iJRASET
International Journal For Research in Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** V **Month of publication:** May 2026

DOI: https://doi.org/10.22214/ijraset.2026.82431

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

Analysis and Interpretation of Electroencephalogram (EEG) Signals for an Automated Diagnosis of Earlier Onset of Stroke using a Convolutional Neural Network (CNN)

Romain Atangana, Danwe Tsobsala, Amstrong Emini Me Zenanga, Daniel Gams Massi, Daniel Tchiotsop, Godpromesse Kenne

Abstract: ***Electroencephalogram (EEG) recording is relatively safe for the patients who are in stroke disease, soi tisoftenusedtodetecttheoccurrenceofstrokeinclinicalpractice.Theobjectiveofthispaperistoapply Deep Learning methodto EEG signal sanalysisinordertoconfirmtheoccurrenceofstrokeduetoinjuriesattack.Anovelapproachusingpolynomialstransformforspectralanalysisof EEGsignalintheTchebychevbasisisimplementedtoobtainspectralcoefficients.Statisticalmetricswereextractedfromthesepolynomialscoefficientst oconstitudethe input vector to a convolutional neural network. The model perform an accuracy of 98 % showing that the methodcan evaluate the condition of brain attack patients and can be a reliable toll of quasi stroke diagnosis.***

Keywords: ***Electroencephalogram(EEG),DiscreteTchebychevTransform(DChT),StrokeDisease,Convolutional Neural Network (CNN), ROC curves.***

I. INTRODUCTION

Astrokeisthesuddendeathofbraincellsinalocalizedareawhichhappenswhenthebloodflowtoanareaofthebrainisinterruptedbyeitherabloodclotor abrokenbloodvessel.Astrokeisamedicalemergencythatkillsmanybraincellsperminuteandcausespermanentbraindamage.Dependingontheregi onofthebrainaffeceted,astrokemaycauseparalysis,speechimpairment,lossofmemoryandreasoningability,comaordeath.Astrokeisalsosometim escalledabrainattackoracerebrovascularaccident(CVA).Therearetwomaintypesofstroke:ischemic,duetolackofbloodflow,andhemorrhagic, duetobleeding.Aboutfouroutofeveryfivestrokesare ischemic. About one in every five stroke is hemorrhagic. AfterDemantia,strokesarethesecondleadingcauseofdisability.Disabilitymayincludelossofvisionand/orspeech,paralysisandconfusion.Once,th edamagebe- comes clinically or radiographically apparent, proper neu-rologicalexamsandimagingareveryusefulfordetectingdelayed cerebralischemiastroke.Thus,EEGcanbeausefulwaytodetectandsubsequentlytreatischemiabeforetheinjurybecomesirreversible.EEGisalsover yusefulforidenfyingthestroke.Intheoperatingroom,EEGhasanestablishedroleinidentifyingischemiapriortothedevelopmentofinfarctionduring carotidendarterectomy (Foremanandclaasen2012)[1]

Strokeisdefinedasaneurologicaldeficitattributedtoanacutefocalinjuryofthecentralnervoussystem(i.e.,brain,retina,orspinalcord),includingischemicstroke andhemorrhagicstroke(Saccoetal.2013)[2].Itisthe second leading cause of death and third leading cause of disabilityintheworld(Kisaetal.2019)[3].Cognitiveimpairmentisacommonconsequenceofstroke(Jokinenetal.2015)[4].Withexcellenttemporalr esolution, EEG(Electroencephalogram)canreflectreal-timeneural electricalactivityofbrain.Itispossibletoassessstroke rehabilitation degreeandassociatedneuro-corticalactiv-itybyEEGbiomarkers(Petrovicetal.2017;Aydin2021) [5,6] .

BrainfunctionisrepresentedonanEEGbyoscillationsof certainfrequencies,slowerfrequencies(typicallydelta (0,5-4Hz)ortheta(4-8Hz)aregeneratedbythalamus andbycellsinlayer[II-V]ofthecortex.Fasterfrequen- cies (or alpha typically (8 -12 Hz) derived from cells in layers IV and V of the cortex. (Amzica et al. 2010). Allfrequenciesaremodulatedbythereticularactivatingsystem, which corresponds to the observation of reactivityontheEEG.PyramidalneuronsfoundinlayersIII,Vand VIareexquisitelysensitivetoconditionsofflowoxygen, suchasischemia,thusleadingtomanyoftheabnormal changesinthepatternsseenonanEEG(Ordan2004).

The common – observed oscillatory – –waves– recordedby anelectroencephalogram(EEG)innormaladulthuman canbegroupedintofivemaincategoriesaccordingtothefrequencyandamplitudenamely:$\delta(0{,}54Hz{,}20100\mu v)$;$\theta(48Hz{,}10\mu V)$;$\alpha(812Hz{,}20200\mu V)$;$\beta(1230Hz{,}510\mu v)and\gamma(3080Hz{,}24\mu V)$.Changesofbrainoscillationpatternshavelongbeenimplicatedinthediseasesofthecentralnervoussystemin- cluding ischemic stroke.

©IJRASET: All Rights are Reserved

II. RELATED WORKS

Thediagnosisofstrokereliespredominantlyontheusedofneuroimaging.Earlyidentificationofstrokeusing Electroencephalogram(EEG)intheclinicalassessmentofstrokehasbeenunderutilisized.MesferAIDuhayyimandal.(2023)«AnEnsembleMachineLearningTechniqueforStrockePrognosis»ComputerSystemScienceandEngineeringInthisworkAuthorsproposedanensemble votingmodelbasedonthreeMachineLearning(ML)algorithms.

RandomForest(RF),ExtremeGradientBoost- ing (XGBoost), and Light Gradient Boosting Machine (LGBM).Theyapplydatapreprocessingtomanagethe outliers and useless instances in the dataset. Furthermore,toaddresstheproblemofimbalanceddata,theyenhancethe minority class's representation using the Synthetic Mi- norityOver-SamplingTechnique(SMOTE),allowingit toengageinthelearningprocessactively.Resultsrevealsthat the suggested model outperforms existing studies and otherclassifierswith96accuracy,97%precision97% Recalland96%F1–Score.Theexperimentdemonstrate thattheproposedensemblevotingmodeloutperforms stateoftheartandothertraditionalapproaches[?].

Sakai Y. and al. (2024) « Validity and Reliability of the JapaneseVersionoftheFrontalAssessmentBatteryin PatientswithStroke»Thisstudyaimedtoinvertigate the validity and reliability of the Japanese version of theFrontalAssessmentBattery(FAB)inpatientswithstroke.TheJapaneseversionoftheFABfordementiawasmodifiedandevaluatedin52patients withstroke.FABmeasurementswereobtainedtwiceovera10dayperiod.ConvergentvaliditywasassessedusingtheStroopColorWordTest(SCWT)andtheTrialMakingTest(TMT)partB.Internalconsistencywasmeasureusing Crombachalpha(Cα).Testrestedevaluationswereperformedusingintraclasscoefficient(ICC[2.5])measurementsandlimitsofaggeement(LOA)werecalculatedusingthetotalFABscore.ResultsshowsthatthetotalFABscorewascorre- latedwithSCWTscoresforpartIthroughIV(r=0.70 to0.77)andtheTMTscoreforpartB(p=-0.53).The LOA were -1.7 to 2.9 points. Conclusion, the Japanese versionoftheFABhadhighervalidityandreliabilityin patientswithstroke[?].

MicheleLauriolaandal.(2024)«RiskofStrokeorHeartAttackinMildCognitiveImpairmentandSubjectiveCognitiveImpairments»Neurol.Thisstudyaimedtoidentify Mild Cognitive Impairment (MCI) as an alert clinical manifestation ofincreasedprobabilityofmajoracutevascularevents(MVEs),suchasIschemicStrokeandHeartattack:inthelongitudinalstudy181(M=81,F=100,meanageof75.8years)patientswereenrolledanddi- videdintothreegroupsbasedondiagnosis.Subjective Cognitive Impairment (SCI), amnstic MIC Single Do- main(aMCI–SD),andamnesticMCIMoreDomain(aMCIMD),clinicalassessmentandthepresenceofvascularriskfactorswerecollected.Theresultsshowedthatthedistributionof MVEsshowedahigherincidencein thefirsttwoyearsoffollow-upof7.4%inSCI,12,17% in a MCI – SD and 8,5 % in a MCI – MD. Acute My- ocardialinfarctionshowedamajorincidenceinoneyear offollow-up(41%)andintwoyearoffollow-up(29%). Also,IschemicStrokeshowedamajorincidenceinone year of follow-up (30 %) and in two year of follow-up (40significant difference in the progression to dementia wasshown(SCI3,75%;aMCI–SD10,4%;aMCI–MD 37 % ; p- value). Conclusion : MCI is considered anexpressionofthesystematicactivationofmechanismsof endothelial damage, representing a diagnosis predictive of increased risk of MVEs.

PuiKitTamandal.(2024)«PrevalenceandOutcomesofOrthostaticHypotensioninHemorrhagicStrokePatients During Hospitalization ». This study aims to examine theprevalenceofOrthostatichypotension(OH),itsrisk factorsandpotentialimpactinpatientswhowerehospi-talized due to hemorrhage stroke. A retrospective analysis ofin-patientsrecordsbetween1January2021and30 April2023wasconductedforpatientswithstrokeduetointracerebralhemorrhage(ICH)orsubarachnoidhemorrhage(SAH)whowerereferredtorehabilitationata tertiaryhospitalinSingapore.OHwasdefinedasadrop in systolic blood pressure of20 mm Hg or diastolic bloodpressureof10mmHgduringthesituptestaspartoftherehabilitationassessment.Additionaldatacollectionincludeddemographicinformation,lengthofstay,antihypertensivemedicationsusedatthetimeofassess-ment, comorbidities, and discharge functional outcomesasmeasuredbyamodifyrankinscale.Resultsshowsthatatotalof77patients(65[84,8%]withICHand12[15,6%]withSAH)wereincludedintheanalysis.Thepreva- lenceofOHwas37,7%,ahistoryofsurgicalinterventionwas identified as the major risk factor for the development ofOH(oddratio4,28,95%confidenceinterval1,37to 13,35, p = 0,009). There was no difference in hospital length of stay or discharge modified Rankin Score be- tween the two groups.

MattiasRosbergandal2024.Inthisworkthegoalwastoexaminethefeasibilityofdetectingstrokeinpatientsus- ing only brain activity data electroencephalography (EEG)machine.EEG-datasetsfrompatientswithandwithout stroke were collected, standardized and preprocessing us-ingdifferentmethods.Thedifferentvariationofthisdatawas then used to train machine learning models and theabilityofeachtrainedmodeltoidentifyEEGrecordingofstrokepatientsweretested.Usingdifferencesprocessingmethodsandwithasufficientamountofdata,themodelwasabletocorrectlydifferentiatestrokeandnon-stroke EEGrecordinginthedatasetwith100%accuracy[?].

Li-Min-Weng and al. 2024 [7] used EEG signal to ex- ploretheEEGcharacteristicsofpatientswithpoststrokeepilepsy and improve the detection rate of inter-seizure epileptiform discharges. Post –stroke epilepsy (PSE) referstoseizuresthatoccurwithinacertaintimeafter strokeinpatientswithoutapriorhistoryofepilepsyorbrainandasystemicdiseases.Thestudyrevealthattheepilepticdischargesdetectedbyelectroencephalogram (EEG)areconsistentwiththelesionsiteofthestroke.

Benghanemetal.2024[8]assessedtheprognosticsignificanceandprevalaenceofearlyelectroencephalogram(EEG)abnormalitiesinadultstrokepatients,receiving mechanical ventilation. The experiment included adult stroke patientsrequiringinvasivemechanicalventilation,whounderwent at least one intermittent EEG examination duringtheirintensecareunit(ICU)stay.Anunreactive EEGbackgroundtoauditoryandpainstimulations(OR 602.95%CL2.27-15.99)wasindependentlyassociatedwithunfavorableoutcomes.AnunreactiveEEGpredicted unfavorableoutcomewithaspecificityof48%.
JinYandal.2024[9]haveidentifybraindamageareasforstroke rehabilitation. The EEG signals were obtained fromstrok patients and Healthy subjects.
These participants di-videdintorightsidedbraininjurygroup,left-sidedbrain injurygroup,BilateralbraininjurygroupandHealthy Controls..First,thewaveletpackettransformwasusedtoperform a time-frequency analysis of the EEG signal andextractedasetoffeatures,.thentoexplorethenonlinear phase coupling information of the EEG signal, phase-lockedvalue(PLV)andpartialdirectedcorrelation(PDC)wereextractedfromthebrainnetworkandthebainnet-work produced a second set of features noted as functionalconnectivity(FC)features.Theyfusedtheextractedmul-tiple featuresandusedtheresnet50convolutionalneural network to classify the fused multi-modal (WPT +FC) features. The classification accuracy of the model was upto99.75%,showingthatthemulti-modalfrequency features can be used as a potential indicator to distinguish regionsofbraininjuryinstrokepatients.

A. RecordingEEGintherestingstate

YuXiaHuandal.2023[10]investigatedwhetherrest- ing –state EEG indicators could improve stroke rehabili-tation evaluation. The participants were divided into threegroups:severe,moderateandmild,thenquantitiveelec- troencephalography(QEEG)andfivenon-linearparametersofrestingstateEEGwerecalculatedforfurtheranalysis.Statisticaltestswereperformedandthegeneticalgorithmsupportvectormachinewasusedtoselectthe bestfeaturecombinaisonforclassification.TheQEEGpa-rametersshowsignificandifferencesinDelta,Alpha1,Alpha2amongthethreegroups.Regardingnonlineraparameters,ApEn,SampZEnLzandCshowedsignificantdifferences.Theoptimalfeatureclassification combina- tionratereached85.3%.(Sutcliffeetal.2022)[11]ex- plained that Surface electroencephalography (EEG) showspromiseforstrokeidentificationandoutcomeprediction. Authorsgaveanswerestothequestions:

1) Can EEG during acute clinical assessment iden- tify.Strokeversusnon-strokemimicconditions?Ischemicversushamorrhagicstroke?Ischemicstroke due to LVO ?
2) Can these states be identified if EEG is applied < 6hs ince onset ?
3) DoesEEGduringacuteassessmentpredictclinical recoveryfollowingconfirmedstroke?

Although studies report important associationswith EEGbiomarker,furthertechnologicaldevelopmentand adequately powered real world studies are required be-fore recommandations can be made regarding applicationduring acutestrokeassessment.(Ag.Lamatal.2023)[12]Thisstudywereconductedtodeterminetherelevanceof EEGanditspredictorswiththeclinicalandstrokefeatures.AccordingtothefindingsthetypeofthestrokeandimagingcharactiristicsareassociatedwithEEGanoma- lies Predictors of focal EEG slowing are NHSS score andanteriorcirculationstroke.Thestudyemphasized that EEG is a simple yetfeasibleinvestigationaltool,andfurthurplansforadvancingstrokeevaluationshouldconsidertheinclusionofthisfunctionalmodality.(YoomA., etal.2021)designedandimplementedahealthmonitoringsystemthatcanpredicttheprecursorsofstrokediseaseintheelderyinrealtimeduringdailywalking. First,rawelectroencephalography(EEG)datafromsix channelswerepreprocessedviaFastFourierTransform (FFT).TherawEEGpowervalueswerethenextracted fromtherawspectra:alpha(α),beta(β),gamma (γ) ,delta (δ) and theta (θ) as well as the low β, high β andθtoβratio,respectively.Theexperimentsconfirm that the important features of EEG biometric signals aloneduring walking can accuratly determine stroke precursorsandoccurrenceinelderywithmorethan90%accuracy. (ForemanandClaassen2012)[12].
Keser(2022)[13]summarizedtheuseofEEGalonein post-stroke, then they demonstrated that EEG-based tech-niquesareaccessibleandvaluablenon-invasiveclinical tools in stroke neurology. Studies have also confirmed thatthequantitativeelectroencephalographic(QEEG)param-etersofstrokepatientsexhibitincreaseddeltaandalpha bands(Jordan2003;Hirschandal.2012;FinniganandPutten2013)[14,16].Inaddition,Finniganetal.(Finniganandal.2016;SfaandAwb2020)[10,17]achieveda highclassificationaccuracyratebetweenstrokepatients andcontrolgroupswithQEEGparameters.
Nonlinear dynamic analysis (NDA) have been widely used in the analysis of EEG signals (Stam 2005). Itcan better represent brain activity and provide more characteristicinformationinvariousneurologicaldis- eases. Based on single-channel EEG complexity and hemisphericdependency/connectivitybetweentwoEEG recordings/channels, Jeong (2004) reviewed EEG non- linear changes for estimating quantitative markers of Alzheimer's disease, focused on the reduction of EEG complexity.

Therearemanynonlinearmethodssuchas approximateentropy(ApEn),permutationentropy(Per-mEn), and Lempel–Ziv complexity (LZC) to measure the complexity of EEG (Aydin and al. 2018) [18] .

Several studies have reported the appearance of certainattributevaluesinstrokepatientswithEEG-basedstroke analysis[Finnigan,andal.2016;Schneideretal.2005;Varelaset al. 2007 ; Ip ,Z et al. 2019) [14,17,19,20] . Forexample,Simonetal.(Finnigan,Setal2019)[21]confirmedthatthemainpropertiesofEEGwithrespecttostrokeincludethegenerationofabnormalandslowsignalsgeneratedatthedeltawave(δ)wavefrequencyrange(14Hz)withthesimultaneousreductionsofnormalandfastactivitiesatthealpha(α)wavefrequencyrange(8–12Hz).Throughtheseexperiments,wecancon-firmthatrelativedeltapower,deltaandalphapowerratio,andtheadditionofdeltaandthetawaveagainstal-phaandbetawaveratioscanbeusedtodetectandpre-dictstroke.

(Schneideretal.2005)studiedEEGfrequencyanalysis and topographic maps and found an increase inlarge deltawavesandadecreaseinalphawaveactivityin17outof20mildstrokepatients.(Panayiotisetal.2017)confirmedthatarhythmicandhighamplitudethetaver-sus deltawaveappearedinapatientwithepilepsyduring astroke.(Ipetal.2019)confirmedthatbrainwavesin stroke patientsthatweremeasuredinthecerebralcortexaffected theactivityandstabilityofthethetawave4of18 andthedeltawave,whilethedeltawave(0.1–3Hz),al- pha(7–13Hz),betawave(13–30Hz),andhighgamma wave(62–200Hz)increasedrapidlyintherighthemisphere.Basedonthesestudies,webelievethatEEGresearchcanhelpminimizemedicalcostsandenabletheearlydetectionstrokediseasesintheelderlyduringtheirdaily activities. A quick literature review found a few stud-iesusingvariousmachine-learningtechniques,includingartificial neural networks (ANN), for stroke diagnosis or prediction (Shanthi, D.et al 2009 ; Nwosu et al. 2019 ; Bentleyetal.2014;Hanifa,etal.2010;Yu,etal.2020]. For example, (Shanthi et al. 2009) reported that an individual'sriskrateforstrokecanbedetectedusingANNbasedonstrokepatientdata.Specifically,theyusedthebackpropagationalgorithmforlearning,and showedimprove-mentsinconsistencyanddiagnosticaccuracyforthepre-diction.(Nwosuetal.2019)studiedtheanalysisandpredictionofriskfactorsassociatedwiththeonsetofstrokeusingdataminingtechniquesandindividualpatientelectronichealthrecords.Accordingtotheexperimentalre-sults,thepredictionaccuracyofdecisiontree(DT)was 74.31%, RandomForestwas74.53%,andANNalgorithmwas75.02%.(Bentleyetal.2014)reportedapredictionmethodconsideringCTinformationandclinicalvariablesinthetreatmentofischemicstroke.Basedoncomputed tomography (CT) images of 16 ischemic stroke patients,theysuccessfullyfound9outof16patientswithhemor-rhagesymptomsusingsupportvectormachines(SVMs).(Hanifaetal.2010)predictedandverifiedtheriskfactorsofstrokebyadjustingtheparametervaluesoftheSVMpredictionmodelusingvariouskernelfunctions.(Yuet al. 2020)publishedastudydetailingapriordetectionandprediction methodology for stroke diseases with machine-learning and deep-learning methodologies by collecting electromyography(EMG)biologicalsignalsfromthighs and calves in real time. More specifically, they measuredandcollectedEMGdatafromtheleftandrightthighsand thecalvesat1500Hzfromthehealthcaredevice.Using thosedata,theyachievedover90%strokediseasepredictionaccuracy.(Yuetal.2019;2020)publishedananalyticalstudybasedonthedecisiontreemethodology,whichisarepresentativeclassificationmodelofmachinelearn-ingordatamining.Inaddition,(Yuetal.2020)attemptedto implement automatic classification and interpretation oftheseverityofNIHSSbasedontheC4.5decisiontreealgorithm.Byanalyzingtherulesontheadditionaloperatingprinciplesprovidedby C4.5decisiontrees,theywereabletodevelopanovelattempttatthesemanticinterpre-tationofstrokeseverity.However,decisiontreesarepre- dictivemodelalgorithmsbynature,whichonlyprovide partial interpretations, thus requiring in-depth analysis in- herentinthedata.Inaddition,(Aminietal.2023)[22] conductedastudytopredictstrokeoutbreaksbasedon abundantmedicaldataonawiderangeofdiseases.However,suchresearchmethodologies,likepriorstudies,are notsuitableforuseinearlypredictionmodelsofstroke symptoms in real time in everyday life. Because these strokes interactwithvariousriskfactorsratherthanwithone factor,studiesofstrokediseasepredictionusingvari-ous statistical methods and machine-learning methods areneeded,andtheyareactivelyunderway.

III. MATERIALS AND METHOD

A. Hardware and software environment

All experiments and simulations were carried out using varioustoolssuchastheANACONDAIDE(version3.5) deployedonalaptoprunninganIntel(R)Core(TM)i5- 6300UwithaProcessorof2.40GHz,8.00GBofRAM and Windows 10 PRO.

B. Methodology used

This work proposes a methodology for the analysis of EEGdatainordertoautomaticallydiagnosestroke As presentedinthefigurebelow,thismethodologyincludes04mainstepswhicharedataacquisition,extractionofinformativeparameters,selectionofrelevantparameterordimensionality reduction, classification and diagnosis inordertodetermineifapatientisaffectedbythestrokeor notasillustratedinthefollowingfigure:

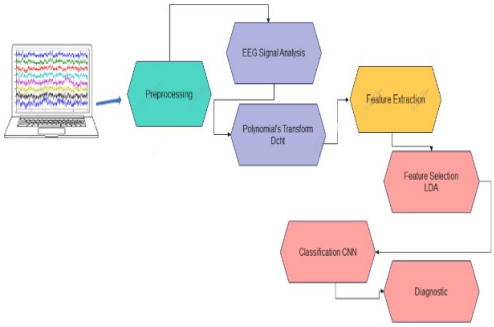


Fig.1.Synopticofthemethodologyproposedtodiagnose Stroke

C. Dataacquisitionandpre-processing

1) ParticipantsWhilerecordingtheEEGsignals

- Thepatientsitsconfortablyinachair;
- Weattachtheelectrodestodifferentplaceson the head:
- Astickypasteisusedtoholdtheelectrodes in place;
- Thepatientwearsacaptowhichtheelec- trodesarealreadyattached;
- The electrodes are connected by wires to the de-vicewhichamplifiesandrecordstheelectrrical activity inside the brain
- Thedevicerecordselectricalactivityaswavy linesproducedbyrowsoftracersonamoving sheetofpaperorasanimagethatisdisplayed on a computer screen.

Fortheparticipantswerecruitedparticipantamong our students and over one year clinical study ac- cross the department of neurology of the recent Re- gionalHospitalCenterofBertouaCameroon.Par- ticipants were divided into those suffering of stroke and healthy subjects. The first group consisted of 50participantswhowerediagnosedbyexperiencedneurologistsassufferingofstroke.Thesecondgroup was constituted of 109 healthy controls. The age groupwasrangingwithin25to80years.

Allparticipantsinthisstudyprovidedinformedcon-sentforthecollectionanduseoftheirEEGdata.Datahave been anonymized to ensure the confidentiality ofparticipants.Theyarestoredonsecureservers,with accesslimitedtoauthorizedpersonnel.

2) EEG recordingdataforthestrokediagnosiswerecol-lected during 5 minutes resting awake period. The ac-quisitionsystemismadeupof6-channelsdeviceas shown in figure 2 below.



Fig.2. Patientdata collection deviceinstalled

Thedeviceusesasamplingfrequencyof200Hz.The electrodeslayoutispresentedinfigure3.

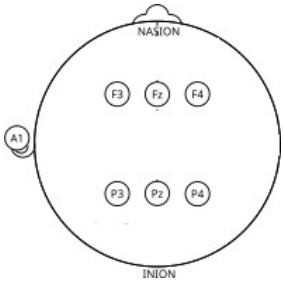


Fig.3.EEGelectrodesplacementforthestrokestudy

Participants were recruited among 109 volunters stu-dents or Healthy controls of the Departement of Com-puterScienceofENSBertouaperformingdifferent imaging motortask[2]and50[subject1-subject50]patients with acute ischemic stroke aged from 25 to 80year.Thesepatientswerediagnosedbyexpiri- encedneurologistsassufferingofacutestrokeover one year clinical study accross the Department of neurologyoftherecentRegionalHospitalCenterof Bertoua–Cameroon.Participantswhilerecording EEGsignalsweresittedconfortablyinachair,weat-tachtheelectrodestodifferentplaces ontheheadwithreduces 6-Channels.Astickypasteisusedtoholdtheelectrodes in place and patients weared a cap to whichthe electrodesarealreadyattached.Theseelectrodesareconnectedbywirestothedevicewhichamplifiesandrecordstheelectricalactivityinsidethebrain.

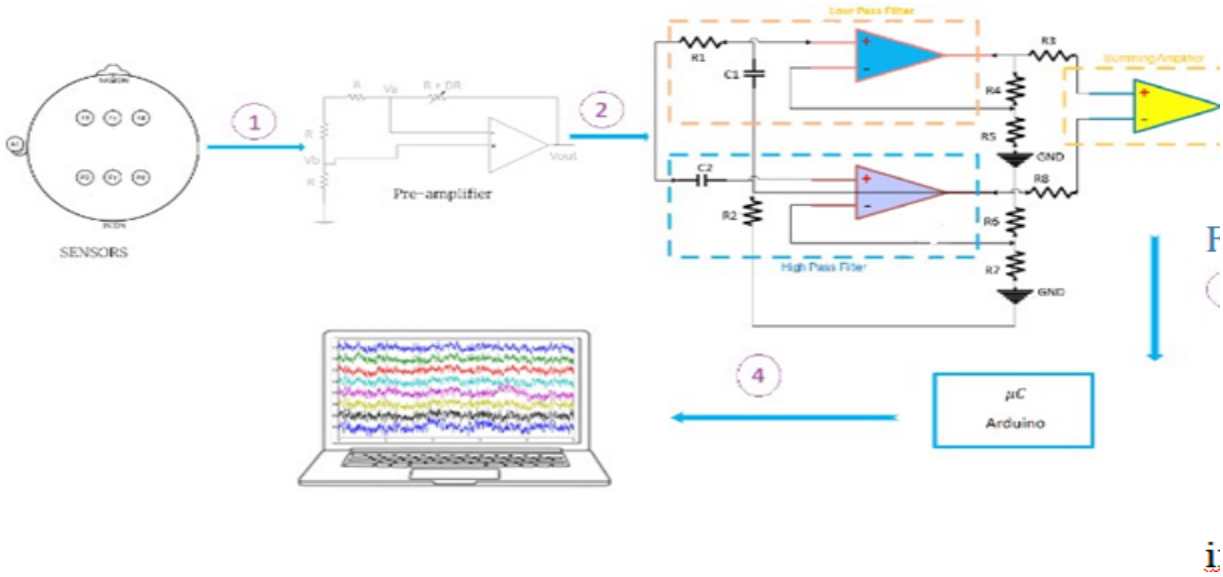


Fig.4.SynopticschemeofthepproposedautomatedEEG- basedstrokesignalsacquisition

Asensortransformsaphysicalquantityintoanelectricalsignalwhichcanbeinterpretedbyacontrolledmonitoringdevice.Duringthisstudywe usedcupuleelectrodesassensors.Theseelectrodesarefilledwithconductivebatteryandarestucktothescalpbyapasteandareconnectedtother ecordingdeviceby meansofsimpleinsulatedwires.

Afilterisanelectroniccircuitthatperformsasignalprocessing operation. In other words it attenuates cer-taincomponentsofasignalandletsotherspass.

ThelowamplitudesofEEGsignalsrequiresamplifi-cationofthelatterthroughachainofpre-amplifiersandamplifierswithhighgain.Inthepre-amplifier part,weusedtheAD8221withagainof10.Subse- quentlywecarriedoutanamplificationwithahigh gain G = 40.

- Microcontroller

ArduinoisanopensourceprogrammedelectronicsplatformwhichisbasedonµC(microcontroller)board and Sofware which is a true integrated develop-mentinvironmentforwrittingcompiling,andtrans- feringtheprogramtothemicrocontrollerboard.

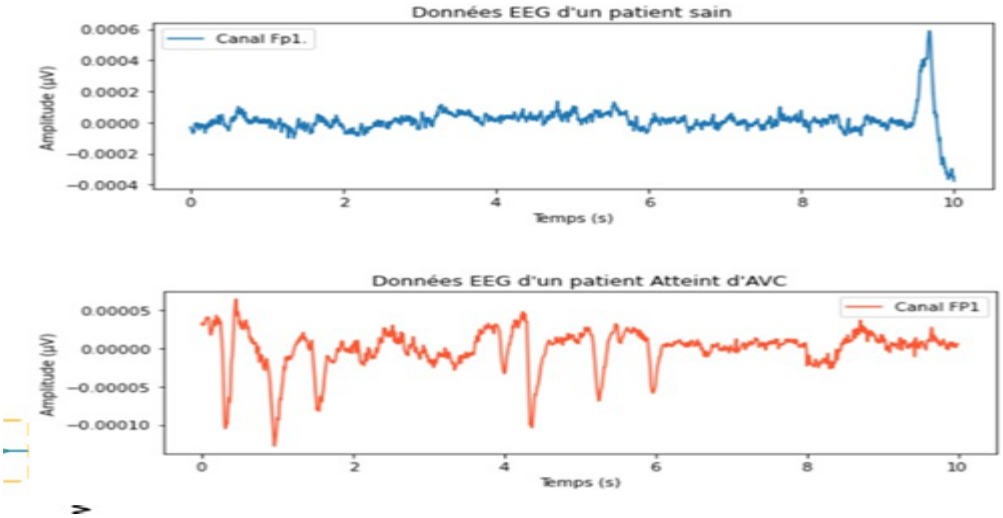


Fig.5.ExampleofEEGsingalsfromcanalFP1for Healthypatient(blue)andastrokepatient:

Mathematical Principles SpectralAnalysis

Theintegraloftheproductoffunctionsonabounded intervalisthesimplestscalarproductoffunctions:

$$\langle f,g\rangle = \int_a^b f(x)g(x)dx \qquad (1)$$

Generally,itispossibletointegratea"weightfunction"W(x)intotheintegral(ontheintegrationinterval]a,b[,W(x)musthavefiniteandstrictlypositive values,andtheintegral oftheproductoftheweightfunctionbyapolyno- mialmustbefinite;thelimits]a,b[canbeinfinite):

$$\langle f,g\rangle = \int_a^b f(x)g(x)W(x)dx \qquad (2)$$

In this definition of the dot product, two functions areorthogonaltoeach otheriftheirdot productiszero (juststwovectorsareorthogonal(perpendicular)iftheirdotproductiszero).Wethenintroducetheassociatednorm.

- **JacobiPolynomials** $P_k^{(\alpha,\beta)}(x)$

$$a=-1, b=1, \omega(x)=(1-x)^{\alpha}(1+x)^{\beta}, \qquad \text{with} \alpha>-1 \text{ and } \beta>-1 \qquad (3)$$

- **LaguerrePolynomials** $L_k^{\alpha}(x)$

$$a=0, b=+\infty, \omega(x)=e^{-x}x^{\alpha}, \qquad \text{avec} \alpha>-1 \qquad (4)$$

- **HermitePolynomials** $H_k(x)$

$$\int_{-\infty}^{+\infty} f(x)e^{-x^2}dx \qquad (5)$$

Forthisstudy,wefocusonChebyshevpolynomials, whichrepresentsaspecificcaseofJacobipolynomials[26].

GeneralitiesonChebychevPolynomials

Theapplicationθ'→cosθisconyinuousandbjectivefrom[0,π]on[−1,1]which means that to each continu-Ousfunction Fon[0,π]isuniquelyassocietedthecontin- uousfunctionfon[-1;1]bytherelation:

$$F(\theta) = f(x) \text{ where } x = \cos\theta \tag{6}$$

Then,

$$\int_0^{\pi} |F(\theta)|^2 d\theta = \int_{-1}^{1} \frac{|F(\theta)|^2}{\sqrt{1-x^2}} dx \text{ with } x = \cos\theta \tag{7}$$

Wededucefromthisthattheapplicationwhichfromafunction Fof[0,π],correspondstothefunctionfof[1,1]extendsintoanisometricbijectionfromthe HilbertspaceL2([0,π],dθ)ontheHilbertspaceL2([1,1],ω(x)dx) similarsquarefunctionson[-1;1]forthedensitymeasure

$\omega(x) = \frac{1}{\sqrt{1-x^2}}$ comparedtothefollowingmeasure:

$$\|f\|_{\omega}^2 = \int_{-1}^{1} \frac{|f(x)|^2}{\sqrt{1-x^2}} dx < \infty \tag{8}$$

Thescalarproductisnoted $\langle f,g\rangle_{\omega} = \int_{-1}^{1} f(x)g(x)\omega(x)dx$:

$$\langle f,g\rangle = \int_{-1}^{1} \frac{f(x)g(x)}{\sqrt{1-x^2}} dx \tag{9}$$

$f,g \in L^2([1,1],\omega(x)dx)$We are in a position of ap- plyingtheresults ofparagraph1. Thefamily1,x,...,xnistotalinthespaceL2([1,1],ω(x)dx)andtheorthogonal-izationprocessofGram-Schmidtmakesitpossibletopro-duceaHilbertianbasis[27].However,theisomorphismhighlightedaboveallowsustoquicklyfindthisHilbertianbase,infactthefunctionsdefinedby: Φn(cosθ)=cos(nθ)formedanorthogonalbasisofL2([0,π],dθ)and wehave:

$$\int_0^{\pi} \Phi_n(\theta)\Phi_m(\theta) = \begin{cases} \frac{\pi}{2}\delta_{nm}, & \sin n, m \neq 0 \\ \pi\delta_{00}, & \text{sinon} \end{cases}$$

It follows that the functions $T_n(x) = \cos(n \cdot \arccos(x))$ form a basis of $L^2([-1,1],\omega(x)dx)$

$$\langle T_n, T_m\rangle_{\omega} = \begin{cases} \frac{\pi}{2}\delta_{nm}, & \sin n, m \neq 0 \\ \pi\delta_{00}, & \sin n \geq 0 \end{cases} \tag{11}$$

Weknowthatcos(nθ)isexpressedbyapolynomialincos(θ),whichresultsinthefactthatTn(x)isapolynomialofdegreeninx,calledtheChebyshevpoly nomial.Weknowthatcos(nθ)isexpressedbyapolynomialincos(θ),whichresultsinthefactthatTn(x)isapolynomialofdegreeninx,calledtheChebys hevpolynomial.

$$\lim_{n\to\infty} \left\| f - \langle f, T_0\rangle_\omega T_0 - \sum_{k=1}^{n} \langle f, T_k\rangle_\omega T_k \right\|_\omega = 0 \quad (12)$$

and:

$$\|f\|_\omega^2 = \frac{1}{\pi}|\langle f, T_0\rangle|^2 + \frac{2}{\pi}\sum_{k=1}^{\infty}|\langle f, T_k\rangle|^2 = 0 \quad (13)$$

We can deduce the following minimization property:

- Parity. For all $n \in \mathbb{N}$, we have:

$$T_n(1) = 1 \quad (14)$$

$$T_n(-x) = (-1)^n T_n(x) \quad (15)$$

- Recurrence relation and trigonometric identity:

$$\cos((n+1)\theta) + \cos((n-1)\theta) = 2\cos(\theta)\cos(n\theta) \quad (16)$$

We deduce then that the Tchebychev polynomials satisfy the following recurrence relation:

$$T_{n+1}(x) + T_{n-1}(x) = 2xT_n(x) \quad (17)$$

The recurrence relation for the Chebyshev polynomials is $T_{n+1}(x) = 2xT_n(x) - T_{n-1}(x)$, with initial conditions $T_0(x) = 1$ and $T_1(x) = x$. This relationship shows that the coefficient of x^n in $T_n(x)$ is 2^{n-1}. It also allows us to calculate T_n by recurrence.

- Generating function. We are looking for a function of two variables (x,z) in such that:

$$G(x,z) = \sum_{n=0}^{\infty} T_n(x) z^n \quad (18)$$

Knowing that $x = \cos(x)$, we have:

$$G(x,z) = \frac{1}{2}\sum_{n=0}^{\infty} e^{in\theta} + e^{-in\theta} z^n, \quad |z| < 1 \quad (19)$$

- Differential equation. For all $n \in \mathbb{N}$, the Tchebychev polynomials T_n satisfy the following second order differential equation : $\cos(\theta)$, which results in the fact that $T_n(x)$ is a polynomial of degree n in x, called the Chebyshev polynomial.

©IJRASET: All Rights are Reserved | SJ Impact Factor 7.538 | ISRA Journal Impact Factor 7.894 |

$$(1-x^2)\frac{d^2T_n(x)}{dx^2} - x\frac{dT_n(x)}{dx} + n^2T_n(x) = 0 \qquad (20)$$

- Roots and extrema of T_n. The roots of T_n. Are easily calculated . Indeed , since $\cos(nx)=0$ if $x=\frac{(2k-1)\pi}{2n}$

$$X_k = \cos\left(\frac{(2k-1)\pi}{2n}\right) \qquad \text{with} 1 \le k \le n \qquad (21)$$

ArethenrootsofT_n.Theyareallreal,simple,distinct andbelongtotheinterval[-1;1].Ontheotherhand, the relationship

$$T_n'(x) = \sqrt{\frac{n}{1-x^2}}\sin(n\arccos(x)) \qquad (22)$$

Showsthat$T_n'(x)=0$six $=x_k'=\cos\frac{k\pi}{n}$ where $-1 \le k \leqslant k-1$.Onededucerapidlythat$T_n$reaches its extremaat[-1;1],atthepointsx_k'andthatatthese points

$$T_n(x_k') = \cos(k\pi) = (-1)^k, \quad 1 \le k \le n$$

(23)Therefore,

$$T_n(x_k') = T_n(1) = 1 \qquad (24)$$

$$T_n(x_0') = T_n(-1) = (-1)^n \qquad (25)$$

Wecannoticethattherootsof$T_n$aresymmetricalwithrespectto0andthatfortheinterval[-1;1].These roots are often used as interpolation points for contin- uous functions on [-1;1]

- MinimizationpropertiesChebyshevpolynomialsplayanimportantroleinthe-

Wherethe$x_j$aretheL+1zerosof$T_(L+1)(x)$.Thus,the discreteChebyshevtransform(DChT)isgivenby:ory ofthe approximation.This is because,asChebyshevshowed,thesearethepolynomialswhichdeviatetheleastfromzeroonthesegment[1;1].Inotherwords,ifwedesignateby$P_n$theset ofpolynomialsof degree x^nwe have:

$$\forall q \in P_n \quad \sup_{|x|\geq 1} |q(x)| \geq \frac{1}{2^n - 1} \quad \sup_{|x|\geq 1} |T_n(x)| = \frac{1}{2^n - 1} \tag{26}$$

TheexpansionofthesignalintheTchebychev basis
ThepolynomialexpansionofasignalS(x)oforderLinthe orthogonal basis of Chebyshev is given by the equation (whichrepresentstheDChTinverse(I-DChT)):

$$S(x) = \sum_{k=0}^{L} \alpha_k T_k(x) \tag{27}$$

Thesequenceofcoefficients$\alpha_k$pour$k$=0,1,...,L constitutes the spectral coefficients of decompositionor projection of the signal:

$$\alpha_k = \frac{\langle S(x), T_k(x) \rangle}{\|T_k\|^2} = \frac{\int_{-1}^{1} S(x) T_k(x) \frac{dx}{\sqrt{1-x^2}}}{\int_{-1}^{1} T_k(x) \frac{dx}{\sqrt{1-x^2}}} = \frac{1}{\rho_{k-1}} \int_{-1}^{1} S(x) T_k(x) \frac{dx}{\sqrt{1-x^2}} \tag{28}$$

Obtainingnumericalvaluesofcoefficientsduringpoly-nomial expansion requires the evaluation of at least oneintegral. In order to better evaluate this integral, severalmethodshavebeenproposed.Amongthesemethods,the
Gaussianquadraturemethodturnsouttobeverypopular
[28].
Therefore, the evaluation of the decomposition coefficients$\alpha_k$is carried out by exploiting the Gauss-Lobattoquadraturemethodwithaquadratureoforder L+1. The Gauss-Labatto method concerns the use of non-regularlyspacedabscissaoftheintegrationdomain. Inshort,theGauss-Labattomethodstipulatesthatfora quadrature of orderL anda familyof orthogonalCheby-shevpolynomials$T_k(x)$intheinterval[-1;1],inrespecttothe weight function $\omega(x)$, the following approximation is made.

$$\int_{-1}^{1} \frac{S(x) T_k(x) dx}{\sqrt{1-x^2}} = \frac{\pi}{M+1} \sum_{j=0}^{M} S(x_j) T_k(x_j) \tag{29}$$

Wherethe$x_j$aretheL+1zerosof$T_{L+1}(x)$.Thus,the discreteChebyshevtransform(DChT)isgivenby:

$$c_0 = \frac{1}{M+1} \sum_{j=1}^{M+1} S(x_j) = \frac{1}{M+1} \sum_{j=1}^{M+1} S\left(\cos\frac{(2j-1)\pi}{2(M+1)}\right) \tag{30}$$

$$c_k = \frac{2}{M+1} \sum_{j=1}^{M+1} S(x_j) \cos\frac{k(2j-1)\pi}{2(M+1)} = \frac{2}{M+1} \sum_{j=1}^{M+1} S\left(\cos\frac{(2j-1)\pi}{2(M+1)}\right) \cos\frac{k(2j-1)\pi}{2(M+1)} \tag{31}$$

With$k$=1,2,...,M.andthesequenceofcoefficientsa_k^Lconstitutes the coefficients spectral decomposi- tion of the signal S in the Chebyshev basis.

- Extractionofinformativeparameters

Theextractionofinformativeparametersorcharacteristicfeaturesisanimportantstepintheprocessofclassifying EEGsignals.Featureextractionconists ofthesetoftechniquesprocessingEEGsignalstoobtainquantitativecharacteristics (features) that are proven or potential indi-catorsofthepresenceorabsenceofagivenphenomenoninthecerebralactivity[7].Thegoalofextractionofparametersistotransformlargerawdataintoafe werfeaturevector.Theextractionofstatisticalanddiscriminativepa-rameterswascarriedouton04differentsignals,namely: thesignalofthespectralcoefficients,itsabsolutevalue, theoriginalsignalandthereconstructedsignal.Thefol-lowingpresentssomeparametersextractedfromthesedif- ferentsignals(thefunctionsrepresentedherearefunctions

- Minimumreturnstheminimumnumberofelements inanarrayandiscalculatedbythefollowingfunc- tion.
- Maximum returns the maximum elements of an array and is calculated by the functionL.
- Themeanreturnstheaverageoftheelementsof A alongthefirstdimensionthearraywhosesizeisnot equalto1.
- The standartdeviation(Std)returnsthestandardde- viationofelementsofAalongthedimensionofthe array whose size is not 1.
- Bydefault,thestanderddeviationisnormalizedby N-1,whereNisthenumberofobservations.Thevari-ance (var) which takes into account the dispersion bof all tha values in a set of data.
- TheKurtosisisthelengthofthetailofasignaldistribution,orequivalently,howpronethesignalistooutlier.Thedevelopmentofdefaultscanincreaseth e numberofoutliers,andthereforeincreasethevalue oftheKurtosismetric.Itsformulais: $\sum_{j=1}^{N} j$
- Thenumberofzerocrossings(nzc)isthenumberof timesthesignalcroseszero,furthermore,itisthe numberofnegativevariablesinaset.
- TheRMSreturnstherootmeansquare(RMS)value of the input X.
- Themagnitudepeakistheratioofpeakamplitude /RMS.Returnstheratiooftheлargestabsolutevalue in X to the effective value (RMS) of X. Calculatethepeak-magnitude-RMSratioofX,dim dimension.
- Theimpulsefactorcomparestheheightofapeakto the average level of the signal.

$$X_{jeF} = \frac{\text{Xp}}{\frac{1}{N}\sum_{j=1}^{N} |X_{je}|} \qquad (33)$$

- The crest factor is the maximum value divided by the RMS. Defaults often first manifest themselves aschangesinthepeakofasignalbeforemanifest- ingthemselvesintheenergyrepresentedbythesig-nal's rootmeansquare.Crestfactorcanprovideearly warningforfaultswhentheyaredevelopedforthe first time :

$$X_{jeF} = \frac{X_p}{\overline{N}\sum_{j=1}|X_{je}|} \qquad (34)$$

- TheformfactoristheRMSdividedbytheaverage of theabsolutevalue.Theformfactordependsonthe shapeofthesignalwhilebeingindependentofthe dimension of the signal.

$$X_{jeF} \quad \frac{X_{\text{rms}}}{\frac{1}{N}\sum_{j=1}^{N} |X_{je}|} \qquad (35)$$

- Higher order statistics provide insight into the systembehaviorthroughthefourthmoment(Kurtosis)and thirdmoment(asymmetry)ofthevibrationsignal.
- PRD(percentrootsquaredifference)issomehow translate the percentage of the normalized relative er-rorintoenergyandmakesitpossibletoquantifytha qualityofthereconstructedsignal:

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

$$PRD = \frac{\sum_{n}^{s}(S_n - \tilde{S}_n)^2}{\sum_{nm} S^2} \quad (36)$$

©IJRASET: All Rights are Reserved | SJ Impact Factor 7.538 | ISRA Journal Impact Factor 7.894 |

Thenumberofzerocrossing(nzc)isthenumberoftimesthesignalcrosseszero.Furthermore,itisthenumberofnegativevariableinaset.

- Dimensionalityreduction

Featureextractionreducestheamountofdatabyus- ingavectoroffeatures.Theaimofdimensionalityreduc-tion in machine learning is to reduce the dimension of a d-dimensional datasetbyprojectingitontoak-dimensional subspace(wherek□d)inordertoeliminateredundant information while retaining relevant information about theoriginal data. With tis in mind, linear and non-linear trans-formations were performed using linear discriminant anal- ysis(LDA).AccordingtoSubasi[29]LDA,alsoknownas Fisher's discriminant analysis, is a supervised algorithmthatcalculatesthelineardiscriminantbymaximisingthedistance between classes and reducing the distance withinclasses.
In contrast, LDA attempts to explicitly represent the dis- tinctionbetweenclasslabelsinthedata.Oncethepro- cedureiscomplete,eachclasswillhaveanormaldistributionofdiscriminantparameters.Theprojectioncanberepresentedusingasinglematrixequati on,suchas:

$$Y=X*W \tag{37}$$

WhereXandYarethenewandoldfeaturesrespec- tively,andWistheprojectionmatrixdxkformedbythe k-vectors$S_W^{-1}S_bS_b$where$S_w$and$S_b$arerespectivelythe intra-class and inter-class dispersion matrices, and are cal- culated as [30] .

$$S_w=\sum_{i=1}^{c}S_i=\sum_{i=1}^{c}\sum_{x_k\in C_i}(x_k-\mu_i)(x_k-\mu_i)^T \tag{38}$$

$$S_b=\sum_{i=1}^{c}n_i(\mu_i-\mu)(\mu_i-\mu)^T \tag{39}$$

TheFishercriterionthatLDAaimstomaximizeis:

$$()=\frac{w^tS_bw}{wS_ww} \tag{40}$$

- ClassificationusingaConvolutionNeuralNet- work

The classification of data into feature spaces is fre- quently necessaryinbiomedicalsignalprocessing,partic- ularly when using EEG signals [31] .
Classificationisamethodthatoffersthepossibilityofac- quiringknowledgeusingthemodelortransferfunction betweenfeaturevectorsandlabels.Giventheinterestinsubjectdiagnosis,oncelabelshavebeenobtainedforeachfeaturevector,itisnecessarytocombine thelabelsasso- ciatedwithaspecificsubjecttoprovideasubjectlabel. Classifiers can be classified into two categories dependingonthetypeofoutputprovided:informativeordiscrimi- native.AccordingtoGonzález[32]informativeclassifiersacquireknowledgeaboutclassmodels.Thus,inordertoclassifyavectorofcharacteristicfeat ures,itisnecessary tocalculatetheprobabilityofeachclassandchoosethe most probable.
Theaimofthisstudyistosetupaconvolutionneuralnet-work that will enable EEG data from stroke patients and healthypatientstobeclassified.
Todothis,weuseone-dimensionalconvolutionlayersbe-cause they are suitable for time series analysis, natural lan-guage processing (NLP) for sequences of words or char-acters, detection of patterns in sequences, etc. We also useone-dimensional convolutionlayersfortimeseriesanaly- sis[33].Intermsofoperation,itappliesakernel(filter) toaslidingwindowalongtheone-dimensionaldimension ofthesequencetoextractlocalfeatures.
Convolutionnal Neural Network architec- ture:Theneuralnetworkusedtodevelopthisbinary classification system follows the architecture shown in the figure below.

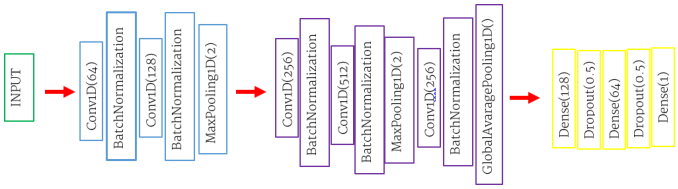


Fig.6.GeneralarchitectureoftheConvolutionalNeural Network.

Thismodelismadeupof17hiddenlayersdividedbetweentheonedimensionalconvolutionlayer,theBatchNormalization,MaxPooling,GlobaAvarage-Pooling,DenseandDropoutlayers.

Description of the ArchitectureThe pro- posed network is based on a four (04) part architecture.Each part can be made up of several types of neurons, withtheexceptionoftheinputlayer,whichcontainsonlythe inputmatrix(thedata).

- TheInputLayer:Definestheformoftheinputimage. Hereisthelengthofthesequenceorthenumberof timesteps,andthenumberoffeaturesateachtime step.
- 1D Convolutional Layer: Apply a large number of convolutionalfilters(64filtersinthecaseofthefirstconvolutionallayer)totheinputimagewithakernelsizeof3.Thisallowslocalpixelstobedetected intheimage.Inalltherestoftheneuralnetwork,forlayers ofthesametype,weusedakernelsizeof3,anac- tivationfunctionreluandapaddingvaluedefinedas same ;
- BatchNormalizationlayers:ABatchNormalization layernormalizestheactivationsofapreviouslayer by recentering and resizing them. More specifically,for eachtrainingbatch,theBatchNormalizationlayer
  - :Normalisetheactivationssothattheyhavea meanofzeroandavarianceofone.
  - AffineTransformation:Afternormalisation,thelayerappliesalineartransformation(affine)toallow the model to readjust the data if necessary.
- 1D Pooling Layer: Reduces the dimensionality of databytakingthemaximumfromawindowofsize
- 2.Thishelpstoreducethesizeoffeatureswhilere- tainingthemostimportantinformation.
- Denselayers:Adenselayerisafullyconnectedlayer.Each neuron is connected to all the neurons in the pre- viouslayer.ItusestheReLUfunction[13]function for non-linearity.
- Global Average Pooling layers: A Global Average Poolinglayertakesasinputafeaturemapproduced by aconvolutionallayerandcalculatestheaverageofeachfeaturemap.Unlikeadenselayer,whichtreats eachelementofthefeaturemapindividually,Glob- alAveragePooling reducestheentirefeaturemaptoa single number.
- Dropoutlayers:Thesearearegularisationtechniqueusedinneuralnetworkstoreducetheriskofoverit-ting (overfitting).Duringtraining,theDropoutlayer randomly "deactivates" (or "zeroes out") a certain per- centageofneuronsinagivenlayerateachiteration.Thismeansthatthe'deactivated'neuronsdonotparticipateinthetrainingphasefortha tspecificiteration.
- The Output Layer: This layer has a single neuron withasigmoidactivationfunction,whichisappropriate for abinaryclassificationproblem.Thesigmoidfunc- tion transforms the output into a probability between0 and 1, indicating the probability of the positive class (sick or not sick).

- **Errorreduction:Learningbyretropropaga- tion**

Gradientdescentlearning:

Outputlayer:Error-guidedcorrectionbetween desiredandactualoutput
Hiddenlayers:Sensitivitycorrection(influence oftheneurononthe erroroutputlayer).

Neuronoutputvalues: data x

$$y_i^t = fa^j{}_t = f\left(\omega \sum_{i=1}^{R} {}_{ij}{}_i + \omega_{i,0}\right) \quad (41)$$

Wherefistheneuronactivationfunction:
$a_t^j = \sum_{i=1}^{R} \omega_{j,i} v_i^t + \omega_{j,0}$ isthecumulativesumoftheinputneurons;
$\omega_{j,i}$ weightofthelinkconnectingneuronjtoneuron i in the previous layer ;
$\omega_{j,0}$ thebiasofneuronj;
v_i^t outputofneuroniinthepreviouslayerforinput data X ;
Rnumberofneuronsonthepreviouslayer.

3. Outputerrortooutputlayer:$A = \{\{x^t, r^t\}\}_{t=1}^{N}$ with

$$r^t = \begin{bmatrix} r_1^t \\ r_2^t \\ r_3^t \\ \vdots \\ r_k^t \end{bmatrix} = \begin{bmatrix} r_1^t & \cdots & r_k^t \end{bmatrix}^T$$

$r_i^t = 1$ si $x_t \in C_j$ and $r_i^t = 0$
Observederrorfordata x^t onneuronjoftheoutput layer :

$$e_j^t = r_j^t - y_j^t$$

Observedquadraticerrorforthedata x^t onallKneu- ronsintheoutputlayer(oneneuronperclass):

$$E^t = \frac{1}{2} \sum_{j=1}^{k} (e_j^t)^2 \quad (42)$$

Theaverageerrorobservedforthedataset X is:

$$E = \frac{1}{N} \sum_{t=1}^{N} E^t \quad (43)$$

4. Correctionoftheerrorfortheoutputlayer:
Weightcorrectionbygradientdescentoftherootmean square error :

$$\Delta\omega_{j,i} = -\eta \frac{\partial E}{\partial \omega_{j,i}} = -\eta \sum_{t=1}^{N} \frac{\partial E^t}{\partial \omega_{j,i}} \quad (44)$$

$$\Delta\omega_{j,i} = -\eta \sum_{t=1}^{N} \frac{\partial E^t}{\partial \omega_{j,i}} \quad (45)$$

Theerrorofneuronjdependsontheneuronsinthe previous layer.

5. Learningfortheoutputlayer:
Adjustment ofoutputlayerweights

$$\Delta\omega_{j,i} = -\frac{\eta}{N}\sum_{t=1}^{N}\frac{\partial E^t}{\partial \omega_{j,i}} = -\frac{\eta}{N}\sum_{t=1}^{N}\frac{\partial E^t}{\partial e^t}\cdot\frac{\partial e}{\partial y_i^t}\cdot\frac{\partial y_i^t}{\partial a_i^t}\cdot\frac{\partial a_i^t}{\partial \omega_{j,i}} \quad (46)$$

$$\Delta\omega_{i,i} = \frac{\eta}{N}\sum_{t=1}^{N} e_i y_i (1-y_i) y_i^t \quad (47)$$

$$\Delta\omega_{j,0} = -\frac{\eta}{N}\sum_{t=1}^{N}\frac{\partial E^t}{\partial \omega_{j,0}} = -\frac{\eta}{N}\sum_{t=1}^{N}\frac{\partial E^t}{\partial e^t}\cdot\frac{\partial e^t}{\partial y^t}\cdot\frac{\partial y^t}{\partial a^t}\cdot\frac{\partial a^t}{\partial \omega_{j,0}} = \frac{\eta}{N}\sum_{t=1}^{N} e_i^t y_i^t (1 \quad (48)$$

6. Deltarule:

Letδ_i^t whichcorrespondstothelocalgradientofneuronjfortheinputdata$X$.

$$\delta_j^t = e_j^t \cdot y_j^t \cdot (1-y_j^t) \cdot y_i^t \quad (49)$$

So,

$$\Delta\omega_{(j,i)} = \frac{\eta}{N}\sum_{t=1}^{N}\delta_j y_i^{tt} \quad (50)$$

and,

$$\Delta\omega_{(j,0)} = \frac{1}{N}\sum_{t=1}^{tt}\delta_j E = \frac{1}{2}\sum_{j=1}^{t2}(e_j) \quad (51)$$

7. Correction of the corresponding error layer :
The gradient of the hidden layer error is:

$$\frac{\partial E^t}{\partial \omega_{(j,i)}} = \frac{\partial E^t \partial y^t_i}{\partial y^t_i} \cdot \frac{\partial a^t_i}{\partial a^t_i} \cdot \frac{\partial a^t_i}{\partial \omega_{(j,i)}} \quad (52)$$

Only $\frac{\partial E^t}{\partial \omega_{(j,i)}}$ changes while $\frac{\partial a^t_i}{\partial \omega_{(j,i)}}$ and $\frac{\partial a^t_i}{\partial a^t_i}$ are the same as on the output layers. The error for a neuron in the hidden layer depends on the error of the K neurons in the next layer (back propagation of the error).

$$= \frac{1}{2}\sum_{j=1}^{t2}(e_j) \quad (53)$$

$$\frac{\partial E^t}{\partial y^t_i} = \frac{\partial}{\partial y^t_i}\left[\frac{1}{2}\sum_{j=1}^{k}(e^t_j)^2\right] = \sum_k e^t_k \cdot \frac{\partial e^t_k}{\partial v^t_k} \quad (54)$$

$$\frac{\partial E^t}{\partial y^t_i} = \sum_k e^t_k \cdot \frac{\partial e^t_k}{\partial a^t_j} \cdot \frac{\partial a^t_j}{\partial y^t_j} = \sum_k e^t_k \cdot \frac{\partial [r^t_k - y^t_k]}{\partial a^t_j} \cdot \frac{\partial \sum_k \omega_{(k,j)} y^t_i + \omega_{(k,0)}}{\partial y^t_i} \quad (55)$$

$$\frac{\partial E^t}{\partial y^t_i} = \sum_k e^t_k \cdot [-y^t_k(1-y^t_k)] \cdot \omega_{(k,j)} \quad (56)$$

$$\delta^t_k = e^t_k \cdot [-y^t_k(1-y^t_k)] \quad (57)$$

$$\frac{\partial E^t}{\partial y^t_i} = -\sum_k \delta^t_k \cdot \omega_{(k,j)} \quad (58)$$

8. Correction of the corresponding error:

$$\frac{\partial E^t}{\partial \omega_{(j,i)}} = \frac{\partial E^t}{\partial y^t_i} \cdot \frac{\partial y^t_i}{\partial a^t_i} \cdot \frac{\partial a^t_i}{\partial \omega_{(j,i)}} = -\sum_k \delta^t_k \cdot \omega_{(k,j)} \cdot \frac{\partial y^t_i}{\partial a^t_i} \cdot \frac{\partial a^t_i}{\partial \omega_{(j,i)}} \quad (59)$$

$$\delta^t_j = e^t_j(1-y^t_j) \cdot \sum_k \delta^t_k \cdot \omega_{(k,j)} \quad (60)$$

$$k$$

$$(j,i) = -\eta \cdot \frac{\partial E}{\partial (j,i)} = -\sum_{t=1}^{N} \frac{\partial}{\partial (j,i)} = \sum_{t=1}^{N} \delta_j \cdot y_i \quad (61)$$

IV. RESULTS

1) Acquiredsignal

1.

Figure(4)showstheEEGsignalsrecordedonthesame

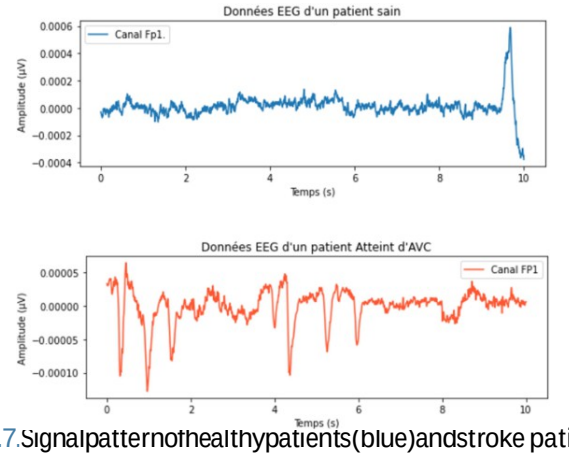


Fig.7.Signalpatternofhealthypatients(blue)andstroke patients (red)

For these signals, we have a duration of 10 seconds each fortheFp1channeltomakeiteasiertoseethesignal. Inreality,thelengthofthesignalforprocessingwillbe 120secondsondatafrom25EEGchannels,whichwill provideenoughinformationtohelpcharacteriseasignal.

2) Spectralanalysisresults

Thisstage,whichfollowsdataacquisitionandpre- processing,wasimplementedbyinterpolatingthesignals. TheirfrequencydistributionsarerepresentedintermsofChebyshev decomposition spectral coefficients.

3) Correctionofthecorrespondingerror:

Figures(5)and(6)showexamplesofsignaldecomposi- tionforhealthyandstrokepatientsrespectively.

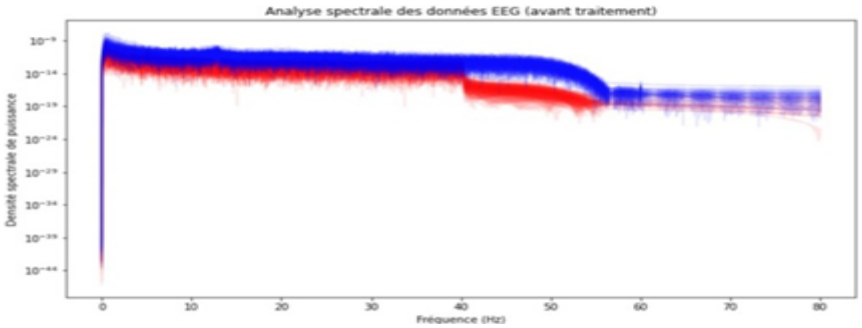


Fig.8.Representationoftheorginalsignal

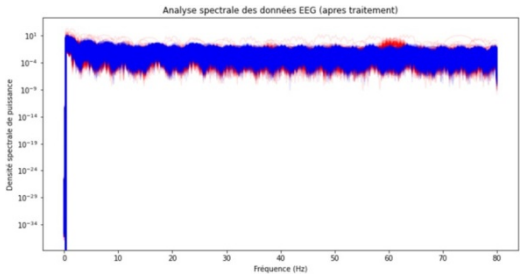


Fig.9.Representationofthereconstructedsignal

The difference between the original signal and there- constructed signal is clearly visible. The blue and red curvesrepresentthesignalfromhealthypatientsandthesignalfromstrokepatientsrespectively.Oneobservationcan bemade:thesignalreconstructionerrorrateafterus- ingDChTislessthan0.0025,whichprovesthatthere- constructed signal after interpolation is almost equal to the original signal.
We can also see that the amount of energy extracted in thereconstructed signal is virtually the same as that extracted in the original signal.

2Dprojectionoftherelevantextractedfeatures.
Toanalyseasignal,onecouldfirstapplytheCheby- shev transform to obtain a compact and smooth represen- tationofthesignal.Then,theresultingcoefficientscouldbeanalysedbyparameterextractiontoextractstatisticalfeaturesthatcanbeusedforvarioussignalanalysistaskssuch as classification, pattern detection, or anomaly detec-tion.
Thefollowingfigureshowsthethe2Dprojectionofthe relevant extracted features from the 2 types of patients:

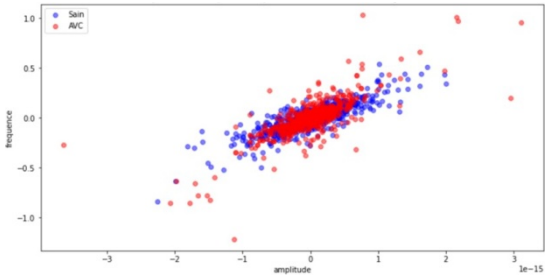


Fig.10.Viewofextractedcharacteristicsofhealthyand stroke patients

Theblueandreddotsshowtheextractedcharacteris- ticsofhealthyandstrokepatientsrespectively.Theiso- lated blue and red dots show the respective characteristicsofhealthyandstrokepatients.Itisthesecharacteristics thatwillenableustofacilitatedecision-making.Thisob-servation shows that healthy and stroke patients are easilydistinguishable,demonstratingthattheyareinformative, representativeanddiscriminative.
Learningoutcomes
Once the features have been extracted, the data is readytobefedintotheneuralnetworkshowninFigure(3).
Theneuralnetworktrainedover20epochsproducesanaccuracy of 98.87 on the training data and 97.12 on the testdata.Asthefollowinglearningcurveshows,themodelis reliablebecauseitavoidsoverlearning.

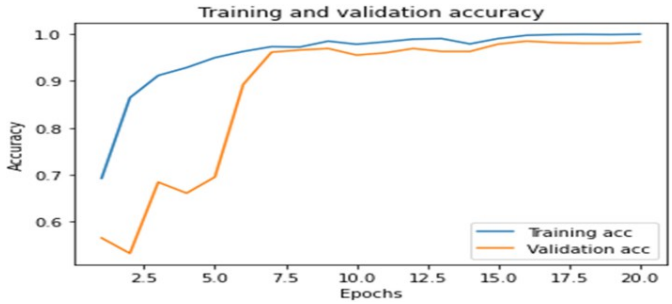


Fig.11.Accuracylearningcurveasafunctionofthenum- ber of

Wecanalsoseethatthelearningprocesswentwell, withdecreasingerrorcurvesreachingvaluesoflessthan 0.12.



Fig.12.Diagramofthe loss learning curve as a function of the number of

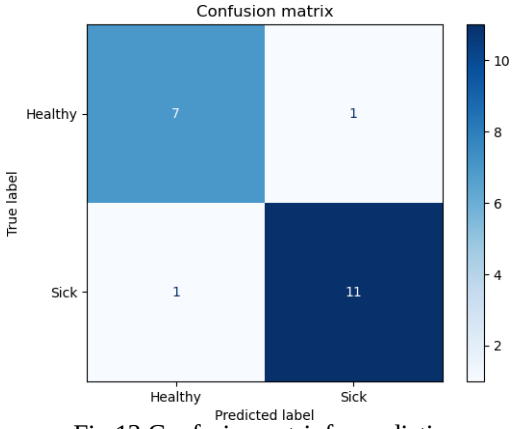
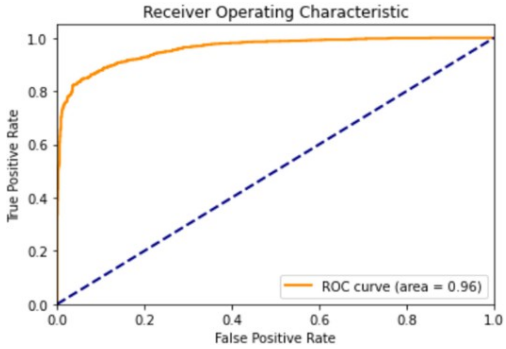


Fig.13.Confusionmatrixforprediction.

InthefollowingFigure(10),itiseasytoseethattheAUCiswellabove0.5(reaching0.96),whichatteststothediscriminatingabilityoftheclassifie



r.Fig.14.RepresentationoftheROCcurve

versus healthycontrols.Theperformanceofclassificationbetweenstrokepatientsandhealthycontrolsdemonstratedthat spectral coefficients of the Tchebychev polynomials transformwereeffectivefeaturestoclassifystrokepa- tientsandhealthycontrols.

In comparison with previous studies on the diagnosisof strokethroughEEGsignals,thereweresomesimilarre- sults.Thetablebelowshowsthecomparativestudy.

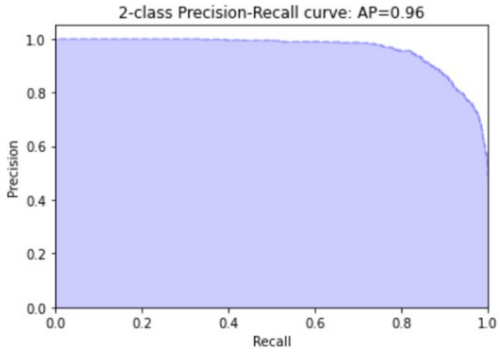


Fig.15.Representationoftheprecisioncurve

V. DISCUSSION

Our results demonstrate that nonlinear properties of the EEGsignalscanbeausefulwaytodetectmodifications of brain state during stroke disease. The work in this studymakestwocontributions.Thefirstcontributionisoures-tablishmentofcorrelationsbetweenEEGsignalswiththeclinical states of stroke patients through statistical metricsextractedfromthespectralcoefficientsofDiscretCheby-chevTransform(DChT).Thesecondcontributionisour desingofaclassifierforthedetectionofstrokepatients. Throughcorrelationanalysis,ithasbeenfoundthatthe occurrenceofstrokehaveactivitychangesinthelesionaland contrelesional hemispheres, and analyses tended tore-late significant changes to stroke onset accross different statisticmetric.EEGbasedtechnologiesareparticularly promissing as diagnostic or predictive biomarkers for indi-vidualstrokepatient.Inclinicaldiagnosisatestwithhighsensitivity is necessary for ruling out disease. Sensitivity of80,88%inthisworkreferstotheabilityoftheanaly- sistocorrectlydetectpatientswithstrokewhodohave, showsthattheconvolutionalneuralnetwork(CNN)clas-sifierusedimprovedthedetectionofpatientswithstroke

Table1.Summaryofanalysismethodsandresults

Authors	MethodofAnalysisandExtractionof patterns	Dimensionalityreduction	Classifiers	Accuracy
Zhang S. et al. (2022)	Temporal-SpectralDistance		WeightedConvolutionalSiamesNetwork	66%-72.8%
LinPJetal.(2022)	BiomarkerandScores		CNN	91%
Choi Ya et al. (2021)	EEGData		CNN	94%
AlArfajA.Aetal.(2022)			TransferLearningTechnique	96.5%
Xu.Fetal.(2023)	MST-CPS		Clustering:K-means	89%
Samar Bouazizietal.(2024)	D-ESNLIMEand ELIS		NovelDiversifiedEcho-StateNetwork	95%
P.Nancyetal.(2023)	DKELM-AS		FHT	95.2%
AkthamSawanetal.(2022)	BiGRU+HS+ MVO		CNN	99.99%
E.W.Guntarietal.(2020)	Wavelet°CNR		GeneticAlgorithm	72.22%-90.00%
Choi,Y.Aetal.(2021)	LSTM		CNN	94.00%
Choi,Y.Aetal.(2021)	FFT		RandomForest	92.51%
MandeepKauretal.(2022)	LSTM,BiLSTM,GRU		FFNN	83%-95.6%
SelonRohanKalahastyetal.	PowerSpectralDensity		———-	94.4%-100%
Li-Min-Weng(2024)	SpectralAnalysis		———	92%

SutCliffeet al. (2022)	SpectralAnalysis		CNN	
YuXiiaHuetal.(2023)	SpectralAnalysis(QEEGparameters)		CNN	85.3%
Benghanemetal.(2024)	ModifiedRankinScales		MultivariableRegressionAnalysis(MVR)	Spof48%
JinY.etal.(2024)	Multi-ModalAnalysisandTime-FrequencyAnalysis(WPT+FC)		10-Fold-CrossValidation	99.75%
Yoon A.etal.(2024)	SpectralAnalysisandFunctionalConnectivity(FFT+FC)		RandomForest+Z-Score	90%-92.52%
Our ProposedSolution	SpectralAnalysis(DChT)	LDA	CNN	98.87%

VI. CONCLUSION

We propose a new health diagnosis sytem that de- tecttheoccurrenceofstrokediseaseswiththeattribute informationofstatisticalmetricextractedfromDicrete Tchebychev Transform (DChT) of raw EEG signal col- lectedfromstrokepatientsandhealthycontrols.Spec- tralanalysis,Extractionofdiscriminativeparameters,Di-mensionality reduction and Classification were performedthrough Tchebychev polynomials transform, Linear dis-criminantanalysisandaoneDimensionalConvolutional Neural Network (1D-CNN). Above all, the health diag- nosissysteminthisstudycandetectandpredicttheoc-currenceofstroke,thusprovidingaccuratepredictionresultsinasystemthatcanbeimplementedatlowcost. Asaresult,thesystemhasgreatadvantagesasitcanprovideindepthanalysisinformationusefulforthebehavioralcharacteristicsbeforeandduringstrokeattack.In ordertoamelioratethisworkitisnecessaryforfurther studiestointegratesimalaranalysiswithECGandEMG signals.

VII. CONFLICT OF INTEREST

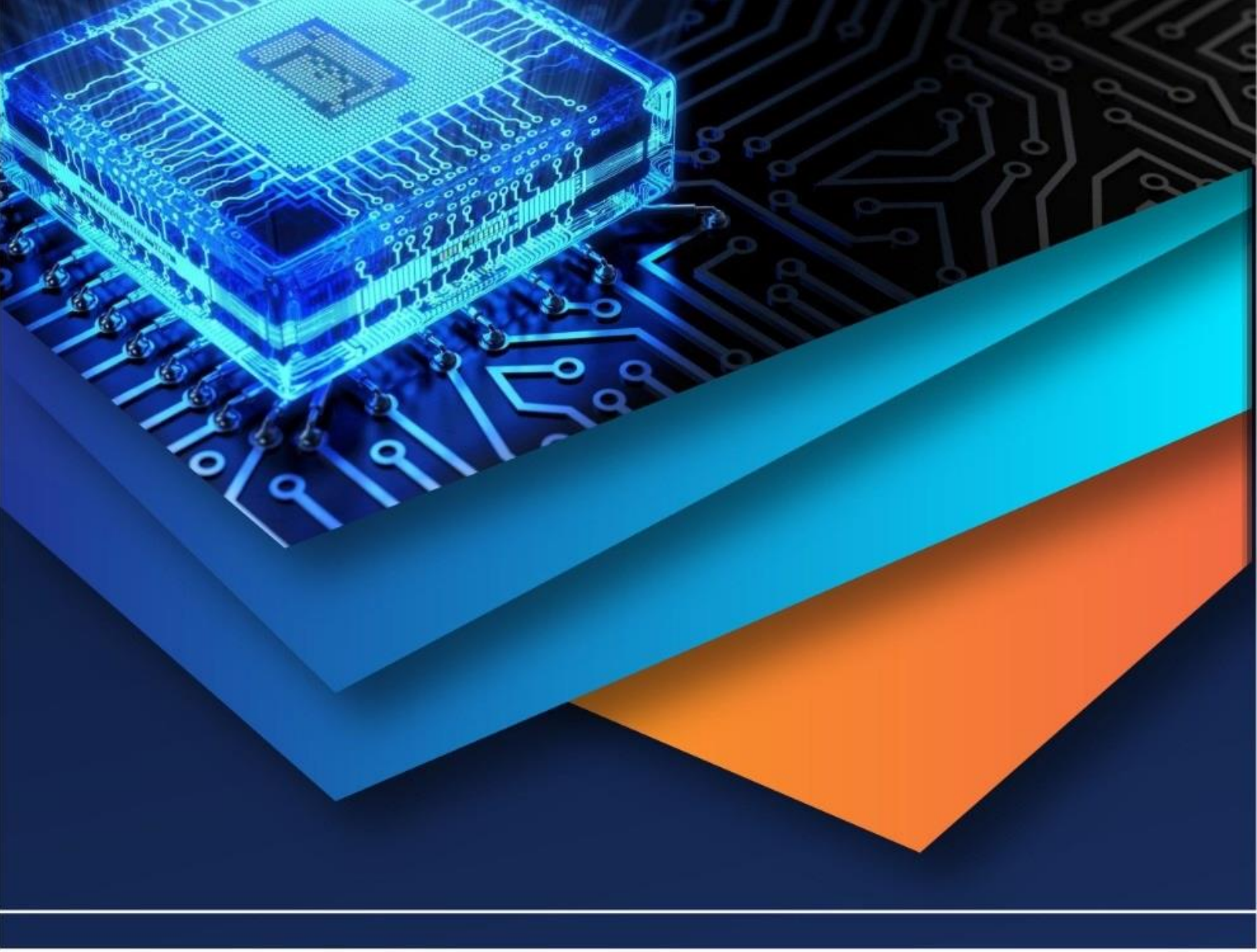
Theauthorsdeclarethattheyhavenoconflictofinter-est.Theauthorsdeclarethatthereisnocompetingfinan-cial interest or personal relationship that could have ap-pearedtoinfluencetheworkreportedinthispaper

REFERENCES

[1] B. Foreman, J. Claassen, K. Abou Khaled, J. Jirsch, D. M.Alschuler, J. Wittman, R. G. Emerson, and L. J. Hirsch,"Generalized periodic discharges in the critically ill: acase-control study of 200 patients," *Neurology*, vol. 79,no. 19, pp. 1951–1960, 2012.
[2] B. Ovbiagele, L. B. Goldstein, R. T. Higashida, V.J. Howard, S. C. Johnston, O. A. Khavjou, D. T. Lackland,
[3] J. H. Lichtman, S. Mohl, R. L. Sacco *et al.*, "Forecastingthefutureofstrokeintheunitedstates:apolicystatementfrom the american heart association and americanstrokeassociation,"*Stroke*,vol.44,no.8,pp.2361–2375,2013.
[4] C.O.Johnson,M.Nguyen,G.A.Roth,E.Nichols,T. Alam, D. Abate, F. Abd-Allah, A. Abdelalim, H. N.Abraha, N.M. Abu-Rmeileh*etal.*, "Global,regional, andnationalburdenofstroke,1990–2016:asystematicanaly-sisfortheglobalburdenofdiseasestudy2016,"*TheLancet Neurology*, vol. 18, no. 5, pp. 439–458, 2019.
[5] H.Jokinen,S.Melkas,R.Ylikoski,T.Pohjasvaara,M. Kaste, T. Erkinjuntti, and M. Hietanen, "Post-strokecognitive impairment is common even after successful clin-ical recovery," *European journal of neurology*, vol. 22,no. 9, pp. 1288–1294, 2015.
[6] J.Petrovic,V.Milosevic,M.Zivkovic,D.Stojanov,O. Milojkovic, A. Kalauzi, and J. Saponjic, "Slower eegalphageneration,synchronizationand"flow"—possiblebiomarkers of cognitive impairment and neuropathology ofminor stroke," *PeerJ*, vol. 5, p. e3839, 2017.
[7] T.Aydin,F.N.Kesiktas¸,M.M.Oren,T.Erdogan,Y.C. Ahisha,T.Kizilkurt,M.Corum,˙I.Karacan,S.Öztürk, andG.Bahat,"Sarcopeniainpatientsfollowingstroke:Anoverlookedproblem,"*InternationalJournalofRehabilita- tionResearch*,vol.44,no.3,pp.269–275,2021.
[8] N.Wright,K.Newell,K.H.Chan,S.Gilbert,A.Hacker,Y. Lu, Y. Guo, P. Pei, C. Yu, J. Lv *etal.*, "Long-term ambi-ent air pollution exposure and cardio-respiratory disease inchina:findingsfromaprospectivecohortstudy,"*Environ-mental Health*, vol. 22, no. 1, p. 30, 2023.
[9] S.Benghanem,N.Kubis,E.Gayat,A.Loiodice,E. Pruvost-Robieux, T. Sharshar, A. Foucrier, S. Figueiredo, V. Bouilleret, E. De Montmollin *et al.*,"Prognostic value of early eeg abnormalities in severestrokepatientsrequiringmechanicalventilation:apre-planned analysis of the spice prospective multicenterstudy," *Critical Care*, vol. 28, no. 1, p. 173, 2024.
[10] Y.Jin,J.Li,Z.Fan,X.Hua,T.Wang,S.Du,X.Xi,andL. Li, "Recognition of regions of stroke injury using multi-modalfrequencyfeaturesofelectroencephalogram,"*Frontiers in Neuroscience*, vol. 18, p. 1404816, 2024.
[11] Y.Hu,Y.Wang,R.Zhang,Y.Hu,M.Fang,Z.Li,L.Shi,Y. Zhang, Z. Zhang, J. Gao *et al.*, "Assessing stroke re-habilitationdegreebasedonquantitativeeegindexandnonlinearparameters,"*CognitiveNeurodynamics*,vol.17,no. 3, pp. 661–669, 2023.
[12] L. Sutcliffe, H. Lumley, L. Shaw, R. Francis, and C. I.Price,"Surfaceelectroencephalography(eeg)duringtheacute phase of stroke to assist with diagnosis and predictionofprognosis:ascopingreview,"*BMCemergencymedicine*,vol. 22, no. 1, p. 29, 2022.

[13] M.S.N.AgLamat,M.S.H.AbdRahman,W.A. WanZaidi,W.N.N.W.Yahya,C.S.Khoo,R.Hod,andH.J.Tan,"Qualitativeelectroencephalogramanditspredictorsinthediagnosisofstroke,"*FrontiersinNeurology*,vol. 14, p. 1118903, 2023.
[14] Z. Keser, S. C. Buchl, N. A. Seven, M. Markota, H. M.Clark, D. T. Jones, G. Lanzino, R. D. Brown Jr, G. A. Worrell,andB.N.Lundstrom,"Electroencephalogram(eeg)with or without transcranial magnetic stimulation (tms) asbiomarkersforpoststrokerecovery:anarrativereview,"*Frontiers in neurology*, vol. 13, p. 827866, 2022.
[15] A. L. Schneider and K. G. Jordan, "Regional attenuationwithout delta (rawod): a distinctive eeg pattern that can aidinthediagnosisandmanagementofsevereacuteischemicstroke,"*Americanjournalofelectroneurodiagnostictech- nology*, vol. 45, no. 2, pp. 102–117, 2005.
[16] B.ForemanandJ.Claassen,"Quantitativeeegforthede-tectionofbrainischemia,"*Criticalcare*,vol.16,pp.1–9,2012.
[17] S.FinniganandM.J.VanPutten,"Eeginischaemicstroke:quantitativeeegcanuniquelyinform(sub-)acuteprog-nosesandclinicalmanagement," *Clinicalneurophysiology*,vol. 124, no. 1, pp. 10–19, 2013.
[18] S. Finnigan, A. Wong, and S. Read, "Defining abnormalslow eeg activity in acute ischaemic stroke: Delta/alpha ratioasanoptimalqeegindex,"*ClinicalNeurophysiology*,vol. 127, no. 2, pp. 1452–1459, 2016.
[19] R.A.Chowdhury,G.Pellegrino,Ü.Aydin,J.-M.Lina,F.Dubeau,E.Kobayashi,andC.Grova,"Reproducibilityofeeg-megfusionsourceanalysisofinterictalspikes:Relevanceinpresurgicalevaluationofepilepsy,"*Humanbrain mapping*, vol. 39, no. 2, pp. 880–901, 2018.
[20] F.DeVicoFallani,L.Astolfi,F.Cincotti,D.Mattia,D. laRocca,E.Maksuti,S.Salinari,F.Babiloni,B.Vegso,G.Kozmann*etal.*,"Evaluationofthebrainnetworkorganizationfromeegsignals:apreliminaryevidenceinstrokepatient,"*TheAnatomicalRecord:AdvancesinIntegrative Anatomy and Evolutionary Biology: Advances in Integra- tiveAnatomyandEvolutionaryBiology*,vol.292,no.12,pp.2023–2031,2009.
[21] Z. Ip, G. Rabiller, J. He, Z. Yao, Y. Akamatsu, Y. Nishi-jima, J. Liu, and A. Yazdan-Shahmorad, "Cortical strokeaffectsactivityandstabilityoftheta/deltastatesinremotehippocampalregions,"in*201941stAnnualInternational Conference of the IEEE Engineering in Medicine and Bi- ology Society (EMBC)*.IEEE, 2019, pp. 5225–5228.
[22] M. W. M. G. A. J. SP Finnigan, SE Rose, "Correlation ofquantitative eeg in acute ischemic stroke with 30-day nihssscore:comparisonwithdiffusionandperfusionmri,"p.5,2019.
[23] J. J. C. H. C. P. H. L. YA Choi, S Park, "Machine-learning-basedelderlystrokemonitoringsystemusingelectroen-cephalography vital signals," p. 5, 2023.
[24] X.L.H.Liu,"Eegdatasetsofstrokepatients,"2023.
[25] G.M.D.H.T.B.N.W.J.Schalk,"Eegmotormovement,"2009.
[26] D.d'HelsinkiLaennec,"Principeséthiquesapplicablesauxrecherchesmédicalessurdessujetshumains,"2002.
[27] D.Tchiotsop,"Modélisationspolynomialesdessignauxecg.applicationàlacompression."2007.
[28] B.H.etA.LOUAIL,"Applicationsdespolynômesorthog-onauxpourrésolutiondeséquationsintégrales,"2021.
[29] V.Rossetto,"Outilsnumériques,"2021.
[30] A. Subasi and M. I. Gursoy, "Eeg signal classification usingpca, ica, lda and support vector machines," *Expertsystems withapplications*, vol. 37, no. 12, pp. 8659–8666, 2010.
[31] K.Fukunaga,*Introductiontostatisticalpatternrecogni- tion*.Elsevier, 2013.
[32] L. C. D. Nkengfack, D. Tchiotsop, R. Atangana, V. Louis-Door, and D. Wolf, "Eeg signals analysis for epilepticseizures detection using polynomial transforms, linear dis-criminantanalysisandsupportvectormachines,"*Biomed- ical Signal Processing and Control*, vol. 62, p. 102141,2020.
[33] R. C. González, "Towards an automated portableelectroencephalography-basedsystemforalzheimer'sdiseasediagnosis,"Ph.D.dissertation,InstitutNationaldelaRecherche Scientifique (Canada), 2018.
[34] R.Chetana,A.S.Rao,andK.Mahantesh,"Applicationofconv-1dandbi-lstmtoclassifyanddetectepilepsyineegdata," *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 6, 2023.

©IJRASET: All Rights are Reserved | SJ Impact Factor 7.538 | ISRA Journal Impact Factor 7.894 |



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 (24*7 Support on Whatsapp)