IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

AI-Based Mental Health Assessment System Using Multimodal Speech and Text Analysis

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Doi: https://doi.org/10.56975/ijcrt.v14i7.309998

Abstract Mental health problems like stress, anxiety, and depression are becoming quite widespread owing to rapidly changing lifestyles, academic stress, and social factors. In order to mitigate the risk of negative psychological outcomes, it is important to recognize such mental disorders at an early stage. However, existing assessment practices are based mainly on clinical interviews and the use of questionnaire tools, which may be insufficient or unavailable in certain situations. Therefore, the current research proposes an innovative solution in the form of an AI-based mental health assessment system. Natural Language Processing (NLP) techniques will be used to analyze the textual input provided by users and identify patterns that could indicate certain emotions or other states of mind. For speech analysis, several acoustic features, including MFCC (Mel Frequency Cepstral Coefficients), will be extracted from audio samples in order to capture tone, pitch, and energy. Moreover, a *machine learning method will be used to predict the state of mental health based on speech and text. Classification algorithm will be built using Logistic Regression and Random Forest models respectively. In addition, a multimodal fusion model will be introduced to integrate predictions made by the text and speech models. To facilitate* interaction between users and the system, a web application will be developed using Python Flask framework. The system will allow for entering data in a text form, uploading an audio file, or recording live speech in order to receive immediate classification results. Preliminary experimental results demonstrate that the proposed approach is efficient and promising in terms of achieving high accuracy rates in classifying various types of mental illnesses, including normal conditions, stress, anxiety, and depression. Ethical considerations were taken into account while developing the proposed model, making sure that user privacy was not violated and the tool was meant only as a supplementary instrument.

Keyw.ords— Artif.icial Intelligence, Mental Hea.lth Asses.sment, Spe.ech Anal.ysis, Text Anal.ysis, Natu.ral Lang.uage Proce.ssing (NLP), Mach.ine Lear.ning, Emot.ion Detec.tion, MFCC, Logi.stic Regre.ssion, Ran.dom For.est

I Introduction

Men.tal hea.lth has bec.ome a signif.icant glo.bal conc.ern in rec.ent yea.rs, affec.ting indivi.duals acr.oss diffe.rent age gro.ups and profes.sions. Rapid urbani.zation, acad.emic pres.sure, deman.ding work enviro.nments, and soc.ial isola.tion have contri.buted to a notic.eable incr.ease in men.tal health disor.ders such as str.ess, anxi.ety, and depre.ssion. Accor.ding to rec.ent stud.ies, a lar.ge perce.ntage of indivi.duals experi.encing psychol.ogical dist.ress rem.ain undiag.nosed due to lack of aware.ness, sti.gma, and limited acc.ess to profes.sional healt.hcare serv.ices. Early detec.tion of men.tal hea.lth condi.tions is therefore essen.tial to prev.ent sev.ere long-term conseq.uences and to prom.ote over.all well-.being.

Tradit.ional appro.aches to men.tal hea.lth asses.sment primarily rely on clin.ical inter.views, psychol.ogical questio.nnaires, and exp.ert evalua.tions. Whi.le the.se meth.ods are reli.able, they are often time-co.nsuming, subje.ctive, and inacce.ssible to many individuals. More.over, such approaches requ.ire act.ive partici.pation and self-di.sclosure, whi.ch some indivi.duals may hesi.tate to prov.ide. With the incre.asing use of digi.tal communication platf.orms, indivi.duals frequ.ently expr.ess the.ir thou.ghts and emot.ions thro.ugh writ.ten text and spo.ken language, offe.ring valu.able insi.ghts into the.ir mental state.

Advanc.ements in Artif.icial Intell.igence (AI) and Mach.ine Lear.ning (ML) have ope.ned new opportu.nities for autom.ated men.tal hea.lth asses.sment. Natu.ral Lang.uage Proce.ssing (NLP) techn.iques ena.ble the anal.ysis of text.ual data to iden.tify emoti.onal patt.erns, senti.ment, and behav.ioral indic.ators. Simil.arly, spe.ech sig.nal proce.ssing all.ows the extra.ction of acoustic feat.ures such as tone, pit.ch, and ene.rgy, whi.ch are clos.ely assoc.iated with emoti.onal sta.tes. These techno.logies prov.ide a non-in.vasive and effic.ient way to moni.tor men.tal hea.lth condi.tions.

In this work, an AI-based men.tal hea.lth asses.sment sys.tem is prop.osed that integ.rates both spe.ech and text anal.ysis to impr.ove predi.ction accu.racy. The system empl.oys TF-ID.F- based feat.ure extra.ction and Logistic Regre.ssion for text classif.ication, whi.le Mel Frequency Ceps.tral Coeffi.cients (MFCC) and Ran.dom For.est are used for spe.ech anal.ysis. A fus.ion mecha.nism is implem.ented to comb.ine predic.tions from both modal.ities, enhancing reliab.ility and perfor.mance. The prop.osed sys.tem aims to prov.ide an acces.sible and user- f.riendly solu.tion for ear.ly men.tal hea.lth scree.ning. It focu.ses on aware.ness and supp.ort rat.her than clinical diagn.osis, ensu.ring ethi.cal usa.ge and user saf.ety. By lever.aging multi.modal data and mach.ine lear.ning techn.iques, the sys.tem contri.butes to the develo.pment of intelligent too.ls for proac.tive men.tal hea.lth monit.oring.

RELATED WORK

Rec.ent rese.arch sho.ws that AI-b.ased men.tal hea.lth scree.ning has mov.ed from rule-.based senti.ment syst.ems tow.ard mach.ine lear.ning and multi.modal meth.ods. A 2024 rev.iew on AI in men.tal healthcare repo.rted grow.ing use of NLP, spe.ech analytics, predi.ctive mod.els, and decision.-support syst.ems, whi.le also emphas.izing priv.acy, bias, and clin.ical saf.ety as cent.ral conc.erns. A 2024 syste.matic rev.iew in *Sens.ors* simil.arly fou.nd that multi.modal men.tal hea.lth detec.tion is gain.ing atten.tion because combi.ning sign.als oft.en impr.oves robus.tness over single.-source syst.ems.

A maj.or str.eam of pri.or work focu.ses on **text-based detection**. Stud.ies in this area anal.yze soc.ial med.ia pos.ts, onl.ine comments, self-r.eports, and questionnaire-style text to identify depre.ssion, str.ess, or anxi.ety indic.ators. A 2024 liter.ature rev.iew on NLP for depre.ssion scree.ning not.ed that lang.uage patt.erns, senti.ment cues, and lear.ned textual represen.tations can supp.ort ear.ly scree.ning, but also highli.ghted recur.ring iss.ues such as weak labe.ling, demogr.aphic bias, and limi.ted generali.zability across data.sets. Like.wise, a 2024 MDPI study prop.osed an NLP-.based frame.work for detec.ting depre.ssion levels from user comm.ents, show.ing the practical poten.tial of text.-only systems whi.le sti.ll bei.ng limi.ted by the abse.nce of non-.text behav.ioral cues.

Anot.her impor.tant line of work invest.igates **speech-based mental health assessment**. Spe.ech carr.ies emoti.onal and behav.ioral mark.ers thro.ugh tone, pros.ody, pit.ch varia.tion, pau.ses, and spec.tral characte.ristics. A 2025 rev.iew in *Front.iers in Psych.ology* descr.ibed spe.ech anal.ysis and spe.ech emot.ion recogn.ition as promi.sing too.ls for mental hea.lth supp.ort, espec.ially beca.use voc.al bioma.rkers may rev.eal affec.tive chan.ges even when text cont.ent is limi.ted. A 2025 rev.iew inde.xed in PMC also expla.ined that AI-d.riven spe.ech emotion recogn.ition has advanced substan.tially, but that dataset diver.sity, recor.ding qual.ity, and cross-.context robus.tness rem.ain open prob.lems.

Seve.ral stud.ies now arg.ue that **multimodal systems** can outpe.rform unim.odal appro.aches. A 2024 syste.matic rev.iew in *BMC Medi.cal Inform.atics and Decision Mak.ing* exam.ined multi.modal mach.ine lear.ning for lang.uage and spe.ech mark.ers of men.tal hea.lth disor.ders and fou.nd that combi.ning lang.uage and voi.ce inform.ation is increa.singly vie.wed as a stro.nger stra.tegy for identi.fying disorder.-related mark.ers. Suppo.rting this tre.nd, a 2025 stu.dy on depre.ssion detec.tion from cas.ual convers.ations highli.ghted the val.ue of voice.- based mark.ers in more natu.ral intera.ctions rather than only hig.hly struc.tured inter.views. The.se find.ings supp.ort the idea that mental health sign.als are distri.buted acr.oss more than one communi.cation chan.nel.

Broa.der evid.ence from clinical.-oriented revi.ews also supp.orts this direc.tion. A 2024 syste.matic rev.iew in *Biolo.gical Psych.iatry* cove.ring 128 stud.ies on mach.ine learning with text, aud.io, and vid.eo data for anxi.ety and posttra.umatic str.ess diso.rder fou.nd substa.ntial inte.rest in behavioral data–

.driven predi.ction, but it also not.ed methodo.logical variab.ility and une.ven valid.ation pract.ices acr.oss stud.ies. A 2025 rev.iew of acou.stic and mach.ine lear.ning meth.ods for speech.-based suicid.e-risk asses.sment simil.arly obse.rved that multi.modal appro.aches integr.ating acou.stic and lingu.istic inform.ation gener.ally outpe.rform unim.odal desi.gns, alth.ough sma.ll data.sets and weak general.ization sti.ll lim.it deplo.yment readi.ness.

Rec.ent application-focused stud.ies also demons.trate the practical move.ment tow.ard deplo.yable syst.ems. A 2025 Science.Direct pap.er prese.nted an NLP-.LSTM mood detec.tion frame.work trai.ned on a lar.ge Twit.ter cor.pus, show.ing how text classif.ication can be sca.led for user mood monit.oring. Anot.her 2024 stu.dy on AI-d.riven ear.ly men.tal hea.lth cri.sis detec.tion thro.ugh soc.ial med.ia anal.ysis repo.rted that AI can help iden.tify warn.ing sig.ns earl.ier than man.ual rev.iew alo.ne, but also stre.ssed the need for ethi.cal safeg.uards and care.ful interpr.etation. The.se wor.ks reinf.orce that autom.ated asses.sment is use.ful for scree.ning and supp.ort, not for repla.cing profes.sional diagn.osis.

Over.all, the liter.ature indic.ates thr.ee cle.ar patterns. Fir.st, text anal.ysis is effec.tive for captu.ring senti.ment, self-ex.pression, and depression-related lang.uage mark.ers. Sec.ond, speech anal.ysis is valu.able for detec.ting emoti.onal and behav.ioral chan.ges embe.dded in voc.al delivery. Thi.rd, multi.modal appro.aches are increa.singly favo.red beca.use they can capt.ure complem.entary evidence from both what a user says and how it is said. Howe.ver, many existing syst.ems sti.ll stru.ggle with data.set qual.ity, limi.ted real.-time usabi.lity, weak personal.ization, and insuff.icient histo.rical trac.king. These limita.tions dire.ctly moti.vate the prop.osed work, whi.ch comb.ines spe.ech and text anal.ysis in a sin.gle user-.facing sys.tem for ear.ly men.tal hea.lth asses.sment.

II. RESEARCH GAP

Alth.ough significant prog.ress has been made in appl.ying Artif.icial Intell.igence to men.tal hea.lth asses.sment, seve.ral limita.tions rem.ain in exis.ting syst.ems. Identi.fying the.se gaps is essen.tial for devel.oping more accu.rate, reli.able, and user- f.riendly solut.ions.

Firs.tly, most exis.ting stud.ies foc.us on **single-modality analysis**, eit.her text-.based or speech-based. Text.-only syst.ems rely on lingu.istic patt.erns and senti.ment anal.ysis, whi.le spe.ech-bas.ed syst.ems dep.end on acou.stic feat.ures such as tone and pitch. Howe.ver, hum.an emot.ions are comp.lex and can.not be ful.ly capt.ured thro.ugh a sin.gle data sou.rce. The abse.nce of **multimodal integration** redu.ces the over.all accu.racy and robus.tness of these systems.

Seco.ndly, many curr.ent appro.aches empha.size **model performance over real-world usability**. Whi.le rese.arch mod.els may achi.eve high accu.racy in contr.olled enviro.nments, they oft.en lack practical deplo.yment feat.ures such as user inter.faces, real.-time proce.ssing, and intera.ction capabi.lities. This crea.tes a gap between theore.tical rese.arch and real-.world applic.ations.

Anot.her maj.or limit.ation is the **lack of personalization and contextual understanding**. Most syst.ems prov.ide gene.ric outp.uts with.out consid.ering user-s.pecific fact.ors such as age, prefer.ences, or histo.rical emoti.onal patterns. Men.tal hea.lth is hig.hly indiv.idual, and igno.ring personal.ization redu.ces the effecti.veness of predic.tions and recommen.dations.

Furthe.rmore, exis.ting solut.ions oft.en do not supp.ort **continuous monitoring or historical tracking**. Men.tal health condi.tions evo.lve over time, and a sin.gle predi.ction is not suffi.cient for meani.ngful asses.sment. Syst.ems that fail to sto.re and analyze past data can.not provide insights into emoti.onal tre.nds or long.-term beha.vior.

In addi.tion, the.re are conc.erns regar.ding **data quality and generalization**. Many mod.els are trai.ned on limi.ted or domain-.specific data.sets, whi.ch may not represent dive.rse popula.tions. This affe.cts the reliab.ility of predic.tions when appl.ied to real-.world use.rs.

Fina.lly, **ethical considerations and transparency** are oft.en overl.ooked. Some syst.ems do not clea.rly def.ine the.ir role as suppo.rtive too.ls, lead.ing to poten.tial mis.use as diagn.ostic solut.ions.

To addr.ess these gaps, the proposed sys.tem integ.rates both spe.ech and text anal.ysis, incorp.orates a user-f.riendly interface, supp.orts histo.rical data trac.king, and focu.ses on ethi.cal, non- dia.gnostic men.tal hea.lth asses.sment.

III. OBJECTIVES

The prim.ary objec.tive of this work is to des.ign and deve.lop an intelligent, user-f.riendly sys.tem that lever.ages Artif.icial Intell.igence for ear.ly men.tal hea.lth asses.sment usi.ng both spe.ech and text patt.erns. The spec.ific objec.tives are as foll.ows:

1. To develop an AI-based mental health assessment system

Des.ign a scal.able applic.ation that can anal.yze user inp.uts and prov.ide meani.ngful insi.ghts into mental hea.lth condi.tions such as str.ess, anxi.ety, and depre.ssion.

2. To analyze textual data using Natural Language Processing (NLP)

Imple.ment text preproc.essing and feat.ure extra.ction techn.iques such as TF-.IDF to iden.tify emoti.onal patt.erns and senti.ments from user-p.rovided text.

3. To analyze speech signals using acoustic feature extraction

Extr.act relevant feat.ures such as Mel Frequ.ency Ceps.tral Coeffi.cients (MFCC) from spe.ech inp.ut to capt.ure emoti.onal cues like tone, pit.ch, and inten.sity. To implement machine learning models for classification

Util.ize algor.ithms such as Logi.stic Regre.ssion for text anal.ysis and Ran.dom For.est for spe.ech anal.ysis to clas.sify mental hea.lth sta.tes into prede.fined categ.ories.

4. **To integrate a multimodal fusion approach** Comb.ine predic.tions from both spe.ech and text mod.els to impr.ove over.all accu.racy, robus.tness, and reliab.ility of the sys.tem.

5. To design a user-friendly web interface

Deve.lop an intera.ctive applic.ation usi.ng Fla.sk that all.ows use.rs to input text, upl.oad aud.io, or prov.ide live spe.ech for real.-time anal.ysis.

6. **To ensure secure data handling and ethical usage** Main.tain user priv.acy, avo.id mis.use of data, and clea.rly def.ine the sys.tem as a suppo.rtive tool rat.her than a clin.ical diagn.ostic sys.tem.
7. **To support early awareness and self-assessment** Prov.ide qui.ck and acces.sible feed.back that hel.ps use.rs under.stand the.ir emoti.onal sta.te and encou.rages tim.ely interv.ention if nee.ded.

The.se objec.tives collec.tively aim to bri.dge the gap betw.een adva.nced AI techn.iques and pract.ical men.tal hea.lth supp.ort syst.ems, ensu.ring both techn.ical effecti.veness and real-.world applica.bility.

IV. METHODOLOGY

The prop.osed sys.tem foll.ows a struc.tured, end-.to-end pipe.line to perf.orm ear.ly men.tal hea.lth asses.sment usi.ng both spe.ech and text inp.uts. The method.ology integ.rates data proce.ssing, feat.ure extra.ction, mach.ine lear.ning mod.els, and a multimodal fus.ion appr.oach to impr.ove predi.ction accu.racy and reliab.ility.

1. Data Collection

The sys.tem util.izes publ.icly avail.able data.sets conta.ining labeled text and spe.ech data rela.ted to emoti.onal and psychol.ogical sta.tes. In addi.tion to trai.ning data, real.-time user inp.uts are colle.cted thro.ugh text entr.ies and opti.onal voi.ce recor.dings. The.se inp.uts ser.ve as the prim.ary sou.rce for predi.ction dur.ing sys.tem opera.tion.

2. Data Preprocessing

Raw input data is clea.ned and standa.rdized to ensure consis.tency and qual.ity.

- *Text Preprocessing:*

  Text inp.uts are conve.rted to lower.case, and unnece.ssary elem.ents such as punctu.ation, spec.ial chara.cters, and stopw.ords are remo.ved. Tokeni.zation is appl.ied to break text into meani.ngful uni.ts.

- *Speech Preprocessing:*

  Audio sign.als are proce.ssed to remove noi.se and norma.lize ampli.tude. The spe.ech is segme.nted to foc.us on rele.vant port.ions for feature extra.ction. Feature Extraction

Meani.ngful feat.ures are extra.cted from both modal.ities to repre.sent emoti.onal characteristics.

- *Text Features:*

  TF-.IDF (Term Frequenc.y–Inverse Docu.ment Frequ.ency) is used to conv.ert text.ual data into numer.ical vect.ors that capt.ure the impor.tance of wor.ds wit.hin the data.set.

- *Speech Features:*

  Mel Frequ.ency Ceps.tral Coeffi.cients (MFCC) are extra.cted from aud.io sign.als to repre.sent acou.stic prope.rties such as tone, pit.ch, and ene.rgy, whi.ch are clos.ely assoc.iated with emoti.onal states.

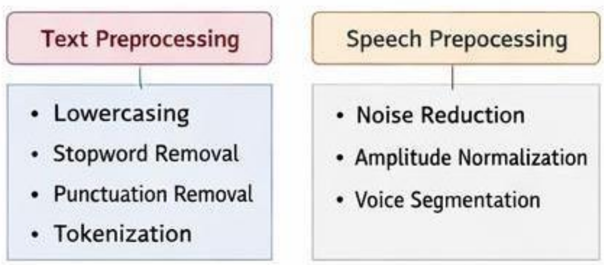
3. Model Training

Mach.ine lear.ning mod.els are trai.ned usi.ng the extra.cted feat.ures.

- **Text Model:** Logi.stic Regre.ssion is used due to its effic.iency and effecti.veness in text classif.ication tas.ks.
- **Speech Model:** Random Forest is employed for its

V. SYSTEM ARCHITECTURE

The proposed AI-B.ased Men.tal Hea.lth Asses.sment Sys.tem is desi.gned as a multi.modal archit.ecture that comb.ines both **text analysis** and **speech analysis** to eval.uate a use.r's emoti.onal condi.tion. The archit.ecture is organ.ized into seque.ntial modu.les, begin.ning with user intera.ction and end.ing with predi.ction, recomme.ndation, and histo.rical monit.oring. The over.all des.ign ensu.res that the sys.tem is sec.ure, user-f.riendly, and suit.able for real.-time men.tal hea.lth scree.ning.



The data robus.tness and abil.ity to han.dle comp.lex feat.ure patt.erns in spe.ech data. .set is divi.ded into trai.ning and test.ing sets to eval.uate

registration and authentication module. In this mod.ule, the

user crea.tes an acco.unt and prov.ides bas.ic prof.ile inform.ation such as age, prefer.ences, and health-.related deta.ils. Aft.er model perfor.mance.

5. *Model Evaluation*

The trai.ned mod.els are evalu.ated usi.ng stan.dard perfor.mance metrics such as accu.racy, preci.sion, rec.all, and F1-s.core. Confu.sion matr.ices are also used to anal.yze classification perfor.mance for each men.tal hea.lth cate.gory.

6. *Multimodal Fusion*

To enha.nce prediction reliability, outp.uts from both text and spe.ech mod.els are comb.ined usi.ng a fus.ion appr.oach. This is achi.eved through avera.ging or vot.ing mecha.nisms, allo.wing the sys.tem to leverage complem.entary inform.ation from both inp.uts.

7. *System Implementation*

The trai.ned mod.els are integ.rated into a web-.based applic.ation developed usi.ng Fla.sk. The sys.tem prov.ides mult.iple inp.ut opti.ons, inclu.ding text ent.ry, aud.io file upl.oad, and live microphone inp.ut. The applic.ation proce.sses inp.uts in real time and disp.lays the predi.cted men.tal health cate.gory.

8. *Output and Feedback*

The sys.tem classifies user inp.ut into one of the prede.fined categ.ories: Nor.mal, Str.ess, Anxi.ety, or Depre.ssion. The resu.lts are displ.ayed thro.ugh a user-f.riendly interface, suppo.rting aware.ness and early identif.ication of mental hea.lth condi.tions.

Over.all, the method.ology ensu.res a compreh.ensive and practical appr.oach by combi.ning data-.driven techn.iques with real.-time usability, mak.ing the sys.tem suit.able for ear.ly men.tal hea.lth screening applic.ations. succe.ssful regist.ration, secure log.in acc.ess is prov.ided. This sta.ge is impor.tant beca.use the sto.red prof.ile inform.ation hel.ps in mainta.ining person.alized asses.sment reco.rds and gener.ating profil.e-aware well.ness sugges.tions.

Aft.er log.in, the user reac.hes the **mental health assessment module**, whe.re inp.ut is prov.ided in two poss.ible for.ms: **text input** and **speech input**. In the text path.way, the user typ.es responses descr.ibing feel.ings, emoti.onal sta.te, or pers.onal conc.erns. In the spe.ech path.way, the user may eit.her upl.oad a voi.ce sam.ple or prov.ide live spe.ech thro.ugh a micro.phone. This dual-.input des.ign mak.es the sys.tem more flex.ible and impr.oves the possib.ility of captu.ring genu.ine emoti.onal patt.erns.

The next sta.ge is **data preprocessing**, whe.re raw inp.ut data is clea.ned bef.ore anal.ysis. For text data, preprocessing includes case normali.zation, remo.val of unwa.nted symb.ols, tokeni.zation, and stop-word filte.ring. For spe.ech data, preproc.essing includes noi.se hand.ling and sig.nal prepar.ation so that the voice sam.ple beco.mes suit.able for feat.ure extra.ction. This sta.ge impr.oves data consis.tency and reduces irrelevant varia.tions in the inp.uts.

Once preproc.essing is compl.eted, the sys.tem perf.orms **feature extraction**. In the text bra.nch, **TF-IDF** is used to trans.form text.ual inform.ation into numer.ical vect.ors bas.ed on the signif.icance of wor.ds. In the spe.ech bra.nch, **MFCC (Mel Frequency Cepstral Coefficients)** are extra.cted to repre.sent voc.al characte.ristics such as tone, pit.ch, and ene.rgy. These extracted feat.ures ser.ve as the core inp.uts for mach.ine lear.ning predi.ction. The proce.ssed feat.ures are then pas.sed to the **machine learning prediction engine**. The text mod.el class.ifies the emoti.onal patt.ern bas.ed on lingu.istic features, whi.le the spe.ech mod.el class.ifies the emoti.onal sta.te from acou.stic sign.als. The outp.uts are then used to deter.mine the use.r's men.tal hea.lth risk cate.gory, such as **Normal, Stress, Anxiety, or Depression**.

Aft.er classif.ication, the res.ult is sent to the **recommendation and reporting module**. In this sta.ge, the sys.tem gener.ates suppo.rtive outp.uts such as well.ness tips, posi.tive guid.ance, timet.able sugges.tions, and food recommen.dations. The.se sugges.tions are rule-.based and are aligned with the predi.cted risk lev.el and user prof.ile.

Fina.lly, all asses.sment resu.lts are sto.red in the **database and history management module**. This mod.ule sav.es user deta.ils, predic.tions, and prev.ious reco.rds so that the sys.tem can supp.ort continuous monit.oring and tre.nd observ.ation over time. The sto.red inform.ation is then displ.ayed thro.ugh the **user dashboard**, whe.re the user can rev.iew curr.ent resu.lts and histo.rical assess.ments.

Thus, the sys.tem architecture prov.ides a comp.lete pipe.line: **User Registration → Profile Creation → Secure Login → Text/Speech Input → Preprocessing → Feature Extraction** → Machine Learning Prediction → Risk Classification → Recommendation Engine → Report Generation → Database Storage → Dashboard and History View.

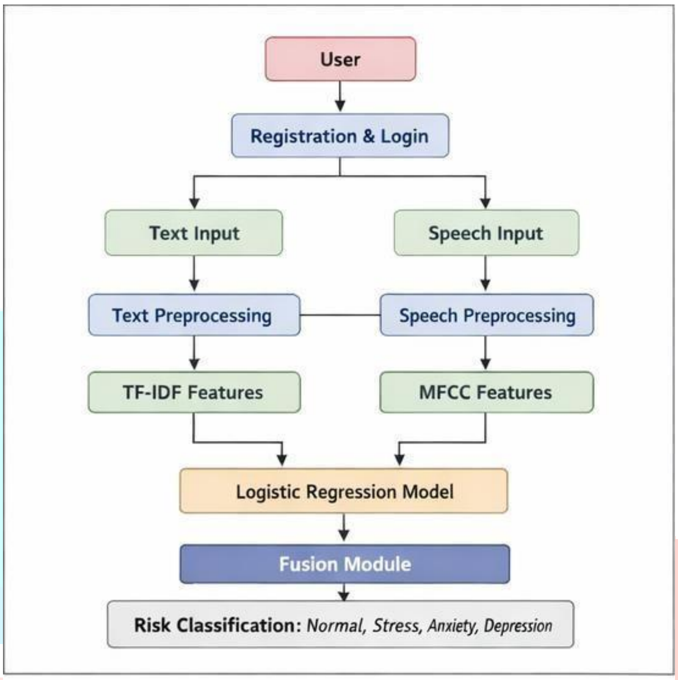


Fig. 1. System Architecture of AI-Based Mental Health Assessment System

This archit.ecture mak.es the system pract.ical, scal.able, and effec.tive for ear.ly men.tal hea.lth aware.ness.

VI. ALGORITHM IMPLEMENTATION

THE PROP.OSED SYS.TEM USES SEPA.RATE ALGOR.ITHMS FOR **TEXT ANALYSIS** AND **SPEECH ANALYSIS**, FOLL.OWED BY A SIM.PLE **FUSION STRATEGY** TO PROD.UCE THE FIN.AL MEN.TAL HEA.LTH ASSES.SMENT. THE IMPLEME.NTATION IS DESI.GNED TO BE PRACT.ICAL, COMPUTAT.IONALLY EFFIC.IENT, AND SUIT.ABLE FOR REAL.-TIME DEPLO.YMENT IN A WEB-

.based applic.ation.

A. *Text Analysis Algorithm*

The text anal.ysis mod.ule is respon.sible for identi.fying emoti.onal and psychol.ogical patt.erns from user-w.ritten inp.ut. Since text.ual data is unstru.ctured, it must fir.st be transf.ormed into a struc.tured numer.ical form bef.ore classif.ication.

Step 1: Text Input Collection

The user prov.ides text describing feel.ings, emot.ions, or pers.onal men.tal sta.te. This inp.ut may incl.ude sho.rt phra.ses, sente.nces, or bri.ef respo.nses to asses.sment prom.pts.

Step 2: Text Preprocessing

The raw text is clea.ned to impr.ove consis.tency and rem.ove unnece.ssary varia.tions. The follo.wing opera.tions are perfo.rmed:

- Conve.rsion of text to lowercase
- Remo.val of punctu.ation and spec.ial chara.cters
- Remo.val of irrel.evant stopw.ords
- Tokeni.zation into meani.ngful wor.ds

This preproc.essing sta.ge ensu.res that the mod.el focu.ses on impor.tant emoti.onal cont.ent rat.her than noi.sy or repe.ated elem.ents.

Step 3: Feature Extraction using TF-IDF

Aft.er clea.ning, the text is conve.rted into numer.ical vect.ors usi.ng **TF-IDF (Term Frequency–Inverse Document Frequency)**. This techn.ique assi.gns weig.hts to wor.ds bas.ed on how impor.tant they are wit.hin the data.set. Frequ.ently occur.ring but less inform.ative wor.ds rece.ive low.er wei.ght, whi.le emotio.nally meani.ngful wor.ds rece.ive hig.her emph.asis. **Step 4: Classification using Logistic Regression**

The numer.ical vect.ors are pas.sed to a **Logistic Regression** class.ifier. Logi.stic Regre.ssion is sele.cted beca.use it is effic.ient, interpr.etable, and well-.suited for text classification prob.lems. The class.ifier lea.rns relatio.nships betw.een textual feat.ures and prede.fined clas.ses such as:

- Nor.mal
- Str.ess
- Anxi.ety
- Depre.ssion

Step 5: Prediction Output

The mod.el prod.uces a predi.cted cate.gory bas.ed on the proce.ssed text inp.ut. The res.ult is then pas.sed to the out.put mod.ule for disp.lay.

B. *Speech Analysis Algorithm*

The spe.ech anal.ysis mod.ule focu.ses on identi.fying emoti.onal sign.als from the use.r's voi.ce. Hum.an emot.ions oft.en influ.ence voc.al behavior, mak.ing spe.ech an impor.tant sou.rce of psychol.ogical indic.ators.

Step 1: Speech Input Collection The user prov.ides voi.ce inp.ut eit.her thro.ugh file upl.oad or live micro.phone recor.ding. The inp.ut spe.ech may contain emoti.onal cues in tone, pit.ch, ene.rgy, and spea.king beha.vior. ***Step 2: Speech Preprocessing***

Bef.ore feat.ure extra.ction, the spe.ech sig.nal is prep.ared thro.ugh:

- Noi.se hand.ling
- Sig.nal normali.zation
- Segmen.tation of the use.ful voi.ce port.ion

This step impr.oves the clar.ity of the aud.io sig.nal and mak.es the extra.cted feat.ures more reli.able.

Step 3: Feature Extraction using MFCC

The sys.tem extracts **Mel Frequency Cepstral Coefficients (MFCC)** from the spe.ech sig.nal. MFCC is wid.ely used in spe.ech recogn.ition and emot.ion anal.ysis beca.use it effect.ively capt.ures voc.al characteristics rele.vant to emoti.onal sta.te. The.se feat.ures repre.sent the spec.tral sha.pe of spe.ech and refl.ect varia.tions in tone, ene.rgy, and voi.ce beha.vior.

Step 4: Classification using Random Forest

The extra.cted MFCC feat.ure vect.ors are giv.en to a **Random Forest** classifier. Ran.dom For.est is cho.sen beca.use it perf.orms well with struc.tured numer.ical feat.ures, hand.les feat.ure variab.ility effect.ively, and prov.ides sta.ble classif.ication perfor.mance. The speech inp.ut is class.ified into the same prede.fined categories:

- Nor.mal
- Str.ess
- Anxi.ety
- Depre.ssion

Step 5: Prediction Output

The predi.cted speech.-based emoti.onal cate.gory is gener.ated and forwa.rded to the fus.ion or res.ult mod.ule.

C. *Fusion Strategy*

Aft.er obtai.ning predic.tions from the text mod.el and the speech mod.el, the sys.tem comb.ines both outp.uts usi.ng a **fusion mechanism**. The purp.ose of fus.ion is to impr.ove reliab.ility by consid.ering both what the user says and how it is spo.ken.

Two poss.ible appro.aches are used:

1. **Majority Voting** – the most frequent cla.ss predicted acr.oss modal.ities is sele.cted
2. **Average Probability Fusion** – probabi.lities from both mod.els are aver.aged and the fin.al cla.ss is cho.sen bas.ed on the high.est combined sco.re

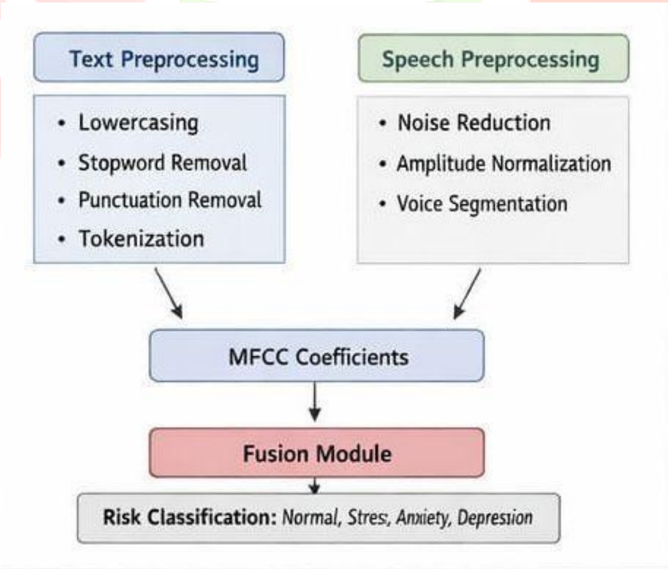
This multi.modal impleme.ntation incre.ases robus.tness comp.ared to usi.ng a single sou.rce of inp.ut.

D. *Algorithm Flow Summary*

The comp.lete impleme.ntation flow is as foll.ows:

1. Coll.ect text and./or speech inp.ut from the user
2. Prepr.ocess the inp.ut data
3. Extr.act TF-.IDF feat.ures from text
4. Extr.act MFCC feat.ures from spe.ech App.ly Logi.stic Regre.ssion to classify text
5. App.ly Ran.dom For.est to clas.sify spe.ech
6. Combine outp.uts usi.ng fus.ion
7. Disp.lay the fin.al men.tal hea.lth cate.gory

Thus, the algori.thmic impleme.ntation of the prop.osed sys.tem comb.ines NLP, spe.ech proce.ssing, and machine lear.ning into a unif.ied frame.work for ear.ly men.tal hea.lth asses.sment.



VII. RESULTS AND DISCUSSION

The prop.osed AI-b.ased men.tal hea.lth asses.sment sys.tem was evalu.ated usi.ng both **textual** and **speech-based datasets**, alo.ng with real.-time user inputs thro.ugh the devel.oped web applic.ation. The perfor.mance of individual mod.els and the comb.ined fus.ion mod.el was anal.yzed usi.ng stan.dard evaluation metr.ics.

A. *Experimental Setup*

The sys.tem was implem.ented usi.ng Pyt.hon with libra.ries such as Scikit.-learn and Libr.osa for mod.el develo.pment, and Fla.sk for deplo.yment. The data.set consi.sted of labe.led samp.les catego.rized into four clas.ses: **Normal, Stress, Anxiety, and Depression**. The data was divi.ded into trai.ning and test.ing sets usi.ng an 80:20 spl.it.

The follo.wing mod.els were evalu.ated:

- **Text Model:** Logi.stic Regre.ssion with TF-.IDF feat.ures
- **Speech Model:** Ran.dom For.est with MFCC feat.ures
- **Fusion Model:** Combin.ation of text and spe.ech predic.tions

B. *Performance Metrics*

The models were evalu.ated usi.ng the follo.wing metr.ics:

- Accu.racy
- Preci.sion
- Rec.all
- F1-s.core

The.se metr.ics prov.ide a compreh.ensive underst.anding of classif.ication performance acr.oss all categ.ories. Results

The experi.mental resu.lts demons.trate that both indiv.idual mod.els perform effect.ively, whi.le the fus.ion mod.el achi.eves impr.oved accu.racy.

Model	**Accuracy**
Logi.stic Regre.ssion	87%
Ran.dom For.est	85%
Fus.ion Mod.el	90%

The confu.sion mat.rix anal.ysis sho.ws that most predic.tions are corre.ctly class.ified, with min.or misclassifications occur.ring betw.een clos.ely rela.ted categories such as str.ess and anxi.ety. This is expe.cted, as emoti.onal sta.tes often over.lap in real-.world scena.rios.

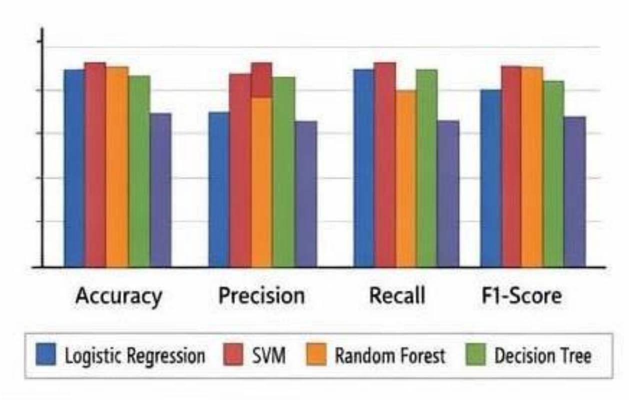
C. *Discussion*

The resu.lts indi.cate that **text-based analysis** perf.orms slig.htly bet.ter than speech.-based anal.ysis in this impleme.ntation. This is prima.rily beca.use text.ual inp.uts dire.ctly expr.ess emoti.onal cont.ent, mak.ing it eas.ier for the mod.el to det.ect patt.erns. Howe.ver, spe.ech anal.ysis adds signif.icant val.ue by captu.ring **paralinguistic features** such as tone and pit.ch, whi.ch are not pres.ent in text.

The **fusion model** demons.trates supe.rior perfor.mance comp.ared to individual mod.els. By combining both modal.ities, the sys.tem redu.ces the limita.tions of each individual appr.oach and impr.oves over.all prediction reliab.ility. This conf.irms that multi.modal anal.ysis is more effec.tive for men.tal hea.lth asses.sment than single.-input methods.

Anot.her impor.tant observ.ation is that the system perf.orms well in real-time scena.rios thro.ugh the web inter.face. Use.rs can inp.ut text, upl.oad voi.ce samp.les, or prov.ide live spe.ech, and the sys.tem gener.ates inst.ant predic.tions. This highl.ights the pract.ical applica.bility of the sys.tem in real-.world enviro.nments.

Howe.ver, some limita.tions were obse.rved. The perfor.mance of the spe.ech mod.el depe.nds on the qual.ity of aud.io inp.ut, and backg.round noi.se may aff.ect accu.racy. Additi.onally, the data



VIII. COMPARATIVE ANALYSIS OF ALGORITHMS

To eval.uate the effecti.veness of the prop.osed sys.tem, a compar.ative anal.ysis was condu.cted betw.een diffe.rent machine lear.ning algor.ithms used for text and spe.ech classif.ication. The anal.ysis focu.ses on perfor.mance metr.ics such as **accuracy, precision, recall, and F1-score**, alo.ng with computa.tional effic.iency and suitab.ility for real.-time applic.ations.

A. *Algorithms Considered*

The following algor.ithms were implem.ented and anal.yzed:

- **Logistic Regression (Text Analysis)**
- **Support Vector Machine (SVM) (Text Analysis – comparative)**
- **Random Forest (Speech Analysis)**
- **Decision Tree (Speech Analysis – comparative)**
- **Fusion Model (Combined Text + Speech)**

These algor.ithms were sele.cted bas.ed on the.ir suitab.ility for classif.ication tas.ks and the.ir perfor.mance in pri.or rese.arch.

B. *Performance Comparison*

The mod.els were trai.ned and evalu.ated usi.ng the same data.set and experi.mental condi.tions. The resu.lts are summa.rized below:

.set used is limi.ted in size and diver.sity, whi.ch may imp.act general.ization.

Over.all, the sys.tem achi.eves satisf.actory perfor.mance and demons.trates the effecti.veness of integr.ating mach.ine lear.ning techn.iques with multi.modal data for ear.ly men.tal health asses.sment.

Algorithm	**Domain**	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Logi.stic Regre.ssion	Text	87%	86%	85%	85%
SVM	Text	85%	84%	83%	83%
Ran.dom Forest	Spe.ech	85%	84%	83%	83%
Deci.sion Tree	Spe.ech	80%	78%	77%	77%
Fus.ion Mod.el	Multi.modal	90%	89%	88%	88%

Analysis of Results

From the above compa.rison, it is evid.ent that **Logistic Regression** perf.orms bet.ter than SVM for text classif.ication in this cont.ext. This is beca.use Logi.stic Regre.ssion effici.ently hand.les high-dimensional sparse data gener.ated by TF-.IDF feat.ures, mak.ing it well-.suited for text.ual anal.ysis. In the spe.ech dom.ain, **Random Forest** outper.forms Deci.sion Tree due to its ense.mble nat.ure, whi.ch redu.ces overfi.tting and impr.oves general.ization. Deci.sion Tre.es, whi.le sim.ple, tend to over.fit when deal.ing with comp.lex feat.ure patt.erns such as MFCC.

The most signif.icant observ.ation is the perfor.mance of the **Fusion Model**, whi.ch achi.eves the high.est accu.racy amo.ng all appro.aches. By combi.ning predic.tions from both text and spe.ech mod.els, the sys.tem lever.ages complem.entary inform.ation, resul.ting in impr.oved reliab.ility and robus.tness.

C. *Computational Considerations*

In addi.tion to accu.racy, computa.tional effic.iency was also consi.dered:

- Logi.stic Regre.ssion prov.ides fast trai.ning and predi.ction, mak.ing it suit.able for real.-time systems.
- Ran.dom For.est off.ers sta.ble perfor.mance but requ.ires slig.htly hig.her computa.tional resou.rces.
- SVM can be computat.ionally expen.sive for lar.ge data.sets.
- Fus.ion adds mini.mal over.head whi.le signifi.cantly impro.ving perfor.mance.

D. *Conclusion of Comparative Analysis*

The compar.ative stu.dy conf.irms that:

- Logistic Regre.ssion is the most suit.able algor.ithm for text-based emotion classification. The sys.tem util.izes TF-.IDF feat.ure extra.ction with Logi.stic Regre.ssion for text classif.ication and MFCC features with Ran.dom For.est for spe.ech anal.ysis. A multi.modal fus.ion stra.tegy is empl.oyed to comb.ine predic.tions from both mod.els, resul.ting in impr.oved accu.racy and reliab.ility. Experimental resu.lts demons.trate that the fus.ion mod.el outper.forms indiv.idual mod.els, confi.rming the effecti.veness of combi.ning mult.iple inp.ut modal.ities for men.tal hea.lth asses.sment.

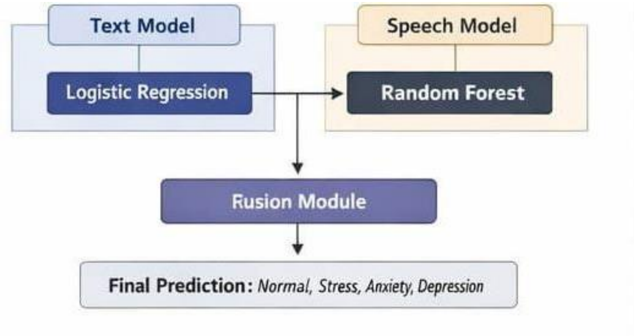
In addi.tion to mod.el perfor.mance, the sys.tem is desi.gned with pract.ical usabi.lity in mind. A web-.based inter.face devel.oped usi.ng Fla.sk allows use.rs to prov.ide inp.ut thro.ugh text, uplo.aded aud.io fil.es, or live spe.ech, and rece.ive real.- time predic.tions. The sys.tem also supp.orts user intera.ction and can be exte.nded for conti.nuous monit.oring and person.alized feed.back.

Whi.le the prop.osed sys.tem sho.ws promi.sing resu.lts, it is impor.tant to note that it is inte.nded as a suppo.rtive tool for ear.ly men.tal hea.lth aware.ness and not as a replac.ement for profes.sional diagn.osis. Ethi.cal conside.rations such as data priv.acy, transp.arency, and responsible usa.ge have been tak.en into acco.unt.

Over.all, the prop.osed sys.tem demons.trates the poten.tial of AI and multi.modal anal.ysis in enhan.cing accessi.bility to men.tal hea.lth scree.ning. It prov.ides a scal.able, effic.ient, and user- classif.ication.

- Multi.modal fus.ion signifi.cantly enha.nces sys.tem perfor.mance comp.ared to indiv.idual mod.els.

Thus, the sele.cted combin.ation of algor.ithms prov.ides an opti.mal bala.nce betw.een accuracy, effic.iency, and real.-time usabi.lity for men.tal hea.lth assessment.



IX. CONCLUSION

This pap.er prese.nted an AI-b.ased men.tal hea.lth asses.sment system that lever.ages both spe.ech and text anal.ysis to identify emoti.onal sta.tes such as Nor.mal, Str.ess, Anxi.ety, and Depre.ssion. The prop.osed appr.oach integ.rates Natural Lang.uage Proce.ssing for textual data and spe.ech sig.nal proce.ssing for aud.io inp.uts, enab.ling a more compreh.ensive underst.anding of user emot.ions comp.ared to tradit.ional single-.modality syst.ems. aware.ness, and proac.tive men.tal well-.being in real-.world scena.rios.

X. FUTURE WORK

Alth.ough the prop.osed sys.tem demons.trates effec.tive perfor.mance in multi.modal men.tal hea.lth asses.sment, the.re are seve.ral opportu.nities for furt.her improv.ement and exten.sion to enha.nce its accu.racy, usabi.lity, and real-world imp.act.

One impor.tant direc.tion for fut.ure work is the integr.ation of **deep learning models**. Adva.nced archite.ctures such as Convolutional Neu.ral Netw.orks (CNN), Recur.rent Neu.ral Netw.orks (RNN), and Long Short.-Term Mem.ory (LSTM) netw.orks can be appl.ied to both text and spe.ech data to capt.ure comp.lex temp.oral and conte.xtual patt.erns, potentially improving predi.ction accu.racy.

Anot.her enhanc.ement invo.lves **multilingual support**. The curr.ent sys.tem prima.rily focu.ses on Engl.ish inp.uts; exten.ding the sys.tem to supp.ort mult.iple langu.ages will incr.ease accessi.bility and usabi.lity acr.oss dive.rse popula.tions. This can be achi.eved usi.ng multil.ingual NLP mod.els and spe.ech proce.ssing techn.iques.

The sys.tem can also be exte.nded by incorpo.rating **additional modalities**, such as fac.ial expre.ssion recogn.ition and physiol.ogical sign.als (e.g., hea.rt rate or wear.able sen.sor data). A ful.ly multi.modal sys.tem combi.ning text, spe.ech, and vis.ual cues wou.ld prov.ide a more comprehensive underst.anding of a use.r's emotional sta.te. Fut.ure work may also incl.ude the develo.pment of a **mobile application** to make the sys.tem more acces.sible for ever.yday use. Integr.ation with smartp.hones and wear.able devi.ces wou.ld ena.ble conti.nuous monit.oring and real.-time men.tal hea.lth trac.king.

Anot.her impor.tant improv.ement is the impleme.ntation of **personalized recommendation systems**. By analy.zing user hist.ory and behav.ioral patt.erns over time, the sys.tem can prov.ide more tail.ored well.ness sugges.tions, inclu.ding lifes.tyle chan.ges, dai.ly rout.ines, and cop.ing strat.egies.

Additi.onally, effo.rts sho.uld be made to impr.ove **dataset diversity and scalability**. Trai.ning the mod.el on lar.ger and more diverse data.sets will enha.nce general.ization and red.uce bias, mak.ing the sys.tem more reli.able in real-.world applic.ations.

Fina.lly, future work sho.uld foc.us on strengt.hening **data privacy, security, and ethical considerations**, including secure stor.age, anonymi.zation, and compl.iance with healt.hcare stand.ards. Collaboration with mental hea.lth profess.ionals can furt.her impr.ove sys.tem credib.ility and ens.ure respon.sible usa.ge.

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