for this study has been taken from the post graduatedissertation. Thesefeaturesarethenreducedtogetafewfeaturessoastoremovethedataredundancyand computationalload.Thebestfeaturesareselectedonthebasisof Fisher's DiscriminantRatio (FDR) and Correlation. Various classifiers are used for classification of the signals intodifferent classes. The classification techniques used are Artificial Neural Networks andLIBSVM.

Chapter 7 is Results and Discussion. This chapter includes various features which havebeen reduced using fisher linear discriminant analysis and correlation. Also, this chapter includesthe various accuracies obtained during the classification of the signals by variousclassifiers. Confusion matrix has also beenplotted.

Chapter 8 is Conclusion and Future scope. In this chapter the conclusion of this study hasbeen mentioned. The significance of the study has been mentioned and the improvements that canbe made have also beendiscussed.

CHAPTER2

ACCELERATEDPLETHYSMOGRAPHY

2.1 Plethysmography

Plethysmographyisanon-invasivetechniqueusedfordeterminationofchangesinvolumeoflimb, bodyoranorganthroughmeasurementofbloodflowingthroughtheveins.Itisawell-established technique widely used because of its basic and clinical applications. These measurementsand variations are registered through an instrument called as ‘Plethysmograph’[7].

2.2 Types of Plethysmography

There are numerous types of plethysmography techniques that are being used. The change inthe dimensionsofthebodyarerecorded,usingadifferenttransducerprincipleforeachtechnique.The fourcommonlyusedplethysmographytechniquesare:AirDisplacementPlethysmography,Strain GuagePlethysmography, Photoelectric Plethysmography and ImpedancePlethysmography.

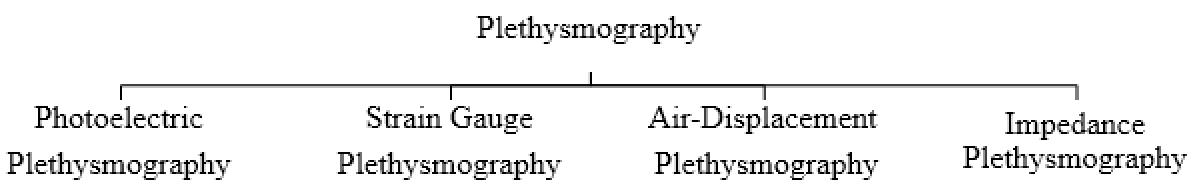

Figure 2.1: Types ofPlethysmography

2.2.1 Photoelectric Plethysmography

PhotoelectricPlethysmographyalsoreferredtoasPhotoplethysmographyisusedtodeterminethe opticalpropertiesoftheselectedregionoftheskin.Theamountofabsorptionofnon-visible infrared light emitted into the skin depends on the volume of blood in the skin. The variationsin thevolumeofbloodcorrespondstotheamountoflightbackscattered.Thesevariationscanbe determinedbyusingtheopticalpropertiesofbloodandtissueandbymeasuringthereflectedlight [8]. The basic arrangement of photo sensor and LED is shown in Figure2.2.

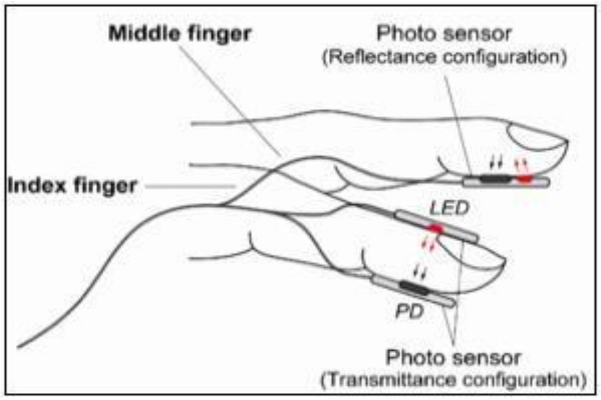

Figure 2.2: Photoelectric Plethysmography[9]

In this a photo sensor and an electrode that consists of an infrared Light Emitting Diode (LED)is placed on the skin. Electrode transmits the light into the skin and this light is then scattered.The tissueabsorbsthelightintheilluminatedarea.Bloodweakensthereflectedlightanddensityof bloodtissuechangestheintensityofreflectedlight.Avoltagesignalisthengeneratedbythephoto sensor and a DC circuit is used to amplify it. The low frequencies passed produce steadytracing comparatively. This resembles to the density of blood in the underlying tissue[10].

2.2.2 Air-DisplacementPlethysmography

Air-displacement Plethysmography measures the volume of an object indirectly by measuringthe volume of air displaced inside a closed chamber. Firstly, the volume of human body ismeasured when the subject sits inside an enclosed chamber. The subject displaces the volume ofair equivalent to volume of his or her body. Thereafter the volume of body is obtained bydeducting theresidualvolumeofairinsidethechamberwhenthesubjectisinsidefromthevolumeofair when the chamber is empty[10].

2.2.3 Strain GaugePlethysmography

In strain gauge Plethysmography a transducer filled with mercury metal alloy conductor isused. When the strain gauge is stretched, its diameter decreases, thus causing an increase in itsvoltage. Acircumferentialmeasurementistakenbywrappingthegaugearoundthelimbsegment.This measurementisthenusedtocalculatetheareaofthelimbsegment.Thevariationsinthe“slice volume” of the limb segment are observed on the contraction and expansion of limb volume[10].

2.2.4 Impedance Plethysmography

In Impedance Plethysmography, a weak current is passed through a limb and electricalresistance totheflowofcurrentisbeingmeasured.Thefourelectrodesortheconductivebandsareused. Twoelectrodesaretheinnerelectrodesandtheothertwoaretheouterelectrodes.Theseelectrodes aretapedaroundthelimb.Theelectricalresistanceisbeingmeasuredbytheinnerpairof electrodes[10].

2.3 PhotoplethysmographyInstrumentation

ModerndayPPGsensorsmakeuseoflesscostlysemiconductortechnologywithaLEDand matchedphotodetectordeviceswhichworkatredand/orclosetoinfraredwavelength.LEDs transform electrical energy into light energy and have a single narrowbandwidth (characteristically50nm).TheuseofLEDsiswidespreadbecauseofcertainadvantageslikethey havealongoperatinglife(greaterthan105hours),canbeoperatedoveranextensiverangeof temperature with small shifts in the peak-emitted wavelengths and are reliable andmechanically robust. However the LEDs should have a constant averaged intensities in order to lessenthe excessiveheatingoflocaltissueandtodecreasethethreatofnon-ionizinghazard.Thelightenergy converted through LED is converted into electric current by a photo detector. Photo detectorsare sensitive,cheapandcompactandhaveaquickresponsetime.Thephotodetectorconnectstoa low noise circuitry which consists of transimpedance amplifier and a filteringcircuitry.

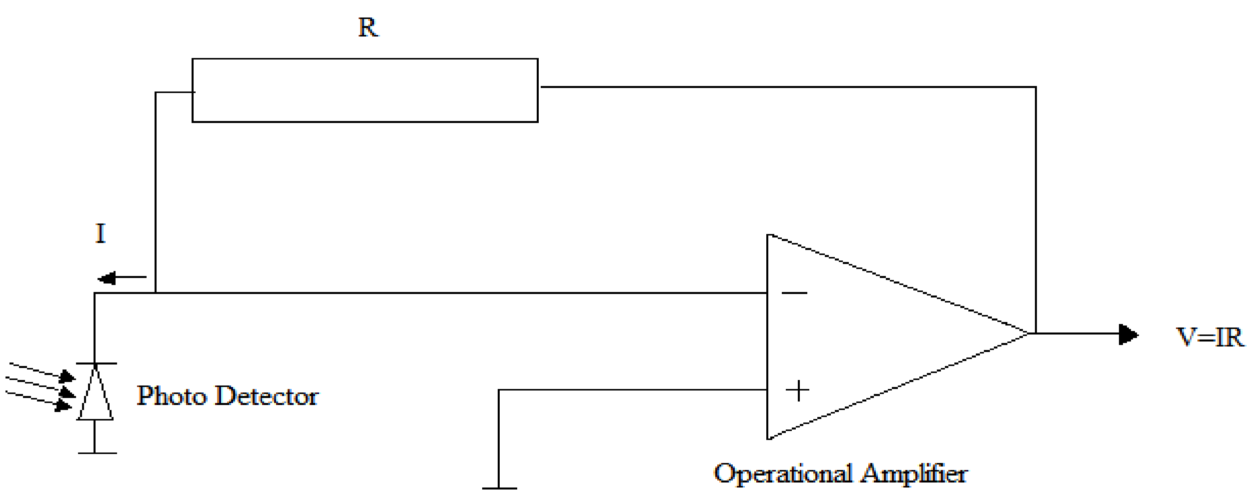

Figure 2.3: Design of a TransimpedanceAmplifier

AhighpassfilterdecreasesthesizeofdominantDCcomponentandpermitsthepulsatileAC component to be enhanced to a nominal one volt peak to peak level. The filtering circuitryshould be carefully chosen in order to remove undesirable high frequency noises such as electricalpick up from 50 Hz mains electricity frequency interferences. Figure 2.3 shows the designof transimpedance amplifier and Figure 2.4 describes the signal conditioningstages.

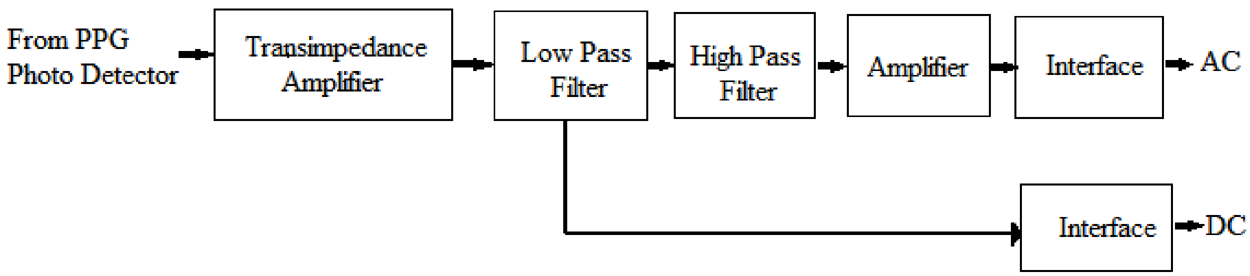

Figure 2.4: Signal conditioningstages

2.4 Clinical Applications of Photoplethysmography

Photoplethysmography have a widespread clinical applications since the technology isemployed incommerciallyexistingmedicaldevices.Itisbeingappliedinwiderangeofclinicalsettings including clinical physiological monitoring (heart rate, blood pressure, respiration, cardiacoutput andbloodoxygensaturation),vascularassessment(tissueviability,venousassessment,arterial disease,endothelialfunction,microvascularbloodflow,arterialcomplianceandageing),and autonomic function (cardiovascular variability assessments, blood pressure and heartrate variability, thermoregulation and vasomotor function)[11].

2.5 Classification ofPhotoplethysmography

Depending upon the physical characteristics of parameters, photoplethysmography isclassified into two groups as shown in Figure2.5.

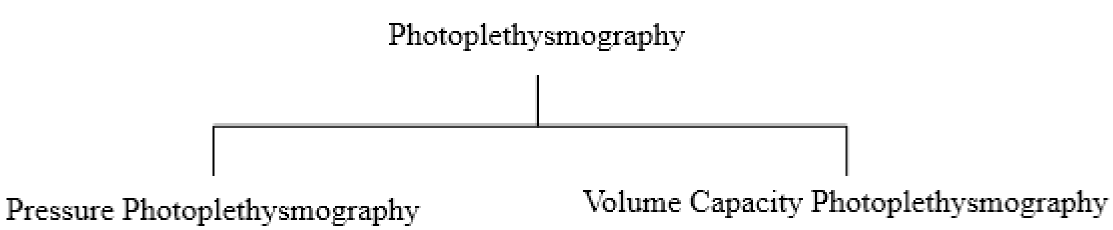

Figure 2.5: Types ofPhotoplethysmography

2.5.1 Pressure Photoplethysmography

It represents the change in intravascular pressure. In this the Photoplethysmography ismeasured in carotid artery, aorta and soon.

2.5.2 Volume CapacityPhotoplethysmography

It represents the change in vascular volume capacity. In this Photoplethysmography ismeasured attipofthefingerortiptoe.PhotoplethysmographybasicallymeansVolumeCapacity Photoplethysmography. Depending upon the method of signal processing it is classifiedas,

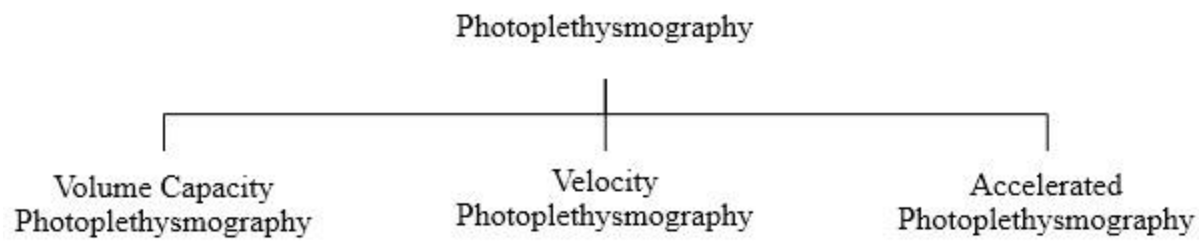

Figure 2.6: Types ofPhotoplethysmography

Photoplethysmography signifies the originally recorded waveform representing itsoriginal characteristics.Theoriginalityofthewaveformhelpstorealizeitsspecificity.Howeverthe originalwaveformhascertainlimitations.Sincetheoriginalwaveformisflatitisdifficultto analyze the course of wave changes. To overcome this limitation the original waveformis differentiatedforitsenhanceduseinclinicalapplications.Thedifferentiatedvalueof Photoplethysmographyisknownas“VelocityPhotoplethysmography”.Theconceptofpulsewave change could be understood clearly with the use of Velocity Photoplethysmography. Howeverit isdifficulttounderstandtheprocessofpulseenergy.Therefore,wedifferentiatethisvelocitypulse waveform to realize the process of pulse energy more specifically in clinical fields. Thisdecisive value is called "Accelerated Photoplethysmography”[12].

2.6 AcceleratedPhotoplethysmography

TheanalysisofPhotoplethysmography(PPG)isdoneindetailbytakingitsderivativetwiceto obtainAccelerationPhotoplethysmography(APG).Thisinterpretstheoriginalwaveeasilyand leads to the recognition of inflection points more precisely[13].

2.7 Analysis of Accelerated Photoplethysmography

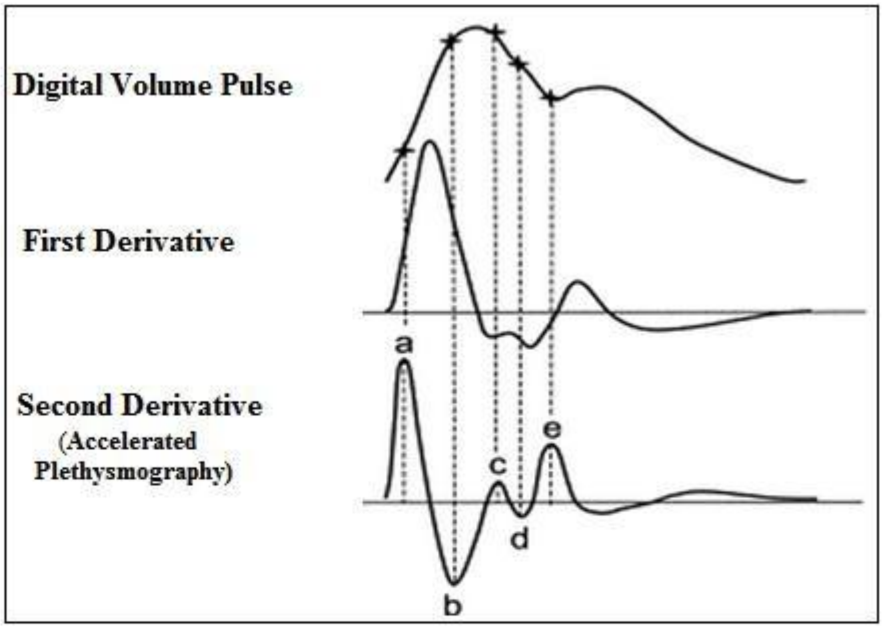

Figure 2.7: Accelerated Plethysmographywaveform

APGconsistsoffoursystolicandonediastolicwaveineachheartbeatcycle.Thesedistinctive waves are: a, b, c, d and e where ‘a’ represents early systolic positive wave, ‘b’ representsearly systolic negative wave, ‘c’ represents late systolic re-increasing wave, ‘d’ represents latesystolic re-decreasing wave and ‘e’ represents diastolic positivewave.

The height from the baseline to the peak of each wave is considered as the value for eachwave. Themostappropriatewaveformforheartratecalculationsis‘a’wavebecauseofitssteepnessand amplitude.ThepatternofAPGwaveformisdeterminedbyproportionof‘b’,‘c’,‘d’and‘e’waves to ‘a’ wave [14]. Figure 2.7 shows the accelerated plethysmographywaveform.

2.8 Classification of AcceleratedPhotoplethysmography

DependinguponthentegrityofcirculationAPGisclassifiedinto7classes.Thewaveformvaries from “normal” to “abnormal6”.

1) Normal-Thewaveofthiskindcommonlyappearsinayoungandhealthypersonandinthe personhavinggoodbloodcirculation.Ifthepersonistraining,thisnormalwaveisshowedinspite of being in the middleage.

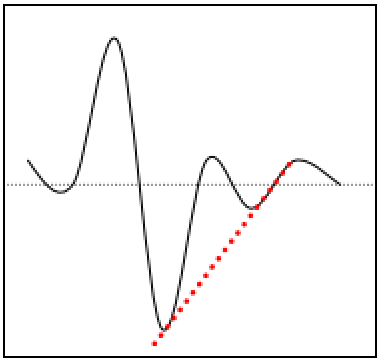

Figure 2.8: Normal APGwaveform

2) Abnormal1-Thewaveofthistypeisdisplayedinthehumanbeingshavingaslightbad circulation, however in a better condition. This waveform have a unique feature that the peak‘c’ isbelowthebaselinebutabovethepeak‘b’,andthepeak‘d’isabove‘b’.Sincethepeaks‘c’and ‘d’ are getting down, it signifies that the blood circulation is heading towards the badstate.

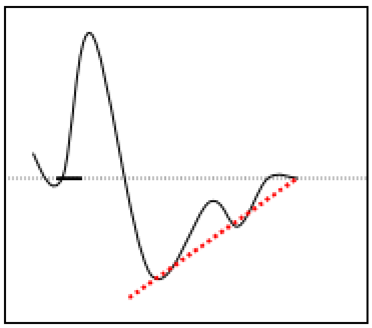

Figure 2.9: Abnormal 1 APGwaveform

3) Abnormal 2-The waveform of this type indicates that the circulation of blood is in arelatively badstate.Anoticeablecharacteristicofthiswaveformisthatthepeak‘d’isdecliningintothe identical level as the peak ‘b’ in contrast to normal and abnormal-1 wave. Certain symptomsare thatthepersonbelongingtothistypeisindangertogetcongestionandhandsandfeetgetchilled.

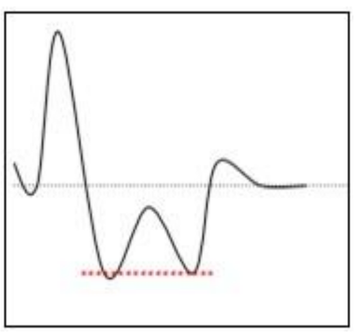

Figure 2.10: Abnormal 2 APGwaveform

4) Abnormal 3-The waveform of this type indicates that the flow of blood is in a remarkablybad state. A marked characteristic is that the peak ‘c’ is at the same level as peak ‘b’ and peak ‘d’in comparisontoabnormal-2waveformandthusbecomesanindeterminatestate.Thepersonsofthis kindshowcertainsymptomslikehandsandfeetgetchilled.Alsotheyfeelheavyintheheador feel like getting a haton.

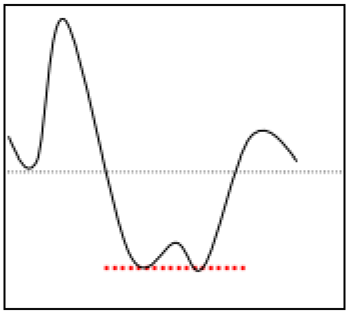

Figure 2.11: Abnormal 3 APGwaveform

5) Abnormal 4- The waveform of this type is observed in individuals having a significantlybad circulationofblood.Ithasaspecialfeaturethatthepeak‘d’isbelowthepeak‘b’,andifthe changeisgettingwide,itsignifiesthatthecirculationofbloodisslowlygoinginthebadstate. Thepersonofthiskindshowcertainsymptomslikeabruptweaknessandpain,abnormalityinthe color of skin and thermo anesthesia.

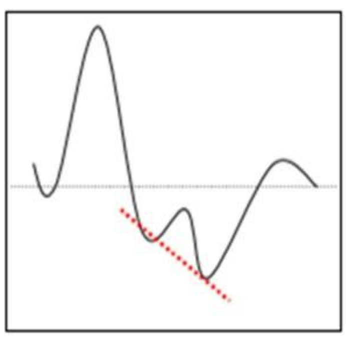

Figure 2.12: Abnormal 4 APGwaveform

6) Abnormal5-Thewaveformofthistypeshowsthatcirculationofbloodisinextremelybad state.Thepeaks‘b’and‘c’arealmostatthesamelevelandthepeak‘d’isinthefarlesserlocation thenthepeaks‘b’and‘c’.Thepersonofthiskindshowcertainsymptomsliketheirhandandfeet could become blue due tocomplications.

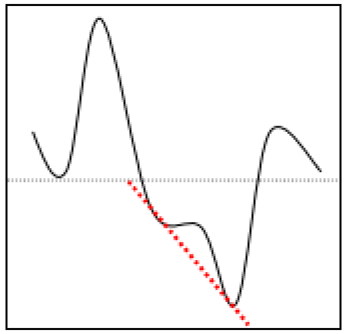

Figure 2.13: Abnormal 5 APGwaveform

7) Abnormal6-Thiswaveindicatesthatthecirculationofbloodisintheworstcondition.Insuch cases, abnormalities are often detected by ECG. This state is liable to infection even after aminor injury.Thereisadangerofstroke,dementiabecauseofcerebrovascularabnormalities.This condition does not recover even after giving the medical treatment [12].

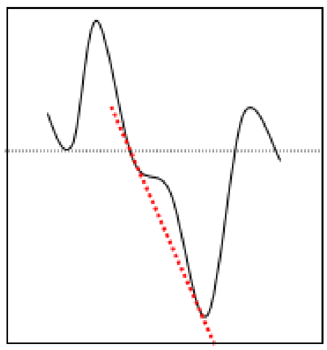

Figure 2.14: Abnormal 6 APGwaveform

CHAPTER3

LITERATURESURVEY

Photoplethysmographysignalsprovidevaluableinformationaboutheartrates.Theanalysisof photoplethysmography signals is done to extract features used for various clinical applications.It isaprimedetectiontool.Photoplethysmographysignalanalysishavebeenwidelyusedfor detecting ayurvedic constituents. Earlier researchers analyzed questionnaires for the detectionof human constituents [15-18]. In early study uniqueness of finger pulse profile was validated andit wasestablishedthatitcanbeusedanalternativebiometricparameter[19].Someresearchers proposedthatasubstantialrelationliebetweenfingerpulsefeaturesandthelevelofpittainthe humanbody[20-22].Alsosecondderivativeoffingerpulseprofilehasbeenusedtodetectthe pitta level [23-25].

Y.Iketani*et al.* (2000) clarified the characteristics of SDPTG and examined the factorseffecting thewavepattern.Thestudywasbeingconductedon775healthysubjectslyinginanagegroupof 3-20years.Afterthedeterminationofbloodpressureofleftbracialarteryintherestingsitting position,thefingertipPTGandSDPTGweremeasuredautomaticallyusingadigitalplethy-smographsensorplacedatcuticleofseconddigitofrighthand.Thevaluesb/a,c/a,d/a,e/aand (SDPTG-AI)wereused.Itwasobservedthattheincreaseinageincreasedtheheight,systolic bloodpressure,c/aande/aratiosanddecreasedb/aratioandSDPTG-AIwhereasincreaseinheight decreasedtheb/aratioandSDPTG-AIandincreasedratiosc/aande/a.Alsotherewasno significant correlation between blood pressure and indices of SDPTG. Also it was observedthat in males, the SDPTG-AI decreased with age from 3-18 years and then increased and in femalesit decreased with age from 3-15 years and then increased[26].

J.Bhattacharya*etal.*(2001)studieddigitalbloodvolumepulsations,acquirednon-invasively through a photo-plethysmographic device, for qualitative evaluation of overall clinical statusand characterizationofcomplicatedcardiovasculardynamicsofthesubject.Theyimplementedanovel conceptforrecognizingthemostinfluentialnon-sinusoidalperiodicityimplantedinthedataseries andtoobtaintherelatedperiodiccomponents.Theidentificationandseparationofperiodic components was performed using a moving window to adapt the variations of the physiological oscillations. They also introduced the characterization of the principal systemconsidering nonlineardynamicalanalysis.Itwasconcludedthatthenormalsubjectsareshowntoactasalow-dimensional system whereas the diseased subjects show comparatively high dimensionalactivity [27].

I.Hlimonenko*etal.*(2003)exploredtheexpansivepropertiesofvasculartreenoninvasivelyin humanbodyasafunctionofagingwiththeuseofshapeofperipheralpulsewave.Itwasconfirmed that the pulse wave must be examined as the superposition of two distinct waves i.e. theincident wave and the reflected wave. The incident wave travels from heart to periphery and thereflected wave travels from the periphery and the region of wave reflection to the heart. The incidentwave isdependentontheleftventricularexcretionandthearterialfirmness,whereasthereflectedwave is associated to arterial firmness and the potential regions of wave reflection. In the youngadults, where arteries are expandable, the pulse wave velocity is relatively low. In older subjects,where the arteries are less expandable the pulse wave velocity is high[28].

M.Soltane*etal*.(2004)presentedArtificialNeuralNetworkapproachestoclassifyPPGsignalinto twodifferentclasses.ThePPGdatausedwasrecordedfromtwogroupofvolunteerswhich consisted37healthy(Type1)and11pathologies(Type2)withinanagegroupof21and64years. Itwasobservedthatthetwoclasseswereclassifiedeffectivelyusingbackpropagation-training algorithmemployedbymultilayerperceptronneuralnetwork.Anaccuracyof100%wasachieved for the training data sets and 94.7% for testing data sets. Out of 170 samples used for testing,114 were healthier and 56 samples were pathologies[8].

H.Takada*et al.* (2004) analyzed the validity of an APG system to calculate heart ratevariability ratherthanusingECG.ForthisanewtypeofAccelerationPlethysmography(APG)machineand asoftwarewasdeveloped.Thesystemworkedtoshowheartratevariabilitybymakinguseof coefficient of variation of a-a intervals (CVaa %). An ECG and PPG (using a two channelAPG system) were recorded simultaneously and difference between the a-a interval (Taa) of anAPG and the R-R interval of an ECG was examined. The APG waveform was recorded for 26diabetic and121healthysubjectsandaverageCVaa%fornormalanddiabeticsubjectsforeachage categorywascalculated.ItwasobservedthatdifferencesbetweentheR-RintervalandtheTaa intervalwereinsidetherangeof10msecandthemultiplecorrelationcoefficientwas0.999175. Also the mean CVaa% decreased with age and was 0.2-1.5% higher than the mean coefficientof variationoftheR-Rintervalsinallagecategories.ItwasconcludedthattheAPGsystemis appropriate to evaluate heart rate variability[29].

J.Simek*etal.*(2005)conductedastudytoinvestigatethesecondderivativeoffingerarterial pressure waveform (SDFAP) in 120 middle-aged subjects with normal health and in 24subjects with required hypertension. The normalized magnitudes i.e. b/a, c/a, d/a, e/a of fiveconsecutive peaksofSDFAP(a,b,c,d,e)werefound.Itwasestablishedthatbothhypertensionandaging decreasetheperipheralarterialpressureintheperiodofearlysystoleandincreaseintheperiodof latesystole.Theearlysystolicindicesi.e.b/aandc/aratiosdiscriminateindividuallyamongst subjects with necessary healthy controls and hypertension. These indices might reflectstructural alteration of arterial walls in subject with required hypertension. The late systolic indices i.e.d/a and e/a primarily reflect pressure augmentation and do not convey independent information[30].

S.C. Millasseau*et al.* (2006) illustrated the background to the contour analysis of digitalvolume pulse.Theydescribedtherelationofthetechniquetocontouranalysisofthepressurepulse.Itwas deducedthatdeterminationofDVPopticallyisasimplemethodforanalyzingpulsecontour. Identicaltothepressurepulse,DVPiseffectedbypressurewavereflectioninthesystemic vasculatureandbylargearterystiffness.Vasculartoneandarterialstiffnesscanbeassessedrapidly bythemeansofcontouranalysisofDVP.Applicationsincludethecharacterizationofarterial ageing, assessment of endothelial function and arterial stiffness[31].

S.Chaplot*etal.*(2006)proposedanovelmethodbyusingwaveletsasaninputtotheneural networkself-organizingmapsandsupportvectormachineforclassificationofmagneticresonance (MR)imagesofahumanbrain.TheMRbrainimageswereclassifiedasnormalorabnormal.The researchwasconductedon52MRbrainimagesandanaccuracyof94%wasobtainedbyusing neural network self-organizing maps and an accuracy of 98% was achieved from supportvector machines.Itwasconcludedthatsupportvectormachineclassifierhaveahigherclassificationrate as compared to self-map-based approach[32].

J.Yao*etal.*(2007)applieddderivativesofphotoplethysmographicsignalstoexaminetwoimportant issues: discriminability between different subjects and consistency within an individualsubject. The experimental results demonstrated that by employing the statistical tools, the features ofan individual's photoplethysmographic signal can be described precisely and can be usedfor identification purposes as bio-measures[33].

R.Gonzalez*etal.*(2008)analyzedthePPGsignalusingacomputerbasedphotoplethysmographic analyzer. The first, second and fourth derivative of signal were calculated. This study wasbeing conducted on 38 subjects, 19 subjects with previously detected cardiovascular diseases(diabetes mellitus, atherosclerosis and hypertension) and 19 healthy volunteers. The calculatedparameters: photoplethysmographicaugmentationindex,stiffnessindex,andtheratiosb/a,c/a,d/a,e/ashowed significant differences between healthy and unhealthy subjects. It was concluded thatthe photoplethysmographic augmentation index has been a non-invasive indicator forvascular assessments[34].

S.Usman*et al.* (2009) established the correlation between diabetes and premature vascularaging. Theyusedthesecondderivativeofphotoplethysmograph(SDPPG)formonitoringthearterial condition of twenty three human subjects. Informal method SDPPG which substituted theformal SDPPGagingindex(SDPPG-AI)wasselectedasasuitablemethodtobeapplied.Itwasobserved that as compared to the healthy subjects, twenty-three diabetic patients exhibited higher indexof vascular aging[35].

D.Korpas*etal.*(2009)presentedareviewpaperwhichdiscussedaboutvariousmethodsof measuringapulsewaveanditsanalysis.Themainfocuswasbeingmadeonthepulsewave measurementparametersandtheresultsobtained.Theparameterstobeevaluatedcanbeassessed from the time domain, velocity domain, frequency domain and derivations. They alsoconsidered the concept of pulse wave measurement and current experience. Pulse wave changes indifferent parts of circulation and is dependent on pathophysiological or physiological state of anorganism. Itispronetosomeheartdiseasesandresultsisearlywavereflection.Eventhoughthistechnology havecertaindrawbacks,itisstillanencouragingnon-invasivetoolforindicatingthestateof cardiovascular system in both experimental and clinical setting[36].

M.Elgendi*et al.* (2010) developed an algorithm for detection of a-waves in the secondderivative ofpulseplethysmogram.Thealgorithmwasdevelopedforsignalswithlowamplitude,high frequencynoise,non-stationaryeffects,afterexerciseandirregularheartbeats.Accuratedetection ofa-wavesinthesecondderivativeofphotoplethysmogramcanbeusedtocalculatethevariability inheartrate.Theperformanceofproposedmethodologywastestedonrecordedmeasurementsof twenty seven healthy male human subjects measured at rest and after doing exercise. Anoverall average sensitivity of 100% and positive predictivity of 99.88% was achieved over 27recorded measurements containing a total of 3370 heartbeats[37].

M.Elgendi*et al.* (2010) used acceleration plethysmography to calculate heart rate (HR) andheart ratevariability(HRV).Theyproposedanalgorithmtodeterminethelengthofa-ainterval.The testwasconductedon26recordedmeasurementstochecktheperformanceofthenetwork.Itwas observedthattheheartrateindices,SDNN(standarddeviationofdurationofheartbeats)and rMSSD(rootmeansquareofthedistinctionoffollowingheartbeats)showednegativecorrelation withtheheartrateandastrongpositivecorrelationbetweenthem.Thisindicatedthatthe20second acceleration plethysmographyrecordings are enough to reliably measure the heart ratevariability [14].

D.Jang*etal.*(2010)calculatedSDPTGusinganalgorithmwhichisthecombinationoflinear fitting algorithm and low pass FIR filters. Their algorithm performed better than a low passFIR filterandwassimilartoahigherorderFIRlowpassfilter.Itwasconcludedthattheirproposed methodologywasrationaltocalculateSDPTGwithlesscomputationalcomplexityandsmalltime delay.AlsoitcanbeusedasasubstituteofhigherorderlowpassFIRfilterstoestimatetheSDPTG [38].

R.MRozi*etal.*(2010)usedsecondderivative(SDPPG)methodofPPGtomonitorthearterial conditionsofelevenhealthysubjects.Theacquireddatawasusedtoanalyzethechangesinsecond derivative at rest and immediately 10 minutes after exercise. It was concluded that theindividuals beforeexercisehavehighindexofvascularagingascomparedtoafterexercise.Resultsalso proved SDPPG as a potential method to monitor arterial condition of an exerciser[39].

B.Thakker*et al.* (2010) compared the power spectrum of radial pulse signals of healthysubjects andthesubjectssufferingfromgastrointestinaldisorders.Theradialpulsesignalresultedin changes in pulse power spectrum on account of variations in its morphology in abnormalhealth conditions. It was noticed that pulse signal carried information of pulse morphologies inthe frequencybandof0to20Hz.Thepowerspectrumexaminationofpulseinnormalsubjects exhibitedthattheenergyin0to4Hzbandwasslightlyhigherascomparedtotherestofthebands. In subjects with abnormal health, right and left hand pulse signals showed changes inthe distribution of energy among frequency bands. The abnormal subjects showed elevationof energies in pulse band (4 to 10 Hz). Due to elevation of energies, the two groups wereclassified withaccuracyof90%,sensitivityof89.7%andspecificityof90.5%forRVpulsepointof5th band. It was concluded that the three bands showed clear difference in the terms of pulseenergy. Outofthese,theband5with8to10Hzfrequencyrangeismoreeffectualindistinguishing abnormal and normal subjects[40].

M.Singh*et al.* (2011) analyzed finger pulse profile of Photoplethysmography (PPG) fordetecting tridosha.AccordingtotheancientscienceofAyurveda,anyimbalanceinthethreedoshasi.e.vata, pittaandkapha,makehumanbeingssuffer.Normallythesedoshasaredetectedbyexperienced mastersbypressingtheradialarteryinthewristwiththeirthreefingers.Inthisresearchfinger pulseprofileofall10fingersof7healthysubjectsisacquiredusingaBIOPACMP150data acquisitionsystem.Itwasfoundthatinall70caseswithoutexceptiontheautocorrelationfora givenfingerofsubjectisalwayshigherthancorrelationwithcorrespondingfingerofanyother subject [19].

M.Elgendi (2012) discussed about Photoplethysmography (PPG). He discussed about artifactsin thePPGsignal,existingindexesandcharacteristicfeaturesofaPPGwaveformtoevaluatefor diagnoses. He also discussed about the increasing importance of PPG, for being anon-invasive, convenientandcheapdiagnostictool.ItwasconcludedthatacommonstructureofanyPPG diagnosticsystemcomprisesofthreestagespreprocessing,featureextractionanddiagnosiswhere the main emphasis of this review was the preprocessing and feature extraction stages[13].

M.Singh*etal.*(2012)analyzedthefeaturesextractedfromfingerpulseplethysmogramtofindthe linkbetweenenhancedpittalevelandperipheralfingerpulse.Thedatawasbeingacquiredfor threesubjectsfrombothleftandrighthand,beforeandinstantlyafterlunch.Thethreeparameters namelyA2/A1,TP2/TPTandTP1/TPTwereextracted.Itwasobservedthatthevarianceof TP2/TP1inringfingerandA2/A1inmiddlefinger,droppedconsistentlyinbothleftandright hands for all the subjects[23].

M.Theodore*etal.*(2013)presentedanimplantableaccelerometertodetectplethysmograms directly.Thesensorprovidedanewmethodforcontinuousmonitoringofbloodpressure.The parameters: Pulse Transit Time (PTT) and Reflected Wave Transit Time (RWTT) showed avery highcorrelationwiththesystolicbloodpressure.Aftervariationsinthebloodpressureitwas observed that the blood pressure from the RWTT agreed better with the theory and simplifiedthe approach. The RWTT for 1800 pulses matched accurately with the systolic blood pressure witha mean deviation of 4.3% and a correlation coefficient of 0.96 [41].

M.Singh*etal.*(2014)explainedanautomatedmethodofidentifyingthesalientfeaturesofPPGin the form of an algorithm. The algorithm developed was for normal young subjects. Iteliminated the tedious task of extracting features manually and also reduced the risk of error. Thealgorithm developed gave an accuracy of 100%. It was concluded that extracting features automaticallyis much easier and saves time [42].

D'Onofrio*etal.*(2015)usedphotoplethysmographytomeasureheartrateduringphysicalexercise. They created a wearable wrist photoplethysmography by using phototransistors andultra-bright LED’swhichallowedusersto keepatrackoftheirheartratewhileexercising.ThePPGsignal wascreatedusingaPICprocessorcodedthroughlanguageC++.Signalprocessingalgorithms were performed to filter out noise because of movements[43].

CHAPTER4

PROBLEMDEFINITION

According to Ayurveda, Pitta level in the normal healthy human body increases duringmid-day andaftertakingmeals.IncreaseinPittaotherwisemaybeduetosomedisease.Thisstudyisbeing conducted with a motive of finding features that may directly link to the enhanced level ofPitta. For this purpose, certain features extracted from the second derivative of PulsePlethysmography (PPG) may be used. Our focus of research isto:

- Optimally select those features which may give high accuracy of enhanced Pittalevel detection
- To develop a suitable Classifier for thisdetection

CHAPTER5

PROPOSEDSOLUTION

TheaimofthisstudyistodesignandvalidateaHighPittaClassifier.Forthispurpose,thefeatures extractedfromthesecondderivativeofPhotoplethysmographyhasbeenanalyzedandreduced optimally using different methods like Fisher Linear Discriminant Analysis andCorrelation. Different threshold values has been taken to select features aftercorrelation.

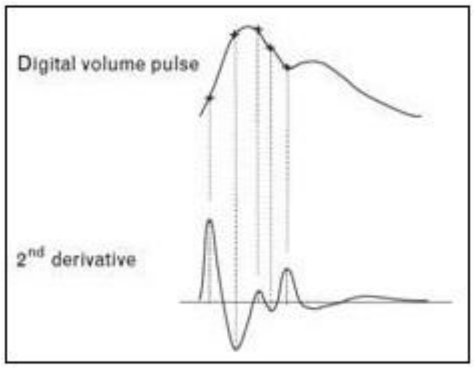

Figure 5.1: A Photoplethysmography waveform and its secondderivative

Threefeaturesetsnamely:TruncatedFeatureSet,ReducedFeatureSetandSuperReducedFeature Sethavebeenobtained.Dataof25healthysubjectshavebeenusedinthisstudy.Theclassification ofthesesignalshasbeendonetoaccuratelyseparatehighPittalevelandlowPittalevel.These featuressetsareclassifiedusingdifferentclassificationtechniqueslikeArtificialNeuralNetworks (singlelayerandmulti-layernetworks)andLIBSVM.Theclassificationtechniqueshavebeen implementedinMATLAB.ThesuitabilityofFeaturesetsisalsocheckedforbestresults.The process illustrated above has been executed and the results have been discussed in theproceeding chapters.

CHAPTER6

METHODOLOGY

6.1 Methodology

The methodology used in this study to design a High Pitta classifier is described below.Various stageshasbeenused.Theflowchartdescribingtheprocessofreductionoffeaturesoptimallyand their classification is shown below infigure

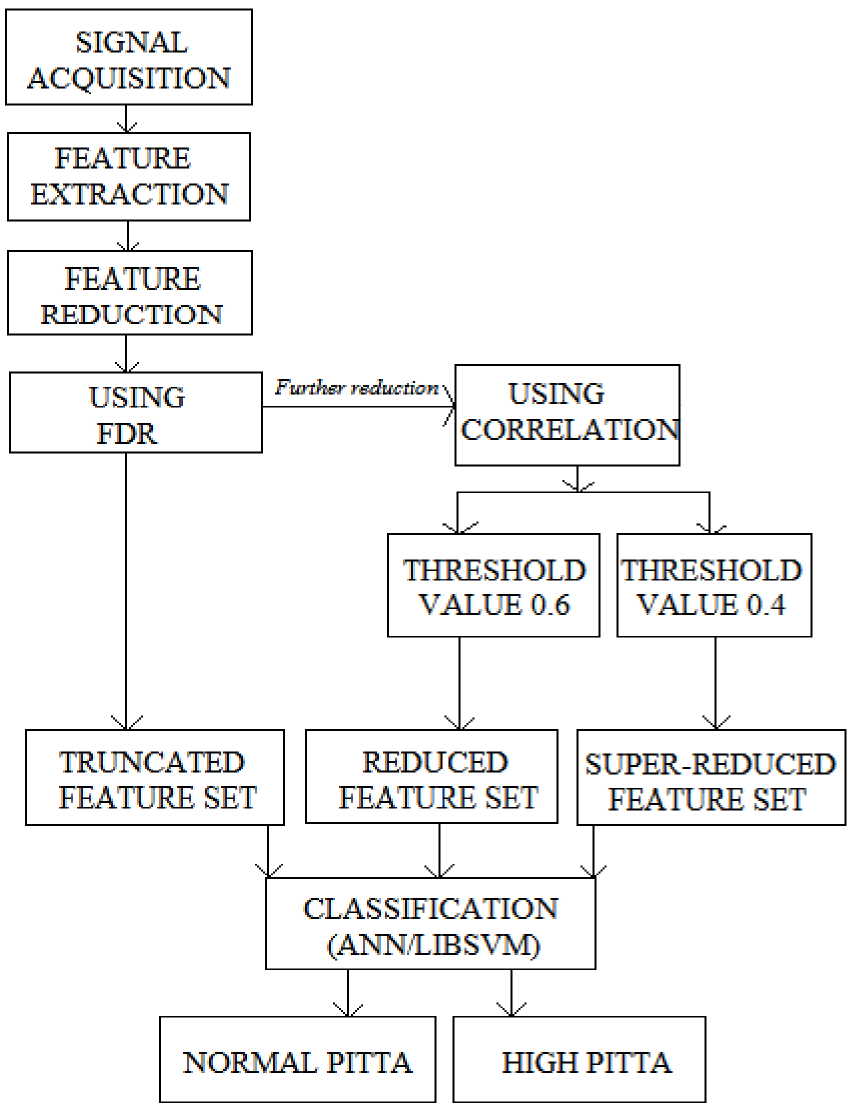

Figure 6.1: Flow Chart describing themethodology

6.2 DataCollection

AnMP150SystemandAcknowledgesoftwarewasusedtorecordthedatafromindex,middleand ring fingers of both the hands for 25 healthy subjects. The PPG was acquired for a givensubject on the same day at three differentinstances-

(i) **ClassA**-Oneandahalfhourafterbreakfastbutbefore10:30am.Theearlypartoftheday ensureslowerPittalevelwhileoneandahalfhourdelayaftertakingmealssubduesenhancedPitta on account of mealdigestion.
(ii) **ClassB**-Immediatelybeforelunchprovidedlunchistakenbetween1-2pm.Themid-day usually enhances Pittalevel.
(iii) **Class C**- Fifteen minutes after lunch. Again mid-day ensures higher Pitta level, whiletaking meals also helps in maintaining high Pitta level and it enhances it further[44].

The data used is documented in Post graduate dissertation titled "Automatic Feature Extractionin Accelerated Plethysmography"[44].

ThesecondderivativeoftheprimaryPPGisderivedtoobtainAcceleratedPlethysmography (APG)asshowninFigure1.APGstabilizesthebaselineandseparatesthecomponentsofthe waveformmoreclearlyascomparedtothefirstderivative[45].FromAPGwaveformfive distinctive peaks: a, b, c, d and e were extracted as shown in Figure6.2.

The amplitude ratios b/a, c/a, d/a and e/a were calculated. Further average and standarddeviation ofeachratiowasobtained.Thus,atotalof8featureswereobtainedforeachfinger.Sincethedata was acquired from six fingers, we have a total of 48 features for each subject[42].

Theentireprocessofextractingfeaturesandcalculatingproportionsandtheiraverageandstandard deviationwasdonebyusingacomputeralgorithm[42].Forthesakeofconveniencethese48 features are referred to as **"Gross FeatureSet".**

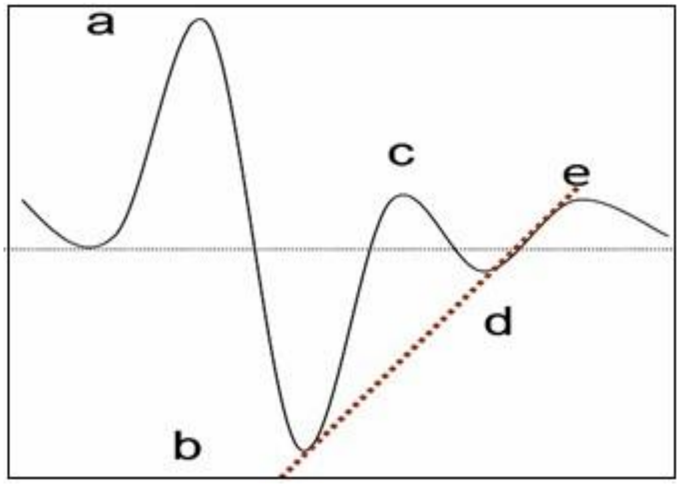

Figure 6.2: Second derivative of photoplethysmography waveform[46]

6.3 FeatureReduction

The data acquired is processed for selected optimal features for enhanced Pitta detection. Forthis purpose the data has been divided into three Comparative Groups: Comparative Group 1 ofAfter Breakfast (Class A) and Before Lunch (Class B), Comparative Group 2 of After breakfast(Class A)andAfterlunch(ClassC)andComparativeGroup3ofBeforeLunch(ClassB)andAfterLunch (ClassC).ForthethreeComparativeGroups,detectionofenhancedPittacanbedoneusing48 extracted features of APG. To optimally select the smallest number of features foreach comparative group various methods can be applied. In this study, Linear FisherDiscriminant Analysis and Correlation have beenemployed.

6.3.1 Feature Reduction Using Linear Fisher DiscriminantAnalysis

Fisherlineardiscriminantanalysisisawidely-usedtechniqueforpatternclassificationandfindsa lineardiscriminantthatyieldsoptimaldiscriminationbetweentwoclasses[47].Thevalueof Fisher Discriminant Ratio (FDR) is givenas,

$$FDR = \frac{|\mu_1 - \mu_2|}{\sqrt{\sigma_1^2 + \sigma_2^2}} \tag{6.1}$$

Here σ is the standard deviation, μ is the average and the subscript represents the twoclasses. Using the above formula, the FDR was calculatedbetween:

- Comparative Group1
- Comparative Group2
- Comparative Group3

Fisher discriminant ratio for all the three Comparative Groups has been arranged in adescending orderandthosefeatureswhichhaveFDRratioabovethedefinedthresholdi.e.‘0.25’areselected. Thefeaturesobtainedafterfisherlineardiscriminantanalysisarereferredtoas**“Truncated FeatureSet”**.

6.3.2 Further Feature Reduction UsingCorrelation

The “Truncated Feature Set” obtained has been further correlated to optimally reduce thenumber offeaturesforfurtheranalysis.Correlationisastatisticalmeasurethatspecifiestheextenttowhich two or more variables vary together. A positive correlation specify the extent to whichthese variables increase or decrease in parallel; a negative correlation specify the extent to whichone variable increases as the other decreases. A correlation matrix has been obtained foreach Comparative Group independently. Different threshold values have been set. The thresholdsset are:

- 0.4
- 0.6

Thefeaturepairshavingcorrelationabovethisthresholdhavebeenselected.Fromtheselected pair of features, the feature having lower FDR is discarded. All other features havinglower correlationarealsoselected.When‘0.6’correlationisset,thefeaturesetobtainedisreferredtoas **“ReducedFeatureSet”** andwhen‘0.4’correlationisset,thefeaturesetobtainedisreferredtoas **“Super Reduced FeatureSet”**.

6.4 Classification

MATLAB was used to develop algorithm to classify the data into two classes: High Pitta andLow Pitta.Classificationreferstotheprocessofdistinguishingtowhichcategoryanewobservation belongto,basedontrainingsetofdataconsistinginstanceswhosecategorymembershiphasbeen known. Classifier has been used for classification. Classifier refers to the mathematicalfunction which is employed by algorithm and maps input data into a particular category. In this study,two classifiers have been used, as listedbelow:

- LIBSVM
- ANN(Artificial NeuralNetwork)

6.4.1 LIBSVM

LIBSVM is a software that is being used for support vector classification, distributionestimation and regression. It has various features like efficient multi-class classification, cross-validationfor theselectionofbestmodel,availabilityofvariousinbuiltkernelslikelinearkernel,polynomial kernel, RBF kernel etc. [48]. The support-vector network is the learning machine forclassifying the data in two groups. The conceptual idea implemented by the machine is that the inputvectors are mapped non-linearly into a very large dimension feature space. The linear decision surfaceis being constructed in the feature space. High generalization ability of the support vectormachine isensuredbythisdecisionsurface[49].Figure6.3showsthebasicclassificationcriteriaofsupport vectormachine.

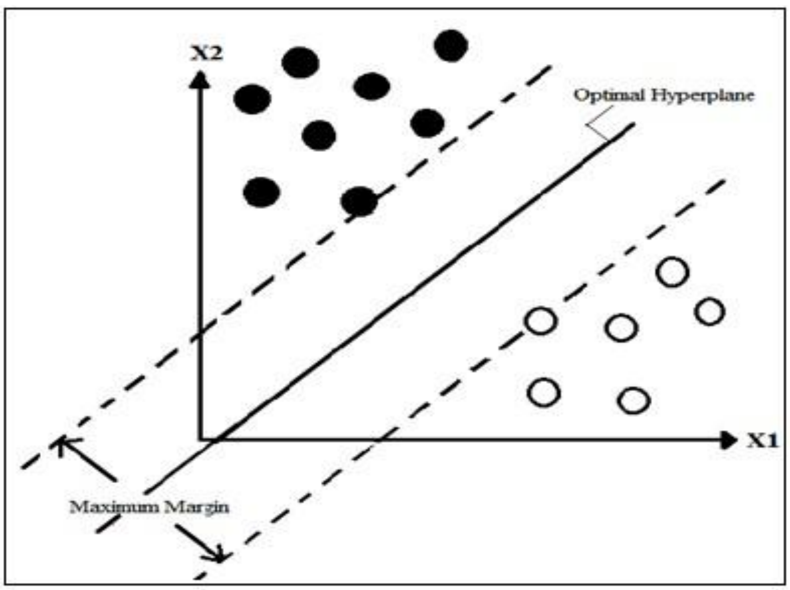

Figure 6.3: General Support VectorClassification

Classification accuracy is then calculated accordingly depending upon how many signalsare classifiedcorrectly.Outofatotalof50samples,traininghasbeenperformedon68%ofdata.Two different kernels i.e. Radial Basis Function (RBF) kernel and Polynomial Kernel have beenused. Best values of cost factor and gamma is determined and the best model has been developedunder observation. The best model obtained was tested on remaining 32% to test the performance ofthe network.

6.4.2 Artificial NeuralNetworks

ArtificialNeuralnetworks(ANN)arethebiologicalstructuresandareinspiredbythefunctioning ofhumannervoussystem.Thesehavewiderangeofapplicationsinthefieldofclassification, pattern recognition etc. Figure 6.4 shows the basic structure ofANN.

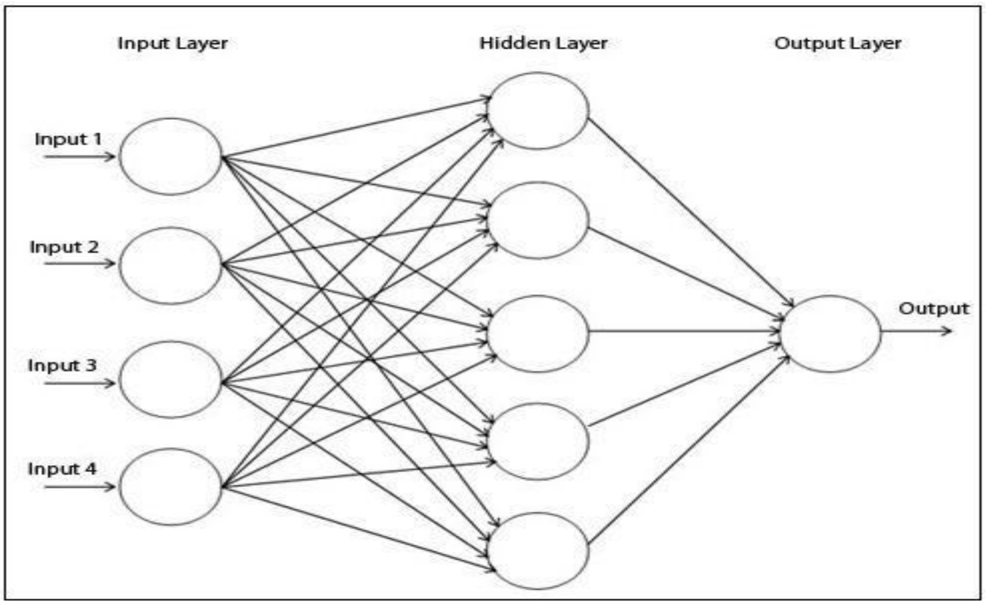

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Figure 6.4: Basic Structure of ANN[50]

A feed-forward back Propagation Network type is used while developing a classifier. Toobtain theforwardpropagationatrainingpatternhasbeenappliedtotheANNandispropagatedthrough thenetworktoobtainthecontinuousvalueofoutput.Thisoutputvalueisthencomparedtothe requiredvalueofthepatternandanerrorvalueisbeinggenerated.Thesynapticweightsofthe neuronsareadjustedbybackpropagatingtheerrorvalue[51].Thedataof25healthysubjectshave been considered for classification. The network has been trained using 34 samples and aseparate 16samplesarekepttotesttheperformanceofthenetwork.Thenumberofneuronsintheinput layer correspond to the number of input features. The number of hidden layers have beenvaried. Thenumberofneuronsinthehiddenlayersarealsovaried.Sigmoidtransferfunctionhasbeen chosen for all thelayers.

CHAPTER7

RESULTS ANDDISCUSSION

APGhasthepotentialtodetecttheAyurvedicdoshaPitta.Inthisstudy,threecomparativegroups hasbeenmadeandfeaturesarereducedtoobtain“TruncatedFeatureSet”,“ReducedFeatureSet” and “Super Reduced Feature Set”. These feature sets are classified into two classes namelyhigh Pitta and low Pitta. The results of this study have been compiledbelow**.**

7.1 Feature Reduction Using Fisher Linear DiscriminantAnalysis

FDRofComparativeGroup1i.e.AfterBreakfast(ClassA)andBeforeLunch(ClassB)isshown below in Table 7.1. Out of a total of 48 features i.e. “Gross Feature Set”, the highlightedportion indicatesthe17featuresthathaveFDRabovethethresholdvalue‘0.25’andthesefeaturesare referred to as the “**Truncated FeatureSet**”.

Table 7.1: Feature selection using FDR (Comparative Group1)

S.NO	FEATURES	FDRVALUE
1	LEFT INDEX e/aAVERAGE	0.485540668
2	RIGHT MIDDLE e/aAVERAGE	0.388081853
3	LEFT RING b/aAVERAGE	0.38513289
4	RIGHT INDEX d/aAVERAGE	0.349564697
5	RIGHT MIDDLE d/aAVERAGE	0.34447214
6	RIGHT RING b/a STANDARDDEVIATION	0.339491678
7	RIGHT INDEX b/a STANDARDDEVIATION	0.329570973
8	LEFT INDEX b/aAVERAGE	0.323443261
9	RIGHT RING d/a STANDARDDEVIATION	0.304748162
10	RIGHT RING e/a STANDARDDEVIATION	0.295245403
11	LEFT INDEX d/a STANDARDDEVIATION	0.285547823
12	RIGHT INDEX e/a STANDARDDEVIATION	0.28252309
13	RIGHT MIDDLE d/a STANDARDDEVIATION	0.266119946
14	LEFT INDEX d/aAVERAGE	0.261269716
15	RIGHT MIDDLE e/a STANDARDDEVIATION	0.257547542
16	LEFT MIDDLE c/aAVERAGE	0.254284819
17	RIGHT INDEX c/a STANDARDDEVIATION	0.249709265
18	LEFT MIDDLE d/aAVERAGE	0.242835192

The features selected arehighlighted

19	LEFT RING d/aAVERAGE	0.2252015
20	RIGHT INDEX d/a STANDARDDEVIATION	0.223197182
21	RIGHT RING d/aAVERAGE	0.222401213
22	RIGHT MIDDLE c/a STANDARDDEVIATION	0.203795798
23	RIGHT MIDDLE b/a STANDARDDEVIATION	0.203700172
24	RIGHT INDEX c/aAVERAGE	0.184903361
25	RIGHT INDEX e/aAVERAGE	0.173166284
26	LEFT MIDDLE e/a STANDARDDEVIATION	0.160832503
27	LEFT MIDDLE c/a STANDARDDEVIATION	0.158693257
28	RIGHT RING b/aAVERAGE	0.158094588
29	RIGHT MIDDLE c/aAVERAGE	0.15478553
30	LEFT INDEX e/a STANDARDDEVIATION	0.153762373
31	LEFT INDEX c/a STANDARDDEVIATION	0.146298243
32	RIGHT INDEX b/aAVERAGE	0.140509813
33	LEFT MIDDLE d/a STANDARDDEVIATION	0.139464934
34	LEFT RING d/a STANDARDDEVIATION	0.12641301
35	RIGHT RING c/a STANDARDDEVIATION	0.122199424
36	RIGHT MIDDLE b/aAVERAGE	0.106500236
37	LEFT MIDDLE b/aAVERAGE	0.098607982
38	RIGHT RING e/aAVERAGE	0.08451596
39	LEFT RING e/aAVERAGE	0.08213197
40	LEFT RING c/aAVERAGE	0.079521212
41	LEFT RING c/a STANDARDDEVIATION	0.079356719
42	LEFT INDEX b/a STANDARDDEVIATION	0.07632933
43	LEFT RING b/a STANDARDDEVIATION	0.072563243
44	LEFT RING e/a STANDARDDEVIATION	0.035008898
45	LEFT INDEX c/aAVERAGE	0.019502961
46	LEFT MIDDLE b/a STANDARDDEVIATION	0.016101735
47	RIGHT RING c/aAVERAGE	0.009127493
48	LEFT MIDDLE e/aAVERAGE	0.00811542

Fisher discriminant ratio of Comparative Group 2 i.e. After breakfast (Class A) and Afterlunch (Class C) is summarized below in Table 7.2. From “Gross Feature Set”, 18 features havingFDR above ‘0.25’ have been selected. This **“Truncated Feature Set”** of 18 features is consideredfor furtheranalysis.

Table 7.2: Feature selection using FDR (Comparative Group2)

S.NO	FEATURES	FDR VALUE
1	LEFT MIDDLE d/a STANARDDEVIATION	0.43154904
2	LEFT MIDDLE b/a STANDARDDEVIATION	0.416672613
3	LEFT MIDDLE e/a STANDARDDEVIATION	0.404427618
4	LEFT INDEX d/aAVERAGE	0.338085848
5	RIGHT RING e/a STANDARDDEVIATION	0.336539478
6	RIGHT INDEX b/aAVERAGE	0.327794377
7	LEFT RING d/aAVERAGE	0.312003219
8	RIGHT INDEX b/a STANDARDDEVIATION	0.310400067
9	RIGHT RING b/aAVERAGE	0.308010964
10	LEFT RING e/aAVERAGE	0.306157011
11	RIGHT RING d/aAVERAGE	0.297259497
12	RIGHT MIDDLE e/a STANDARDDEVIATION	0.296454759
13	LEFT INDEX c/a STANDARDDEVIATION	0.296178405
14	LEFT RING c/a STANDARDDEVIATION	0.276053601
15	LEFT MIDDLE c/a STANDARDDEVIATION	0.274148472
16	RIGHT MIDDLE b/aAVERAGE	0.271858207
17	RIGHT INDEX c/aAVERAGE	0.253260108
18	LEFT MIDDLE d/aAVERAGE	0.252925157
19	LEFT INDEX d/a STANDARDDEVIATION	0.23009828
20	LEFT RING b/aAVERAGE	0.229535601
21	LEFT RING e/a STANDARDDEVIATION	0.217640114
22	RIGHT MIDDLE d/aAVERAGE	0.19626043
23	LEFT INDEX b/a STANDARDDEVIATION	0.19493547
24	RIGHT MIDDLE b/a STANDARDDEVIATION	0.193815811
25	LEFT MIDDLE e/aAVERAGE	0.188646499
26	RIGHT RING b/a STANDARDDEVIATION	0.185018002
27	LEFT RING b/a STANDARDDEVIATION	0.183427953
28	RIGHT MIDDLE c/aAVERAGE	0.164838647
29	LEFT MIDDLE b/aAVERAGE	0.161065448
30	RIGHT MIDDLE e/aAVERAGE	0.132672492
31	RIGHT MIDDLE d/a STANDARDDEVIATION	0.122061308
32	LEFT RING c/aAVERAGE	0.098458169
33	RIGHT RING c/aAVERAGE	0.095583867
34	LEFT INDEX e/a STANDARDDEVIATION	0.093824833

35	RIGHT INDEX d/a STANDARDDEVIATION	0.068214163
36	RIGHT INDEX d/aAVERAGE	0.068125337
37	RIGHT RING c/a STANDARDDEVIATION	0.067069265
38	LEFT RING d/a STANDARDDEVIATION	0.063243873
39	RIGHT MIDDLE c/a STANDARDDEVIATION	0.061978282
40	RIGHT RING d/a STANDARDDEVIATION	0.056271453
41	LEFT INDEX e/aAVERAGE	0.053551454
42	LEFT MIDDLE c/aAVERAGE	0.031814104
43	RIGHTINDEX e/a STANDARDDEVIATION	0.030889449
44	LEFT INDEX b/aAVERAGE	0.018778868
45	RIGHT INDEX e/aAVERAGE	0.01024219
46	RIGHT INDEX c/a STANDARDDEVIATION	0.006230603
47	LEFT INDEX c/aAVERAGE	0.001945723
48	RIGHT RING e/aAVERAGE	0.00058241

The features selected arehighlighted.

FisherdiscriminantratioofComparativeGroup3i.e.Beforelunch(ClassB)andAfterlunch (ClassC)isshownbelowinTable7.3.Outoftotal48features,18featureshavingFDRabove 0.25 have been selected. The 48 features represent the “Gross Feature Set” and the highlighted18 features represent the **“Truncated FeatureSet”**.

Table 7.3: Feature selection using FDR (Comparative Group3)

S.NO	FEATURES	FDRVALUE
1	LEFT INDEX d/aAVERAGE	0.557494638
2	LEFT RING d/aAVERAGE	0.51046367
3	RIGHT INDEX b/aAVERAGE	0.48464012
4	RIGHT RING d/aAVERAGE	0.477976282
5	RIGHT MIDDLE d/aAVERAGE	0.470670476
6	LEFT MIDDLE d/aAVERAGE	0.4474165
7	LEFT INDEX e/aAVERAGE	0.446649895
8	LEFT MIDDLE b/a STANDARDDEVIATION	0.404636742
9	RIGHT MIDDLE b/aAVERAGE	0.399124209
10	RIGHT INDEX d/aAVERAGE	0.384797748
11	LEFT INDEX d/a STANDARDDEVIATION	0.379325084
12	LEFT MIDDLE d/a STANDARDDEVIATION	0.361774591
13	LEFT INDEX c/a STANDARDDEVIATION	0.353952096
14	RIGHT INDEX d/a STANDARDDEVIATION	0.289303038

15	LEFT MIDDLE e/a STANDARDDEVIATION	0.287046195
16	RIGHT RING d/a STANDARDDEVIATION	0.266290367
17	RIGHT INDEX c/a STANDARDDEVIATION	0.251379439
18	RIGHT MIDDLE c/a STANDARDDEVIATION	0.245837624
19	RIGHT INDEX e/a STANDARDDEVIATION	0.232513464
20	LEFT RING e/aAVERAGE	0.21938762
21	RIGHT RING b/a STANDARDDEVIATION	0.211815021
22	RIGHT MIDDLE d/a STANDARDDEVIATION	0.2062529
23	LEFT RING c/a STANDARDDEVIATION	0.205916869
24	LEFT MIDDLE c/aAVERAGE	0.2034347
25	LEFT MIDDLE c/a STANDARDDEVIATION	0.201324425
26	LEFT MIDDLE e/aAVERAGE	0.1961526
27	LEFT RING b/aAVERAGE	0.186118637
28	LEFT RING e/a STANDARDDEVIATION	0.172466289
29	LEFT RING b/a STANDARDDEVIATION	0.163652908
30	LEFT RING d/a STANDARDDEVIATION	0.160553312
31	RIGHT INDEX e/aAVERAGE	0.149608892
32	RIGHT MIDDLE e/aAVERAGE	0.133032306
33	RIGHT RING e/a STANDARDDEVIATION	0.11512928
34	LEFT INDEX b/aAVERAGE	0.099117588
35	RIGHT RING c/aAVERAGE	0.091537371
36	RIGHT INDEX c/aAVERAGE	0.078056978
37	RIGHT INDEX b/a STANDARDDEVIATION	0.071286412
38	RIGHT MIDDLE c/aAVERAGE	0.069389691
39	LEFT MIDDLE b/aAVERAGE	0.06567369
40	RIGHT RING e/aAVERAGE	0.061981437
41	RIGHT MIDDLE e/a STANDARDDEVIATION	0.058210431
42	LEFT INDEX b/a STANDARDDEVIATION	0.039579349
43	LEFT INDEX c/aAVERAGE	0.025365308
44	RIGHT RING c/a STANDARDDEVIATION	0.024710639
45	LEFT INDEX e/a STANDARDDEVIATION	0.018679264
46	RIGHT MIDDLE b/a STANDARDDEVIATION	0.018036483
47	LEFT RING c/aAVERAGE	0.017969417
48	RIGHT RING b/aAVERAGE	0.01787147

The features selected arehighlighted.

7.2 Further Reduction in Feature Set usingCorrelation

The “Truncated Feature Set” obtained after Fisher Linear Discriminant Analysis isfurther correlated with each other to optimally reduce the number of features for furtheranalysis.

- **Taking Correlation Threshold Value as‘0.6’**

Firstly,athresholdvalueof0.6forcorrelationhasbeentakenandfeaturepairshavingcorrelation abovethisthresholdareselected.Fromtheselectedpairoffeatures,thefeaturehavinglowerFDR is discarded. All other features having lower correlation are also selected. The correlationmatrix obtainedinComparativeGroup1issummarizedinFigure7.1.Fromatotalof17featuresin “Truncated Feature Set”, 12 features were shortlisted for furtheranalysis.

S.NO	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	1																
2	0.78519	1															
3	0.032765	-0.18193	1														
4	0.246365	0.358479	0.24162	1													
5	0.264326	0.489834	0.277949	0.856412	1												
6	-0.10557	0.054748	0.230998	0.499212	0.455004	1											
7	0.044202	0.269801	-0.23386	-0.02993	0.221539	-0.01887	1										
8	0.155566	0.057281	-0.04033	-0.54416	-0.28774	-0.5081	0.164722	1									
9	-0.18356	-0.28219	0.099856	-0.1942	-0.1811	0.084789	-0.10732	-0.10251	1								
10	-0.31226	-0.174	-0.04248	-0.09238	-0.0632	0.377195	0.120103	-0.13494	0.634626	1							
11	0.062691	0.010087	0.16274	-0.38413	-0.21599	-0.26226	0.288793	0.359871	0.107074	0.116093	1						
12	-0.07571	-0.24287	0.526719	-0.18487	-0.13048	-0.09057	0.021046	0.270063	0.366271	0.204614	0.431978	1					
13	-0.09863	-0.02119	-0.27652	-0.20317	-0.10894	-0.09397	0.236812	0.356759	0.214473	0.341443	0.374904	0.257291	1				
14	0.318911	0.38481	0.077364	0.556382	0.592645	0.307372	0.285394	-0.1527	-0.11636	-0.04812	0.056159	-0.20051	-0.0871	1			
15	-0.13003	0.066323	-0.44224	-0.14653	-0.141129	-0.00142	0.2983333	0.127856	0.178263	0.415135	0.192935	0.140409	0.7368	-0.05006	1		
16	-0.13956	-0.32052	0.350504	0.333828	0.144613	0.380266	-0.34724	-0.5049	-0.05387	0.087982	-0.323	-0.21975	-0.25963	0.234939	-0.30516	1	
17	-0.39644	-0.43065	0.175117	-0.1211	-0.10247	0.182688	0.023953	0.097274	0.254967	0.141848	0.261668	0.576538	0.258073	-0.11772	0.108715	-0.20463	1

Figure 7.1: Feature selection using Correlation matrix (Comparative Group1)

The following 12 features are referred to as “Reduced Feature Set” and these features mightlink to the enhanced pitta level. Table 7.4 represents the **“Reduced FeatureSet”**.

Table 7.4: Reduced Feature Set (Comparative Group1)

S.NO	Features
1	Left index e/aaverage
2	Left ring b/aaverage
3	Right index d/aaverage
4	Right ring b/a standarddeviation
5	Right index b/a standarddeviation
6	Left index b/aaverage
7	Right ring d/a standarddeviation
8	Left index d/a standarddeviation

9	Right index e/a standarddeviation
10	Right middle d/a standarddeviation
11	Left middle c/aaverage
12	Right index c/a standarddeviation

Similarly,correlationbetween18featuresselectedfromtheComparativeGroup2isfoundand certain features are discarded. The matrix obtained is shown in the Figure 7.2. The"Reduced Feature Set" of Comparative Group 2 is given in Table7.5.

S.N	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	1																	
2	0.527474	1																
3	0.946451	0.04269	1															
4	-0.08239	0.0332	-0.09113	1														
5	0.31008	-0.02878	0.29724	-0.01684	1													
6	-0.25524	-0.39227	-0.24086	-0.04014	-0.37813	1												
7	-0.14557	0.20756	-0.11609	0.72871	-0.33185	0.05943	1											
8	-0.04852	0.33903	0.04731	0.22678	0.1201	-0.13941	0.19369	1										
9	-0.04718	-0.06867	-0.08271	-0.15852	-0.3741	0.18466	-0.02456	-0.06523	1									
10	-0.09655	-0.02046	-0.01635	0.22165	-0.19532	-0.26602	0.48488	0.03434	0.33191	1								
11	0.1679	-0.04148	0.11111	0.4203	-0.25436	0.00217	0.23002	-0.25981	0.21438	0.01944	1							
12	0.15882	-0.00024	0.10219	0.01664	0.59427	-0.37921	-0.17002	0.39682	-0.11735	-0.12769	-0.04019	1						
13	-0.09504	0.019757	-0.13393	-0.31127	-0.12962	-0.07047	0.047475	0.07056	0.32649	-0.03239	-0.33152	0.05331	1					
14	-0.00246	-0.21243	-0.04784	-0.00894	0.08006	-0.11008	-0.10417	-0.0727	-0.28629	-0.154	0.29814	0.08813	-0.1314	1				
15	0.82628	0.56321	0.85144	-0.14477	0.16192	-0.25737	-0.07692	0.0917	-0.14703	0.00794	-0.01433	0.13424	-0.08931	0.03991	1			
16	-0.32546	-0.26102	-0.38709	0.11013	-0.42545	0.5647	-0.07423	0.09759	0.12901	-0.35229	0.16507	-0.34845	-0.23081	-0.08591	-0.32518	1		
17	-0.09389	-0.21782	-0.10789	0.31042	-0.22029	0.63887	0.36414	-0.12398	0.07959	0.03094	0.11879	-0.45232	-0.24159	-0.07049	-0.05081	0.53424	1	
18	0.16443	0.25855	0.15102	0.79159	-0.07595	-0.1303	0.76449	0.21874	-0.11124	0.21758	0.42605	0.05283	-0.05201	-0.11845	0.14334	-0.01955	0.28212	1

Figure 7.2: Feature selection using Correlation matrix (Comparative Group2)Table

7.5: Reduced Feature Set (Comparative Group2)

S.NO	Features
1	Left middle d/a standarddeviation
2	Left middle b/a standarddeviation
3	Left index d/aaverage
4	Right ring e/a standarddeviation
5	Right index b/aaverage
6	Right index b/a standarddeviation
7	Right ring b/aaverage
8	Left ring e/aaverage
9	Right ring d/aaverage
10	Left index c/a standarddeviation
11	Left ring c/a standarddeviation
12	Right middle b/aaverage

Similarly,correlationbetween18featuresselectedfromtheComparativeGroup3isfoundand certainfeaturesarediscarded.ThematrixobtainedisshownintheFigure7.3.The**“Reduced Feature Set”** of Comparative Group 3 is given in Table7.6.

S.NO	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	1																	
2	0.544641	1																
3	-0.15653	-0.06538	1															
4	0.450479	0.769838	-0.38664	1														
5	0.378331	0.48873	-0.41134	0.717578	1													
6	0.596108	0.676095	-0.29882	0.634251	0.699717	1												
7	0.490032	0.257773	-0.15224	0.216234	0.017527	-0.007	1											
8	-0.03824	0.198495	-0.06865	0.149546	0.368639	0.11274	0.083996	1										
9	-0.06475	0.181229	0.472377	-0.27593	-0.4429	-0.21719	0.223673	0.08319	1									
10	0.41616	0.57531	-0.22755	0.731733	0.852922	0.680817	-0.02917	0.04399	-0.43406	1								
11	0.404182	-0.0898	-0.33875	-0.17349	-0.07978	0.287642	-0.03427	-0.25123	-0.09244	-0.10718	1							
12	-0.19864	0.021773	-0.15261	0.275672	0.627349	0.294106	-0.26257	0.42329	-0.25981	0.408182	-0.14557	1						
13	0.18282	-0.19035	-0.22763	-0.29495	-0.16011	0.113899	-0.10451	-0.27417	-0.04582	-0.23841	0.785712	-0.076695	1					
14	-0.03843	-0.13363	-0.05443	-0.04292	-0.34004	-0.28825	-0.01756	-0.07171	0.026035	-0.32618	0.370932	-0.050092	0.374274	1				
15	-0.21282	-0.0881	-0.07154	-0.02955	0.298708	-0.10321	-0.02057	0.57377	0.035793	-0.04274	-0.19223	0.614327	-0.080112	-0.01233	1			
16	-0.11651	-0.0296	-0.15247	0.04046	-0.17911	-0.2968	0.250706	0.01462	0.083516	-0.23113	-0.0285	-0.046393	0.184013	0.660853	0.121332	1		
17	0.064746	-0.1627	-0.06503	-0.07991	-0.18032	-0.15698	-0.08178	-0.04497	-0.09841	-0.27237	0.328701	-0.003644	0.484517	0.812965	0.134229	0.546609	1	
18	-0.097	-0.22335	-0.18864	-0.06957	0.26579	0.007437	-0.26693	0.50701	-0.21732	-0.10261	0.044596	0.450415	0.151046	0.19408	0.621426	0.051092	0.53483	1

Figure 7.3: Feature selection using Correlation matrix (Comparative Group3)Table

7.6: Reduced Feature Set (Comparative Group3)

S.NO	Features
1	Left index d/aaverage
2	Left ring d/aaverage
3	Right index b/aaverage
4	Left index e/aaverage
5	Left middle b/a standarddeviation
6	Right middle b/aaverage
7	Left index d/a standarddeviation
8	Left index c/a standarddeviation
9	Right index d/a standarddeviation

- **Taking Correlation Threshold Value as‘0.4’**

Whenthethresholdvalueof0.4forcorrelationisbeingset,7featuresareobtainedfromthe ComparativeGroup1,8featuresfromComparativeGroup2and4featuresfromComparative Group 3. The correlation matrix showing the selected features for Comparative Group1, Comparative Group 2 and Comparative Group 3 is summarized in Figure 7.4, Figure 7.5and Figure7.6respectively.The“SuperReducedFeatureSet”forthethreeComparativeGroupsis listed in Table 7.7, Table 7.8 and Table7.9.

S.NO	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	1																
2	0.78519	1															
3	0.032765	-0.18193	1														
4	0.246365	0.358479	0.24162	1													
5	0.264326	0.489834	0.27795	0.856412	1												
6	-0.10557	0.054748	0.231	0.499212	0.455004	1											
7	0.044202	0.269801	-0.2339	-0.02993	0.221539	-0.01887	1										
8	0.155566	0.057281	-0.0403	-0.54416	-0.28774	-0.5081	0.164722	1									
9	-0.18356	-0.28219	0.09986	-0.1942	-0.1811	0.084789	-0.10732	-0.10251	1								
10	-0.31226	-0.174	-0.0425	-0.09238	-0.0632	0.377195	0.120103	-0.13494	0.634626	1							
11	0.062691	0.010087	0.16274	-0.38413	-0.21599	-0.26226	0.288793	0.359871	0.107074	0.116093	1						
12	-0.07571	-0.24287	0.52672	-0.18487	-0.13048	-0.09057	0.021046	0.270063	0.366271	0.204614	0.431978	1					
13	-0.09863	-0.02119	-0.2765	-0.20317	-0.10894	-0.09397	0.236812	0.356759	0.214473	0.341443	0.374904	0.257291	1				
14	0.318911	0.38481	0.07736	0.556382	0.592645	0.307372	0.285394	-0.1527	-0.11636	-0.04812	0.056159	-0.20051	-0.0871	1			
15	-0.13003	0.066323	-0.4422	-0.14653	-0.14113	-0.00142	0.298333	0.127856	0.178263	0.415135	0.192935	0.140409	0.7368	-0.05006	1		
16	-0.13956	-0.32052	0.3505	0.333828	0.144613	0.380266	-0.34724	-0.5049	-0.05387	0.087982	-0.323	-0.21975	-0.25963	0.234939	-0.30516	1	
17	-0.39644	-0.43065	0.17512	-0.1211	-0.10247	0.182688	0.023953	0.097274	0.254967	0.141848	0.261668	0.576538	0.258073	-0.11772	0.108715	-0.20463	1

Figure 7.4: Feature Selection using Correlation matrix (Comparative

Group1)Table 7.7: Super Reduced Feature Set (Comparative

Group1)

S.NO	Features
1	Left index e/aaverage
2	Left ring b/aaverage
3	Right index d/aaverage
4	Right index b/a standarddeviation
5	Right ring d/a standarddeviation
6	Left index d/a standarddeviation
7	Right middle d/a standarddeviation

S.NO	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	1																	
2	0.527474	1																
3	0.946451	0.04269	1															
4	-0.08239	0.0332	-0.09113	1														
5	0.31008	-0.02878	0.29724	-0.01684	1													
6	-0.25524	-0.39227	-0.24086	-0.04014	-0.37813	1												
7	-0.14557	0.20756	-0.11609	0.72871	-0.33185	0.05943	1											
8	-0.04852	0.33903	0.04731	0.22678	0.1201	-0.13941	0.19369	1										
9	-0.04718	-0.06867	-0.08271	-0.15852	-0.3741	0.18466	-0.02456	-0.06523	1									
10	-0.09655	-0.02046	-0.01635	0.22165	-0.19532	-0.26602	0.48488	0.03434	0.33191	1								
11	0.1679	-0.04148	0.11111	0.4203	-0.25436	0.00217	0.23002	-0.25981	0.21438	0.01944	1							
12	0.15882	-0.00024	0.10219	0.01664	0.59427	-0.37921	-0.17002	0.39682	-0.11735	-0.12769	-0.04019	1						
13	-0.09504	0.019757	-0.13393	-0.31127	-0.12962	-0.07047	0.047475	0.07056	0.32649	-0.03239	-0.33152	0.05331	1					
14	-0.00246	-0.21243	-0.04784	-0.00894	0.08006	-0.11008	-0.10417	-0.0727	-0.28629	-0.154	0.29814	0.08813	-0.1314	1				
15	0.82628	0.56321	0.85144	-0.14477	0.16192	-0.25737	-0.07692	0.0917	-0.14703	0.00794	-0.01433	0.13424	-0.08931	0.03991	1			
16	-0.32546	-0.26102	-0.38709	0.11013	-0.42545	0.5647	-0.07423	0.09759	0.12901	-0.35229	0.16507	-0.34845	-0.23081	-0.08591	-0.32518	1		
17	-0.09389	-0.21782	-0.10789	0.31042	-0.22029	0.63887	0.36414	-0.12398	0.07959	0.03094	0.11879	-0.45232	-0.24159	-0.07049	-0.05081	0.53424	1	
18	0.16443	0.25855	0.15102	0.79159	-0.07595	-0.1303	0.76449	0.21874	-0.11124	0.21758	0.42605	0.05283	-0.05201	-0.11845	0.14334	-0.01955	0.28212	1

Figure 7.5: Feature Selection using Correlation matrix (Comparative Group2)

Table 7.8: Super Reduced Feature Set (Comparative Group2)

S.NO	Features
1	Left middle d/a standarddeviation
2	Left index d/aaverage
3	Right ring e/a standarddeviation
4	Right index b/aaverage
5	Right index b/a standarddeviation
6	Right ring b/aaverage
7	Left index c/a standarddeviation
8	Left ring c/a standarddeviation

S.NO	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	1																	
2	0.544641	1																
3	-0.15653	-0.065383	1															
4	0.450479	0.769838	-0.386635	1														
5	0.378331	0.48873	-0.411344	0.717578	1													
6	0.596108	0.676095	-0.298819	0.634251	0.699717	1												
7	0.490032	0.257773	-0.152244	0.216234	0.017527	-0.006998	1											
8	-0.03824	0.198495	-0.068647	0.149546	0.368639	0.11274	0.0839963	1										
9	-0.06475	0.181229	0.472377	-0.275926	-0.442898	-0.217189	0.2236726	0.0831876	1									
10	0.41616	0.57531	-0.227547	0.731733	0.852922	0.680817	-0.029168	0.0439929	-0.4340562	1								
11	0.404182	-0.089805	-0.338751	-0.173485	-0.079782	0.287642	-0.034266	-0.251227	-0.0924403	-0.1071804	1							
12	-0.19864	0.021773	-0.152605	0.275672	0.627349	0.294106	-0.262572	0.4232886	-0.2598074	0.4081817	-0.145574	1						
13	0.18282	-0.19035	-0.227633	-0.29495	-0.160108	0.113899	-0.104507	-0.274172	-0.045815	-0.2384063	0.7857117	-0.076695	1					
14	-0.03843	-0.133633	-0.05443	-0.042922	-0.340043	-0.28825	-0.017564	-0.071709	0.0260351	-0.3261834	0.3709315	-0.050092	0.3742742	1				
15	-0.21282	-0.088096	-0.071538	-0.029554	0.298708	-0.103209	-0.020571	0.5737742	0.0357931	-0.0427359	-0.192229	0.6143269	-0.080112	-0.012333	1			
16	-0.11651	-0.029601	-0.152466	0.04046	-0.179111	-0.296797	0.2507063	0.0146181	0.083516	-0.2311256	-0.028501	-0.046393	0.184013	0.6608529	0.1213322	1		
17	0.064746	-0.1627	-0.065032	-0.079909	-0.180318	-0.156983	-0.081784	-0.044969	-0.098408	-0.2723735	0.3287013	-0.003644	0.4845167	0.8129649	0.1342289	0.5466087	1	
18	-0.097	-0.22335	-0.188637	-0.069572	0.26579	0.007437	-0.266931	0.5070144	-0.2173217	-0.1026148	0.0445957	0.450415	0.1510464	0.19408	0.6214262	0.051092	0.5348299	1

Figure7.6: Feature Selection using Correlation matrix (Comparative Group3)Table 7.9: Super Reduced Feature Set (Comparative Group3)

S.NO	Features
1	Left index d/aaverage
2	Right index b/aaverage
3	Left middle b/a standarddeviation
4	Right index d/a standarddeviation

ReductioninnumberoffeaturesforallthreeComparativeGroupsismadeonthebasisof(i) Thresholdvalueof‘0.25’ofFDRtoarriveat“**TruncatedFeatureSet**”(ii)Thresholdvalueof 0.6 of correlation to arrive at **“Reduced Feature Set”** (iii) Threshold value of 0.4 ofcorrelation to arrive at “**Super Reduced Feature Set”.** The number of features selected in these sets forthe three Comparative Groups is given in Table7.10.

Table 7.10: Selected features for enhanced PittaDetection

FeatureSet	**Number ofFeatures**		
	Comparative Group1	**Comparative Group2**	**Comparative Group3**
Gross FeatureSet	48	48	48
Truncated FeatureSet	17	18	18
Reduced FeatureSet	12	12	9
Super Reduced FeatureSet	7	8	4

7.3 Classification

7.3.1 Using LIBSVM as aClassifier

LIBSVM is widely used for data classification. Firstly, radial basis function kernel (defaultorder 3)hasbeenusedandtwofoldcross-validationisperformed.Secondlydataisclassifiedusinglow order polynomial kernel. The order of polynomial kernel is varied i.e. order 2 and order 3.Each feature set has been classified using these kernels. The accuracies achieved whileclassifying differentComparativegroupsarelistedbelow.Table7.11showstheaccuraciesachievedwhile classifyingComparativeGroup1.TheattainedaccuraciesarerepresentedgraphicallyinFigure 7.7.

Table 7.11: Accuracies achieved while classifying Comparative Group1

FeatureSet	**Accuracy achieved using different kernels(%)**		
	Radial BasisFunction	**Polynomial (order2)**	**Polynomial (order3)**
Truncated FeatureSet	68.75	68.75	75
Reduced FeatureSet	75	62.5	68.75
Super Reduced FeatureSet	62.5	68.75	62.5

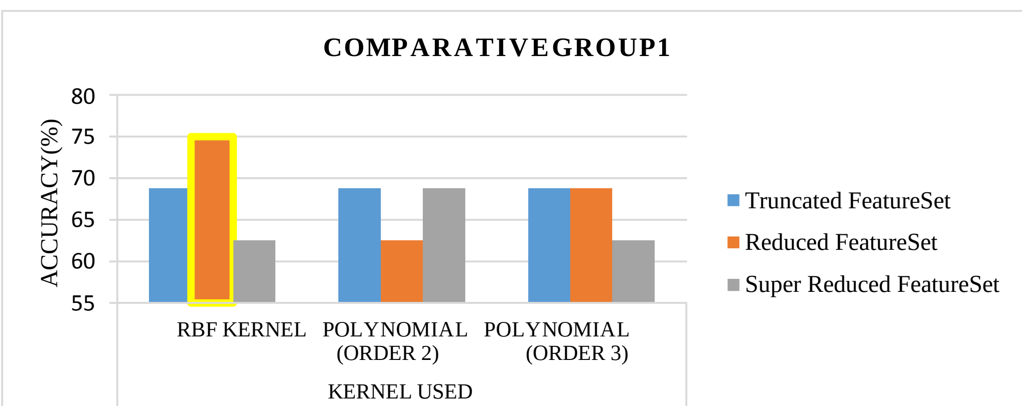

Figure 7.7: Graphical representation of accuracies achieved while classifying Comparative Group1

Table7.12andTable7.13showsaccuraciesachievedwhileclassifyingComparativeGroup2and Comparative Group 3 respectively. The attained accuracies for Comparative Group 2and Comparative Group 3 are represented graphically in Figure 7.8 and Figure7.9.

Table 7.12: Accuracies achieved while classifying Comparative Group2

FeatureSet	Accuracy achieved using different kernels(%)		
	Radial BasisFunction	**Polynomial (order2)**	**Polynomial (order3)**
Truncated FeatureSet	68.75	62.5	68.75
Reduced FeatureSet	75	68.75	62.5
Super Reduced FeatureSet	68.75	62.5	68.75

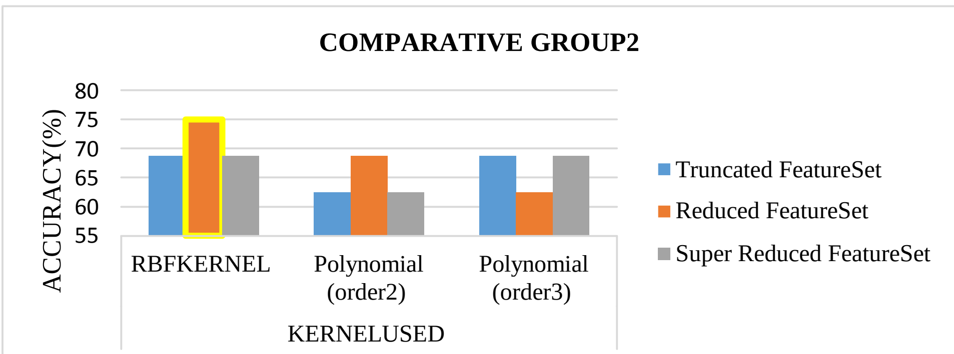

Figure 7.8: Graphical representation of accuracies achieved while classifying Comparative

Group2Table 7.13: Accuracies achieved while classifying Comparative Group3

FeatureSet	Accuracy achieved using different kernels(%)		
	Radial BasisFunction	**Polynomial (order2)**	**Polynomial (order3)**
Truncated FeatureSet	62.5	62.5	62.5
Reduced FeatureSet	68.75	68.75	68.75
Super Reduced FeatureSet	62.5	62.5	62.5

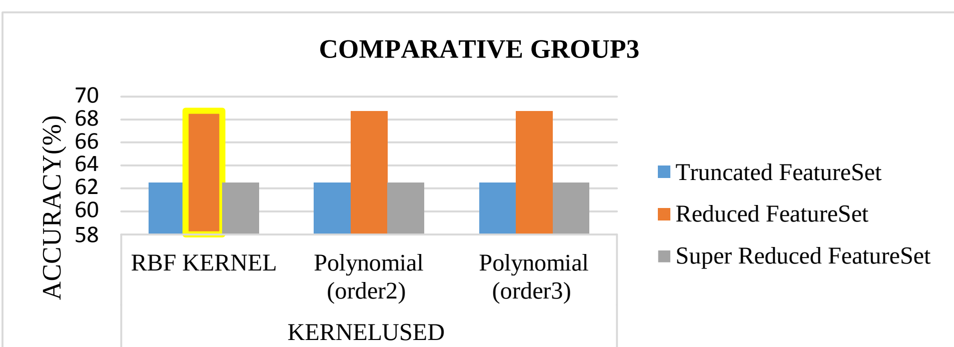

Figure 7.9: Graphical representation of accuracies achieved while classifying Comparative Group3

Thehighlightedbarindicatesthebestaccuracyachieved.Ithasbeenobservedthatthebest accuraciesareachievedwhenRadialBasisFunctionkernelisused.Anaccuracyof75%isattained while classifying Comparative Group 1, an accuracy of 75% is attained whileclassifying ComparativeGroup2andanaccuracyof68.75%isattainedwhileclassifyingComparativeGroup 3.AlsoreducedfeaturesetisgivingustheconsistentresultsfortheenhancedPittadetection.The confusion matrix for the best accuracies obtained while classifying reduced feature set isformed andfurthersensitivityandspecificityarecalculatedandareshowninTable7.14.Theinformation about the actual and predicted class is contained in the confusion matrix. TP (true positive)here depicts the number of samples correctly classified as High Pitta. TN (true negative) signifiesthe number of samples correctly classified as Low Pitta. FN (false negative) and FP (falsepositive) signifiesthenumberofsamplesincorrectlyclassifiedaslowPittaandhighPittarespectively.The confusion matrix is shown below in Figure7.11.

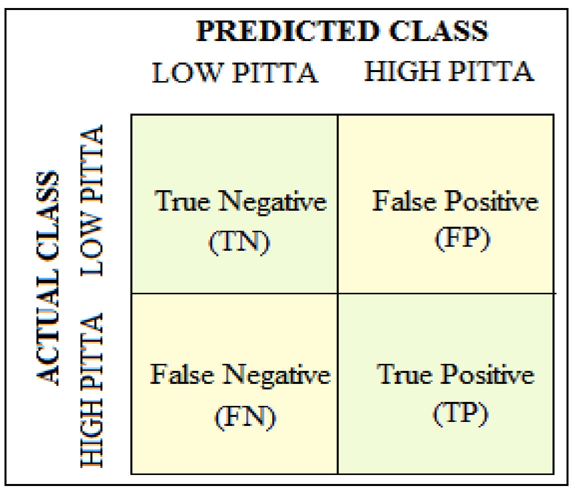

Figure 7.10: Formulation of ConfusionMatrix

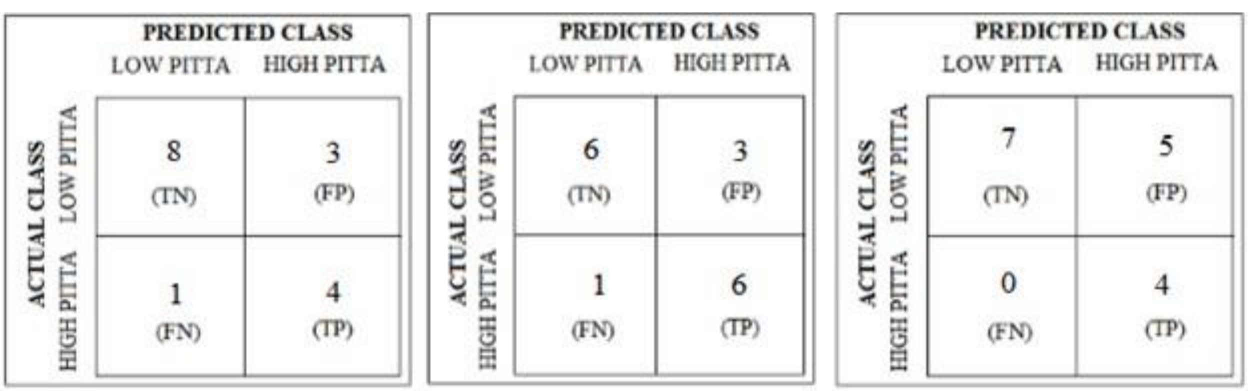

Figure 7.11: (a) Confusion Matrix (Comparative Group1) (b) Confusion Matrix (Comparative Group2) (c) Confusion Matrix (Comparative Group3)

Table 7.14: Classification results with Reduced FeatureSet

Classificationresults	Comparative Group1	Comparative Group2	Comparative Group3
Accuracy(%)	75	75	68.75
Sensitivity(%)	80	85.71	80
Specificity(%)	72.72	66.66	60

7.3.2 Using ANN as aclassifier

Firstly,wehavedesignedthenetworkusingthreelayersi.e.inputlayer,hiddenlayerandanoutput layer.Thenumberofneuronsinthehiddenlayerwereincreasedonebyonetoobtainthebest results.ThenumberofinputneuronsvariedforeachfeaturesetofComparativeGroups.However thenumberofneuronsintheoutputlayerwerefixed.Table7.15,Table7.16andTable7.17shows the results of classification for each comparative group, obtained by varying the numberof neurons.Thegraphicalrepresentationofaccuraciesachievedforeachfeaturesetareshownbelow in Figure 7.12, Figure 7.13 and Figure7.14.

Table 7.15: Accuracies obtained by using Truncated FeatureSet

Numberof Neurons	Accuracy		
	Comparative Group 1(%)	Comparative Group 2(%)	Comparative Group 3(%)
2	81.30	81.30	68.80
3	75	75	68.80
4	75	68.80	68.80
5	68.80	68.80	75
6	68.80	81.30	75
7	68.80	81.30	68.80

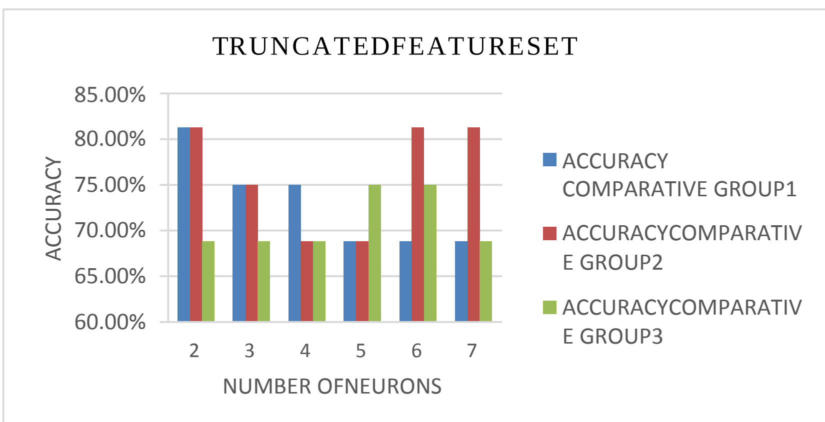

Figure 7.12: Graphical representation of accuracies obtained by Truncated FeatureSet

Table 7.16: Accuracies obtained by using Reduced FeatureSet

Numberof Neurons	Accuracy		
	Comparative Group 1(%)	**Comparative Group 2(%)**	**Comparative Group 3(%)**
2	81.30	87.50	68.80
3	75	87.50	68.80
4	81.30	75	68.80
5	75	81.30	68.80
6	68.80	81.30	75
7	75	75	75

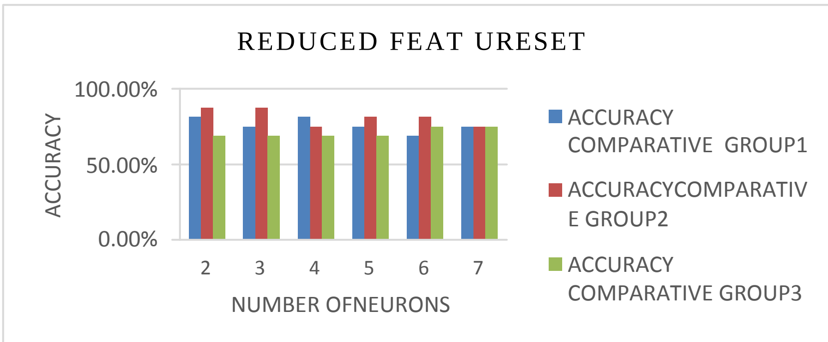

Figure 7.13: Graphical representation of accuracies obtained by Reduced FeatureSetTable 7.17: Accuracy obtained by using Super Reduced FeatureSet

Numberof Neurons	Accuracy		
	Comparative Group 1(%)	**Comparative Group 2(%)**	**Comparative Group 3(%)**
2	81.30	81.30	62.50
3	75	75	62.50
4	75	81.30	62.50
5	68.80	68.80	68.80
6	81.30	68.80	68.80
7	75	75	68.80

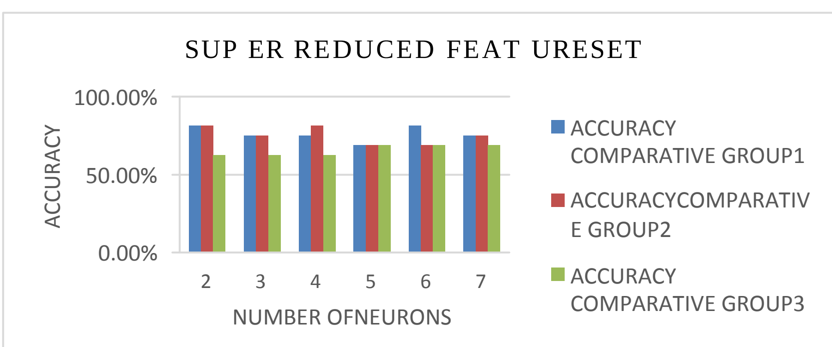

Figure 7.14: Graphical representation of accuracies obtained by super reduced featureset

IthasbeenobservedthattheComparativeGroup1andComparativeGroup2areclassifiedeasily whereasComparativeGroup3isnoteasilyclassified.Thenumberofneuronsusedinhiddenlayers while classifying Comparative Group 3 are more as compared to the neurons usedwhile classifying Comparative Group 1 and Comparative Group 2. Also it has been found that thebest results are attained while classifying “Reduced Feature Set”. Thus, the features of this featureset could be used for further consideration. Further, the number of hidden layers have beenincreased to two, and the number of neurons have been varied in each hidden layer. The results soobtained foreachfeaturesetareshownbelowinTable7.18,Table7.19andTable7.20.Thegraphical representation of the accuracies achieved is shown below in Figure 7.15, Figure 7.16 andFigure 7.17.

Table 7.18: Accuracy obtained by using Truncated FeatureSet

Number ofNeurons	**Accuracy**		
Hidden layer(1,2)	**Comparative Group1(%)**	**Comparative Group2(%)**	**Comparative Group3(%)**
2,4	62.50	68.80	68.80
2,5	68.80	62.50	56.30
2,6	62.50	50.00	56.30
3,5	75.00	56.30	68.80

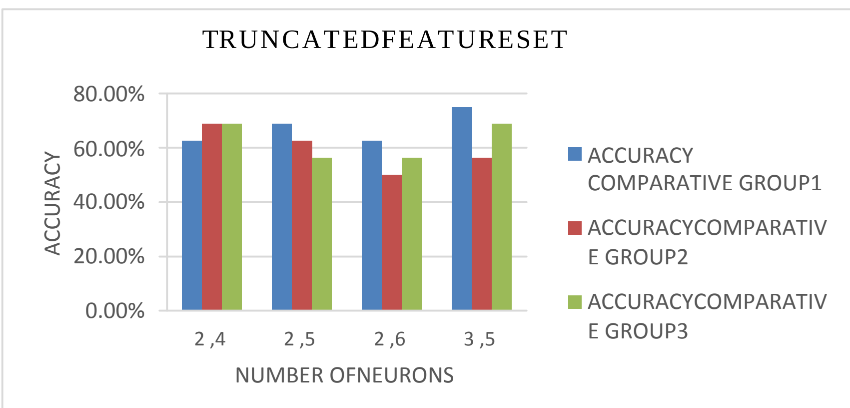

Figure 7.15: Graphical representation of accuracies obtained by Truncated featuresetTable

7.19: Accuracy obtained by using Reduced FeatureSet

Number ofNeurons	**Accuracy**		
Hidden layer(1,2)	**Comparative Group1(%)**	**Comparative Group2(%)**	**Comparative Group3(%)**
2,4	75.00	75.00	62.50
2,5	62.50	68.80	56.30
2,6	62.50	62.50	62.50
3,5	50.00	62.50	56.30

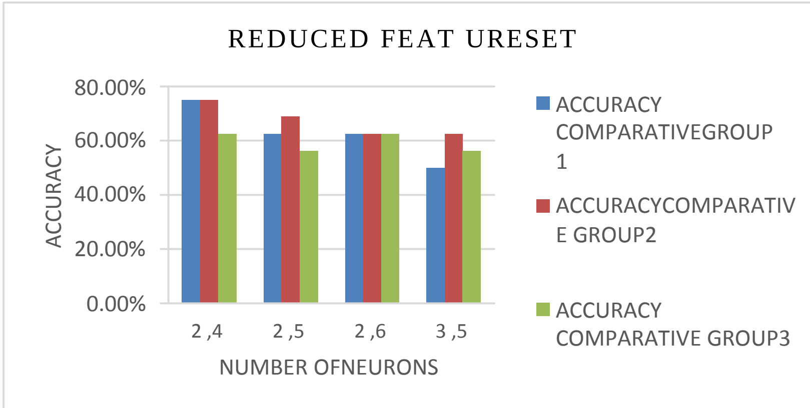

Figure 7.16: Graphical representation of accuracies obtained by using Reduced FeatureSetTable

7.20: Accuracy obtained by using Super Reduced FeatureSet

Number ofNeurons	**Accuracy**		
Hidden layer (1,2)	**Comparative Group1(%)**	**Comparative Group2(%)**	**Comparative Group3**
2,4	43.80	62.50	56.30
2,5	62.50	56.30	62.50
2,6	68.80	75.00	56.30
3,5	75.00	62.50	62.50

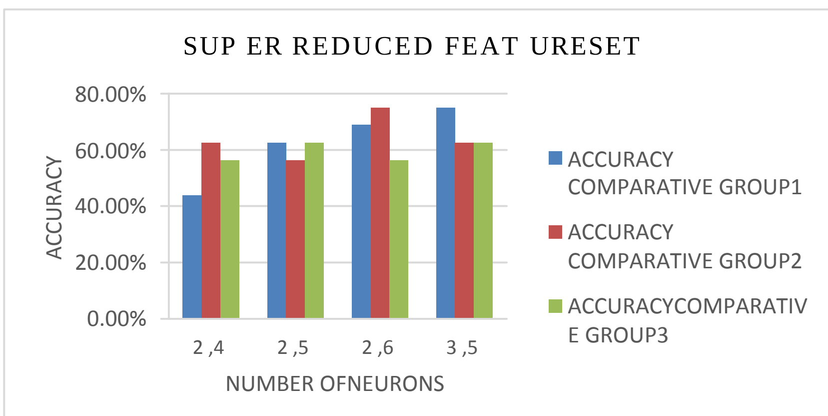

Figure 7.17: Graphical representation of accuracies obtained by using Super Reduced FeatureSet

Theaccuracyofthenetworkdecreasedwhennumberofhiddenlayersareincreased.Sincethe networkistrainedeffectivelyusingasinglehiddenlayer,thereisnoneedtoincreasethe complexityofthesystembyincreasingthenumberoflayers.Thus,consideringalltheabove results it has been observed that the best results are obtained while classifying “ReducedFeature Set”.Anaccuracyof81.30%isachievedusing2neuronsinthehiddenlayerwhileclassifying Comparative Group 1, 87.50% is achieved using 2 neurons in the hidden layer while classifying

Comparative Group 2 and 75% is achieved using 6 neurons in the hidden layer whileclassifying Comparative Group3.

Table 7.21: Best AccuraciesAchieved

ComparativeGroups	Number of HiddenLayers	Number ofNeurons	Accuracy Achieved(%)
Comparative Group1	**1**	**2**	**81.30**
Comparative Group2	**1**	**2**	**87.50**
Comparative Group3	**1**	**6**	**75**

ConfusionMatrix

The Confusion Matrix showing best results attained while classifying Reduced Feature Set ofthe three Comparative Groups is shown below. The values of accuracy, sensitivity and specificityin terms of true negative, true positive, false negative and false positive are givenbelow.

ACTUAL CLASS \ PREDICTED CLASS	LOW PITTA	HIGH PITTA
LOW PITTA	8 (TN)	3 (FP)
HIGH PITTA	0 (FN)	5 (TP)

(a)

ACTUAL CLASS \ PREDICTED CLASS	LOW PITTA	HIGH PITTA
LOW PITTA	6 (TN)	0 (FP)
HIGH PITTA	2 (FN)	8 (TP)

(b)

ACTUAL CLASS \ PREDICTED CLASS	LOW PITTA	HIGH PITTA
LOW PITTA	5 (TN)	1 (FP)
HIGH PITTA	3 (FN)	7 (TP)

(c)

Figure7.18:(a)ConfusionMatrix(ComparativeGroup1)(b)ConfusionMatrix(ComparativeGroup2) (c) Confusion Matrix (Comparative Group3)

The confusion matrix of the best trained network for the three Comparative Groups isillustrated in Figure 10. The values of accuracy, sensitivity and specificity are calculated as listed belowin Table 7.22. The values obtained are given in Table7.23.

Table 7.22: Accuracy, Sensitivity and Specificity Parameters from ConfusionMatrix

Accuracy	TN+TP/(TP+TN+FP+FN)
Sensitivity	TP/(TP+FN)
Specificity	TN/(TN+FP)

Table 7.23: Classification results with Reduced FeatureSet

ClassificationResults	**Comparative Group1**	**Comparative Group2**	**Comparative Group3**
Accuracy(%)	81.25	87.5	75
Sensitivity(%)	100	80	70
Specificity(%)	72.72	100	83.33

CHAPTER8

CONCLUSION AND FUTURESCOPE

8.1 Conclusion

Pitta is one of the three AyurvedicDoshas. This Dosha occur even in normal subjectsespecially in middle of the day and during middle of the digestion. Photoplethysmography signalsacquired fromthreefingersofboththehandsof25healthysubjectsareusedforthedetectionofPittaDosha. Second derivative of photoplethysmography known as Accelerated Plethsymography (APG)has beenemployedforthispurpose.48featuresfromAPGhavebeenconsideredforhighPitta detection. For efficient classification, reduction in a total of 48 features for all threeComparative Groups has been made on the basis of (i) Threshold value of ‘0.25’ of FDR to obtain“Truncated FeatureSet”(ii)Thresholdvalueof0.6ofcorrelationtoobtain“ReducedFeatureSet”(iii) Thresholdvalueof0.4ofcorrelationtoobtain“SuperReducedFeatureSet”.Theobtainedfeature setshasbeenclassifiedeffectivelyintotwoclassesnamely:HighPittaandLowPitta,using different classification techniques. While performing LIBSVM based classification, it hasbeen observed that Comparative Group 1 and Comparative Group 2 are classified effectively withan accuracyof75%whereasComparativeGroup3achievedanaccuracyof68.75%.Thereduced featuresethasbeengivingtheconsistentresultsfortheenhancedPittadetection.Further,after comprehensive exercise to develop ANN based enhanced Pitta classifier the followingpoints emerged:(i)Sincewehaveobtainedbestaccuracyof87.5%forhighpittadetection,wemay conclude that Pitta classification using APG is feasible (ii) Comparative Group 1 classifieshigh Pitta on the basis of effect of Mid-day only. 81.30% accuracy is achieved using ArtificialNeural Network having 2 neurons in the hidden layer (iii) Comparative Group 2 classifies on the basisof mid-dayaswellasdigestionfollowingtheconsumptionofmeals.87.5%accuracyisachieved usingArtificialNeuralNetworkhaving2neuronsinthehiddenlayer.Thisindicatesthatthe consumption of meals also have some role in the enhanced pitta level (iii) Comparative Group3 classifies on the basis of digestion following the consumption of meals.75% accuracy is achieved usingArtificialNeuralNetworkhaving6neuronsinthehiddenlayer(iv)Sincethebestresultsare obtainedwhileclassifyingReducedFeatureSet,thisfeaturesetisbestsuitablefordetectionof intensified pitta level (v) Single layer network is the most appropriate network (vi) Effect ofmiddayisprominent(vii)Effectofconsumptionofmealsisalsothere(viii)Effectofmid-dayismore as compared to consumption of meals as the classification of Comparative Group 3 requiresmore number of neurons and gives less accuracy (xi) Classification using Artificial Neural Networksis more efficient than usingLIBSVM.

8.2 FutureScope

Nostudyiscompleteinitselfandalwayshaveascopeformoreimprovement.Thefeatures selectedinthisdissertationworkcanbeclassifiedmoreefficientlyusinganotherclassifiersto achieve a higheraccuracy.

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