IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

A Hybrid Machine Learning and Deep Learning Framework for Fertility Prediction Using Clinical and Ultrasound Data

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Doi: https://doi.org/10.56975/ijcrt.v14i7.309988

Abstract Infertility is a complicated health issue that involves numerous complex relations between several different physiological, hormonal, and even lifestyle variables. The traditional means of diagnosing infertility include separate testing and manual image analysis that can be inconsistent and time-consuming. In order to overcome these drawbacks, this paper proposes a hybrid Artificial Intelligence (AI) model for predicting fertility status that will incorporate techniques of Machine Learning (ML) and Deep Learning (DL).

For the purposes of the proposed algorithm, a clinical dataset containing 23 parameters will be used. These parameters will include the values of female fertility indicators (FSH, LH, AMH, endometrium thickness), parameters related to male fertility (sperm count, morphology, motility), as well as lifestyle characteristics (smoking, alcohol intake, stress level, exercise habits). As for machine learning techniques, a Random Forest classifier will be used because of the ability to account for complicated feature interactions. As for the DL component, the Convolutional Neural Network will be used to detect such issues as healthy ovaries, cysts, and polycystic ovary syndrome based on ovarian ultrasound images.

In order to obtain superior predictive performance, a method of fusion between DL and ML components will be developed. Finally, the entire algorithm will be deployed on the basis of Flask framework in order to provide a real-time web-based inference. It will allow using patient information and uploading images to make a fertility prediction. The experimental results obtained with this hybrid approach proved its superiority over separate machine/deep learning approaches in terms of generalization and consistency.

Keyw.ords— Fertility Predi.ction, Hyb.rid Mach.ine Lear.ning Mod.el, Deep Learning, Ran.dom Forest Class.ifier, Convolu.tional Neu.ral Network, Medi.cal Ima.ge Anal.ysis, Ultra.sound Imag.ing, Predictive Healt.hcare, Clin.ical Deci.sion Supp.ort Sys.tem, Artif.icial Intell.igence in Healt.hcare, Feat.ure Fus.ion, Reprod.uctive Hea.lth Analy.tics

I Introduction

Infert.ility is a signif.icant glo.bal hea.lth conc.ern affec.ting mill.ions of coup.les world.wide. It is comm.only defi.ned as the inabi.lity to conceive aft.er one year of regular unprot.ected interc.ourse. Accor.ding to rec.ent repo.rts, nea.rly 15–20% of coup.les exper.ience fertilit.y-related iss.ues due to vari.ous biolo.gical, environ.mental, and lifes.tyle factors. Both male and fem.ale part.ners contr.ibute equa.lly to infert.ility, mak.ing it essen.tial to anal.yze mult.iple param.eters simulta.neously for accu.rate diagn.osis.

Tradit.ional ferti.lity asses.sment meth.ods rely on clin.ical examin.ations, horm.onal test.ing, sem.en anal.ysis, and ultra.sound imaging. Whi.le these appro.aches prov.ide valu.able insi.ghts, they are oft.en time-co.nsuming and requ.ire exp.ert interpr.etation. More.over, the.se meth.ods typic.ally anal.yze individual param.eters indepen.dently, with.out consid.ering the comp.lex relatio.nships betw.een diffe.rent ferti.lity fact.ors. This fragm.ented appr.oach can lead to inconsis.tencies in diagn.osis and del.ay in treat.ment plan.ning.

In recent yea.rs, Artif.icial Intell.igence (AI) has emer.ged as a powe.rful tool in healt.hcare, offe.ring impr.oved accu.racy and effic.iency in predi.ctive anal.ysis. Machine Lear.ning (ML) techn.iques are capa.ble of analy.zing lar.ge volu.mes of struc.tured data and identi.fying hid.den patt.erns that are not eas.ily detec.table thro.ugh conven.tional meth.ods. Algor.ithms such as Ran.dom Forest, Deci.sion Tre.es, and Supp.ort Vec.tor Mach.ines have been succes.sfully appl.ied in medi.cal prediction syst.ems.

At the same time, Deep Lear.ning (DL), particularly Convolutional Neural Networks (CNNs), has sho.wn remar.kable perfor.mance in medi.cal ima.ge anal.ysis. CNN mod.els can automat.ically extr.act spat.ial feat.ures from ima.ges and are wid.ely used for dise.ase detec.tion, classif.ication, and diagn.osis. In ferti.lity anal.ysis, ultra.sound imaging pla.ys a cruc.ial role in identi.fying ovar.ian conditions such as cys.ts and polycystic ova.ry synd.rome (PCOS). Howe.ver, man.ual interpr.etation of the.se ima.ges can be subje.ctive and pro.ne to err.or.

To over.come these limita.tions, this pap.er prop.oses a hyb.rid ferti.lity predi.ction sys.tem that integ.rates Mach.ine Lear.ning and Deep Lear.ning appro.aches. The sys.tem uses structured clin.ical data from both male and fem.ale part.ners alo.ng with ultra.sound ima.ges to generate accu.rate predic.tions. A Ran.dom For.est class.ifier is empl.oyed for analy.zing tabu.lar data, whi.le a Convolu.tional Neural Netw.ork is used for image.-based classif.ication.

The prop.osed sys.tem is implem.ented as a web-.based applic.ation usi.ng Fla.sk, enab.ling use.rs to inp.ut clinical data, upl.oad ultra.sound ima.ges, and rece.ive real.-time predic.tions alo.ng with recommen.dations. By combining mult.iple data sour.ces and adva.nced AI techn.iques, the sys.tem aims to prov.ide a reli.able and effic.ient solu.tion for ferti.lity asses.sment and deci.sion supp.ort.

II. RELATED WORK

Rec.ent adva.nces in reproductive medi.cine show that AI is increa.singly bei.ng used for ferti.lity asses.sment, ovar.ian imag.ing, IVF outc.ome predi.ction, and broa.der assi.sted reprod.uction workf.lows. Revi.ews publi.shed in 2025 rep.ort that AI applic.ations in assi.sted reprod.uction are expan.ding from emb.ryo selec.tion and cyc.le optimi.zation to outc.ome predi.ction, alth.ough adop.tion in rout.ine prac.tice sti.ll depe.nds on tru.st, transp.arency, and clin.ical integr.ation. (Front.iers)

A maj.or line of prior work focu.ses on **machine learning with structured clinical data**. The.se stud.ies use demogr.aphic, horm.onal, stimul.ation, and treatmen.t-related feat.ures to pred.ict infert.ility treat.ment succ.ess or ovar.ian resp.onse. A 2025 compar.ative stu.dy on ICSI outc.ome predi.ction usi.ng over 10,000 reco.rds and 46 clin.ical features repo.rted that Ran.dom For.est achi.eved the high.est AUC amo.ng the evalu.ated mod.els, highli.ghting the suitab.ility of ense.mble lear.ning for reprod.uctive tabu.lar data. (Science.Direct) Simil.arly, a 2024 stu.dy on ovar.ian stimul.ation resp.onse sho.wed that mach.ine lear.ning mod.els can supp.ort person.alized predi.ction of oocyte-related outc.omes usi.ng clin.ical and gene.tic varia.bles, reinfo.rcing the val.ue of featur.e-rich struc.tured data.sets in ferti.lity analy.tics. (Nat.ure) In addi.tion, rec.ent liter.ature reviews conc.lude that machine lear.ning is increa.singly effec.tive in predi.cting infert.ility treat.ment succ.ess, but mod.el generali.zability and data.set qual.ity rem.ain impor.tant conc.erns. (PMC)

A sec.ond maj.or direc.tion is **deep learning on medical images**, espec.ially ultra.sound. Beca.use ovar.ian morph.ology, foll.icle patt.erns, and cys.tic struc.tures are visu.ally inform.ative, CNN-.based meth.ods have bec.ome attra.ctive for autom.ated reprod.uctive imag.ing. A 2025 open-.access stu.dy intro.duced an ovar.ian ultra.sound data.set cove.ring nor.mal ova.ry, polyc.ystic ova.ry, and domi.nant follicle clas.ses, and demons.trated the feasib.ility of AI-po.wered ovarian-.condition diagn.osis from ultra.sound sca.ns. (PMC) Rela.ted work in 2023 prop.osed a deep lear.ning fus.ion frame.work for PCOS diagn.osis from ova.ry ultra.sound ima.ges, showing that autom.ated feat.ure extra.ction can impr.ove detec.tion of PCOS morph.ology. (Wil.ey Onl.ine Libr.ary) Other rec.ent stud.ies have also sho.wn that deep lear.ning and radio.mics from ultrasound ima.ges can estimate ovar.ian reserve indic.ators such as AFC and AMH, sugge.sting that image.-based mod.els can contr.ibute bey.ond sim.ple classif.ication. (Nat.ure) More broa.dly, ultrasou.nd-based deep lear.ning syst.ems have demons.trated str.ong clin.ical util.ity in ovar.ian imag.ing tas.ks, inclu.ding autom.ated assis.tance for ovar.ian tum.or diagn.osis, whi.ch supp.orts the wid.er applica.bility of CNN-.based anal.ysis in gyneco.logic imag.ing. (Spri.nger)

Anot.her emer.ging the.me is **hybrid and multimodal modeling**, whe.re struc.tured clin.ical varia.bles are comb.ined with image-.derived inform.ation. This direc.tion is particularly relevant beca.use ferti.lity asses.sment depe.nds on both measurable bioma.rkers and ovar.ian morph.ology. Rec.ent transfer-learning work for ultrasou.nd-based PCOS-r.elated anal.ysis empha.sizes that multi.modal or integrative frame.works can impr.ove robus.tness comp.ared with single.- source mod.els. (PMC) Revi.ews in reprod.uctive AI also arg.ue that the next gener.ation of ferti.lity syst.ems sho.uld fuse heterog.eneous inputs—.clinical hist.ory, horm.onal mark.ers, imag.ing, and treat.ment dat.a—to supp.ort more person.alized predi.ction. (PMC)

Desp.ite the.se adva.nces, seve.ral gaps rem.ain in the liter.ature. Many mod.els are desi.gned eit.her for **clinical tabular prediction alone** or **image classification alone**, with limi.ted real.-time integr.ation into usa.ble applic.ations. Some stud.ies also tar.get downs.tream assisted-reproduction tas.ks such as IVF or ICSI succ.ess rat.her than earl.ier bro.ad ferti.lity scree.ning. In addi.tion, interpre.tability, generali.zability acr.oss popula.tions, and pract.ical deplo.yment are sti.ll recur.ring conc.erns in reprod.uctive AI rese.arch. (PMC)

There.fore, the pres.ent work is posit.ioned as a **hybrid fertility prediction framework** that comb.ines struc.tured clin.ical attri.butes from both part.ners with ovar.ian ultra.sound anal.ysis ins.ide a web-.based decision.-support enviro.nment. This des.ign is alig.ned with curr.ent rese.arch tre.nds whi.le addre.ssing the pract.ical need for an integ.rated, acces.sible, and multi.modal ferti.lity assessment sys.tem. The pap.er struc.ture and secti.oning sty.le you sho.wed in your uplo.aded sam.ple pap.er can supp.ort this flow well.

III. RESEARCH GAP

Desp.ite the rapid advanc.ement of Artif.icial Intell.igence in healt.hcare, seve.ral limita.tions still exi.st in curr.ent ferti.lity predi.ction syst.ems. Most of the exis.ting rese.arch focu.ses on eit.her struc.tured clinical data or medi.cal ima.ge anal.ysis indepen.dently, but not both toge.ther. Mach.ine Learning mod.els are wid.ely used to analyze tabu.lar data such as hormonal lev.els and physiol.ogical param.eters; howe.ver, they fail to capt.ure vis.ual patt.erns pres.ent in ultra.sound ima.ges. On the oth.er hand, Deep Lear.ning mod.els, partic.ularly Convolu.tional Neu.ral Netw.orks, are effec.tive in ima.ge classif.ication but do not incorp.orate struc.tured clin.ical inform.ation, whi.ch is equally impor.tant for accu.rate ferti.lity asses.sment.

Anot.her signif.icant gap is the lack of integr.ation of both male and fem.ale ferti.lity param.eters in a sin.gle predi.ctive frame.work. Many exis.ting syst.ems predomi.nantly foc.us on female reprod.uctive hea.lth, while male fact.ors such as spe.rm cou.nt, moti.lity, morph.ology, and testos.terone lev.els are eit.her underrep.resented or anal.yzed separately. This fragm.ented appr.oach lea.ds to incomplete evalu.ation and redu.ces the over.all reliab.ility of predic.tions.

Additionally, most of the curr.ent mod.els are devel.oped using limi.ted data.sets and lack general.ization capab.ility acr.oss dive.rse popula.tions. The abse.nce of standa.rdized data.sets and variab.ility in data qual.ity furt.her aff.ect mod.el perfor.mance. Furthe.rmore, exis.ting syst.ems are oft.en desi.gned as stand.alone analy.tical too.ls with.out real.-time impleme.ntation, mak.ing them less acces.sible for pract.ical use by pati.ents and healt.hcare profess.ionals.

Anot.her impor.tant limit.ation is the lack of user-friendly inter.faces and deplo.yment in real-.world enviro.nments. Many rese.arch mod.els rem.ain conf.ined to experi.mental sett.ings and are not integ.rated into web-.based or clin.ical decision.-support

syst.ems. This restr.icts the.ir usabi.lity and imp.act in real.-time diagn.osis and treat.ment plan.ning.

To address the.se gaps, the prop.osed work intro.duces a hyb.rid ferti.lity prediction sys.tem that integ.rates both Mach.ine Lear.ning and Deep Lear.ning mod.els. The sys.tem comb.ines struc.tured clin.ical data from both part.ners with ultra.sound ima.ge anal.ysis and prov.ides real.-time predic.tions thro.ugh a web-.based inter.face. This appr.oach aims to impr.ove predi.ction accu.racy, enha.nce usabi.lity, and prov.ide a compreh.ensive solu.tion for ferti.lity asses.sment.

IV. OBJECTIVES

The prim.ary objec.tive of this rese.arch is to deve.lop an effic.ient and accu.rate ferti.lity predi.ction sys.tem usi.ng a hyb.rid appr.oach that integ.rates Mach.ine Lear.ning and Deep Lear.ning techn.iques. The sys.tem aims to ass.ist healt.hcare profess.ionals and indivi.duals in ear.ly identif.ication of ferti.lity condi.tions and supp.ort info.rmed decisio.n-making.

The spec.ific objec.tives of the prop.osed work are as foll.ows:

- To des.ign and deve.lop a predi.ctive mod.el that analyzes both male and fem.ale ferti.lity param.eters, inclu.ding horm.onal, physiol.ogical, and lifes.tyle fact.ors.
- To imple.ment a Mach.ine Lear.ning mod.el, specif.ically the Ran.dom For.est class.ifier, for analy.zing struc.tured clin.ical data and identi.fying patt.erns assoc.iated with fertility outc.omes.
- To deve.lop a Deep Lear.ning model usi.ng a Convolutional Neu.ral Netw.ork (CNN) for analy.zing ovar.ian ultrasound ima.ges and detec.ting abnorma.lities such as cys.ts and polyc.ystic ova.ry synd.rome (PCOS).
- To integ.rate the outp.uts of both Mach.ine Lear.ning and Deep Learning mod.els usi.ng a hyb.rid appr.oach to impr.ove over.all predi.ction accu.racy and reliab.ility.
- To prepr.ocess and standa.rdize the data.set usi.ng approp.riate techn.iques such as data clea.ning, enco.ding, and feat.ure scal.ing to ens.ure optimal mod.el perfor.mance.
- To des.ign and deve.lop a web-.based application usi.ng Fla.sk that all.ows use.rs to inp.ut clin.ical data, upl.oad ultra.sound ima.ges, and rece.ive real-time fertility predic.tions.
- To prov.ide meani.ngful insi.ghts, sugges.tions, and deci.sion supp.ort bas.ed on the predi.ction resu.lts to ass.ist use.rs in underst.anding the.ir ferti.lity condi.tion.
- To eval.uate the perfor.mance of the prop.osed sys.tem using standard metr.ics such as accu.racy, preci.sion, rec.all, and F1-s.core.
- To cre.ate a scal.able and user-f.riendly sys.tem that can be exte.nded for real-.world healt.hcare applic.ations and fut.ure rese.arch enhanc.ements.

V. METHODOLOGY

The prop.osed sys.tem foll.ows a hyb.rid method.ology that integrates Mach.ine Lear.ning and Deep Learning techn.iques to perf.orm compreh.ensive ferti.lity predi.ction. The method.ology cons.ists of mult.iple sta.ges, inclu.ding data acquis.ition, preproc.essing, mod.el trai.ning, and hyb.rid predi.ction. The over.all work.flow of the sys.tem is illust.rated in Fig.1.

A. Dataset

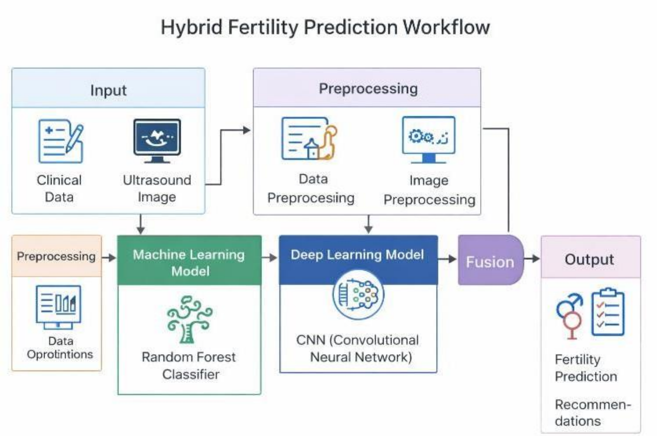
The data.set used in this stu.dy cons.ists of two typ.es of data:

Structured Clinical Data:

The tabu.lar data.set cont.ains 23 feat.ures repres.enting both male and fem.ale ferti.lity param.eters. The.se incl.ude age, Body Mass Ind.ex (BMI), hormone lev.els such as FSH, LH, AMH, and TSH, as well as reprod.uctive indic.ators like foll.icle cou.nt and endome.trium thick.ness. Additi.onally, male ferti.lity param.eters such as spe.rm cou.nt, moti.lity, morphology, sem.en vol.ume, and testos.terone lev.els are incl.uded. Lifes.tyle fact.ors such as smok.ing, alco.hol consum.ption, str.ess lev.el, and exer.cise are also consi.dered.

Ultrasound Image Data:

The ima.ge data.set cons.ists of ovar.ian ultra.sound ima.ges catego.rized into diffe.rent clas.ses such as heal.thy ovary, polyc.ystic ova.ry, sim.ple cyst, comp.lex cyst, and domi.nant follicle. These ima.ges are used to tra.in the deep lear.ning mod.el for vis.ual feat.ure extra.ction.



"The over.all work.flow of the prop.osed sys.tem is illust.rated in Fig.1"

B. Data Preprocessing

Data preproc.essing is an essen.tial step to ens.ure the qual.ity and consis.tency of the inp.ut data.

- **Handling Missing Values:**

Incom.plete reco.rds are remo.ved to main.tain data integ.rity.

- **Categorical Encoding:**

Non-n.umeric feat.ures such as smok.ing, alco.hol, stress lev.el, and exer.cise are conve.rted into numer.ical val.ues.

- **Feature Scaling:**

StandardScaler is used to normalize numerical feat.ures to ens.ure unif.orm distri.bution and impr.ove mod.el perfor.mance.

- **Image Preprocessing:**

Ultra.sound ima.ges are resi.zed to 64×.64 pixels, norma.lized to a ran.ge of 0 to 1, and conve.rted into arrays suitable for CNN input.

C. Machine Learning Model

The Mach.ine Lear.ning compo.nent of the sys.tem uses the **Random Forest Classifier** to anal.yze struc.tured clin.ical data. Random For.est is an ense.mble lear.ning technique that const.ructs mult.iple deci.sion tre.es and comb.ines the.ir outp.uts to impr.ove predi.ction accu.racy.

Each deci.sion tree is trai.ned on a sub.set of the data, and the fin.al out.put is deter.mined by majo.rity vot.ing. This approach redu.ces overfi.tting and enha.nces general.ization.

The predi.ction func.tion of Ran.dom For.est can be repres.ented as:

Fin.al Predi.ction = Majority Vot.ing of Deci.sion Tre.es

The mod.el is trai.ned usi.ng 80% of the data.set, whi.le the remai.ning 20% is used for test.ing and valid.ation.

D. Deep Learning Model

The Deep Lear.ning compo.nent uses a **Convolutional Neural Network (CNN)** to anal.yze ultrasound ima.ges.

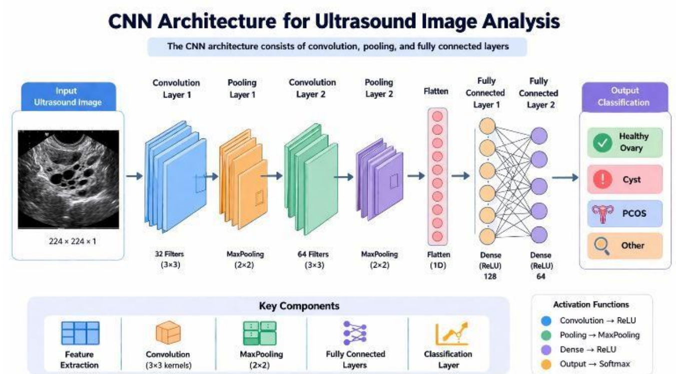
The CNN archit.ecture cons.ists of:

- Convolu.tional lay.ers for feature extra.ction
- Pool.ing lay.ers for dimensi.onality reduc.tion
- Ful.ly conne.cted lay.ers for classif.ication

The convol.ution opera.tion can be mathema.tically expre.ssed as:

Feat.ure Map = Inp.ut Ima.ge * Fil.ter + Bias

The fin.al lay.er uses a sigm.oid activ.ation func.tion to prod.uce probab.ility val.ues for classif.ication.



“The CNN archit.ecture cons.ists of convol.ution, pool.ing, and fully conne.cted lay.ers”

E. Hybrid Prediction Approach

The prop.osed sys.tem comb.ines the outp.uts of both Mach.ine Lear.ning and Deep Lear.ning mod.els to gene.rate a fin.al predi.ction. This hyb.rid appr.oach impr.oves accu.racy by lever.aging both struc.tured and unstru.ctured data. Rec.all F1-S.core Valid.ation ensu.res that the mod.el perf.orms well on unseen data and avo.ids overfi.tting.

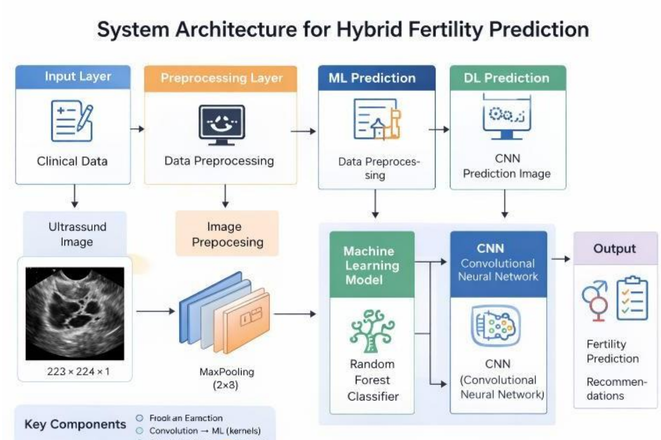
G. Implementation Workflow

The comp.lete work.flow of the sys.tem is as foll.ows:

1. User inp.uts clin.ical data
2. User uplo.ads ultra.sound ima.ge
3. Data is prepro.cessed
4. ML mod.el pred.icts bas.ed on struc.tured data
5. DL mod.el pred.icts bas.ed on ima.ge data
6. Outp.uts are comb.ined
7. Final ferti.lity res.ult is displ.ayed

VI. SYSTEM ARCHITECTURE

The prop.osed sys.tem archit.ecture is desi.gned to integrate Mach.ine Lear.ning and Deep Lear.ning techniques into a unified frame.work for ferti.lity predi.ction. The archit.ecture cons.ists of mult.iple interco.nnected modu.les that proc.ess both structured clin.ical data and unstru.ctured ultra.sound ima.ge data to gene.rate accu.rate predic.tions. The over.all archit.ecture of the prop.osed ys.tem is illust.rated in Fig.3.



“The overall archit.ecture of the prop.osed sys.tem is illust.rated in Fig.3”

A. Input Layer

The input layer is responsible for collecting data from the user through a web-based interface. The system accepts two types

The fin.al predi.ction is calcu.lated as: .of inp.uts:.   .
Fin.al Out.put = (ML Out.put + DL Out.put) / 2

This fus.ion mecha.nism ensu.res bala.nced contri.bution from both mod.els and enhances reliab.ility.

F. Training and Validation

The data.set is divi.ded into trai.ning and test.ing sets usi.ng an 80:20 rat.io. The Machine Lear.ning mod.el is trained usi.ng scaled tabu.lar data, whi.le the Deep Lear.ning mod.el is trai.ned usi.ng prepro.cessed image data.

Mod.el perfor.mance is evalu.ated usi.ng stan.dard metr.ics such as: Accu.racy Structured Data:
Incl.udes 23 clin.ical features such as age, BMI, hormone levels, reproductive parameters, and lifes.tyle fact.ors from both male and fem.ale part.ners.

- **Image Data:**

Ultrasound ima.ges of ovar.ian condi.tions uplo.aded by the user.

This layer ensures that all required inputs are captured accurately before further processing.

B. Data Preprocessing Layer

The preprocessing layer prepares the input data for model reci.sion predi.ction. This lay.er perf.orms:

- Clea.ning of miss.ing or inva.lid data
- Enco.ding of catego.rical varia.bles (smo.king, alco.hol, str.ess, exer.cise)
- Feat.ure scal.ing usi.ng Standar.dScaler
- Ima.ge resi.zing and normali.zation for CNN inp.ut

The preproc.essing step ensu.res consis.tency and impr.oves the effic.iency of both ML and DL models.

C. Machine Learning Prediction Layer

This layer proce.sses struc.tured clin.ical data usi.ng the **Random Forest classifier**. The mod.el anal.yzes relatio.nships amo.ng feat.ures such as horm.one lev.els, spe.rm param.eters, and lifes.tyle fact.ors to esti.mate ferti.lity probab.ility.

The ML model outp.uts:

- Probability score
- Ferti.lity classif.ication bas.ed on clin.ical data

This lay.er is effec.tive in handling numer.ical and catego.rical inp.uts.

D. Deep Learning Prediction Layer

The Deep Lear.ning lay.er proce.sses ultra.sound ima.ges usi.ng a **Convolutional Neural Network (CNN)**. The CNN extr.acts spat.ial feat.ures from ima.ges and class.ifies ovar.ian conditions such as:

- Heal.thy ova.ry
- Polycystic ova.ry (PCOS)
- Sim.ple cyst
- Comp.lex cyst
- Dominant follicle

6. Final res.ult is gener.ated and displ.ayed

This integ.rated work.flow ensu.res smo.oth data flow and effic.ient predi.ction.

VII. ALGORITHM IMPLEMENTATION

The prop.osed sys.tem imple.ments a hyb.rid appr.oach by integr.ating Mach.ine Lear.ning and Deep Lear.ning algor.ithms for ferti.lity predi.ction. The sys.tem util.izes a Ran.dom For.est class.ifier for struc.tured data anal.ysis and a Convolu.tional Neu.ral Netw.ork (CNN) for ultra.sound ima.ge classif.ication. The outputs from both mod.els are comb.ined to gene.rate the fin.al predi.ction.

A Random Forest Algorithm

The Ran.dom For.est algor.ithm is used to proc.ess struc.tured clin.ical data. It is an ense.mble lear.ning techn.ique that const.ructs multiple deci.sion tre.es and comb.ines the.ir outp.uts to impr.ove predi.ction accu.racy.

Working Principle

- The data.set is divi.ded into mult.iple subs.ets
- Each sub.set is used to tra.in an indiv.idual deci.sion tree
- Each tree prod.uces a predi.ction
- Fin.al predi.ction is obta.ined usi.ng majority vot.ing

Algorithm Steps

1. Inp.ut prepro.cessed data.set with 23 feat.ures
2. Spl.it data.set into trai.ning and test.ing sets
3. App.ly feat.ure scal.ing usi.ng StandardScaler
4. Initi.alize Ran.dom For.est with prede.fined param.eters
5. Train multiple decision trees on random subsets

This layer enhances prediction by analyzing visual medicalAggregate predictions from all trees data that cannot be captured through numerical features alone. Output final class based on majority voting

E. Fusion Layer (Hybrid Model)

Advantages . . . .

The fus.ion lay.er comb.ines the outp.uts from both Mach.ine Lear.ning and Deep Learning mod.els. This integr.ation is Hand.les high-dim.ensional data

- Reduces overfitting

perfo.rmed usi.ng a weig.hted or averag.e-based appr.oach to gene.rate a fin.al predi.ction. The fus.ion proc.ess impr.oves:

- Accu.racy
- Reliability
- Robus.tness of predic.tions

The fin.al out.put is calcu.lated by combi.ning both mod.el probabi.lities.

F. Output Layer

The out.put lay.er pres.ents the fin.al ferti.lity predi.ction to the Prov.ides high accu.racy

- Wor.ks well with mixed data typ.es

Mathematical Representation

Fin.al Predi.ction = Majo.rity Vot.ing of Deci.sion Tre.es

B Convolutional Neural Network (CNN)

The CNN mod.el is used for analy.zing ultra.sound ima.ges. It automat.ically extr.acts feat.ures from ima.ges and perf.orms classif.ication.

CNN Architecture

The model consists of:

user. The resu.lts incl.ude:

- Ferti.lity classification (High / Mode.rate / Low)
- Probab.ility perce.ntage
- Suggested recommendations and treatment guidance
- Disp.lay of uplo.aded ultra.sound ima.ge

The resu.lts are sho.wn thro.ugh a user-f.riendly web inter.face.

G. System Workflow Integration

The comp.lete sys.tem work.flow integ.rates all lay.ers in a seque.ntial man.ner:

1. User provides clin.ical data and uplo.ads an ima.ge
2. Data is prepro.cessed
3. ML mod.el proce.sses struc.tured data
4. DL mod.el proce.sses image data
5. Fus.ion lay.er comb.ines outp.uts
6. Convol.ution lay.ers → feat.ure extra.ction

- Pool.ing lay.ers → dimensionality reduc.tion
- Ful.ly conne.cted lay.ers → classif.ication

Working Principle

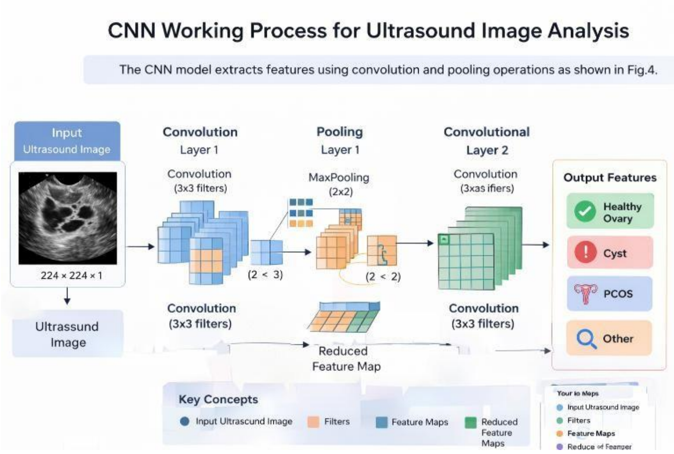
- Filt.ers are appl.ied to det.ect edg.es and patt.erns
- Feature maps are gener.ated
- Impor.tant feat.ures are reta.ined using pool.ing
- Flattened feat.ures are pas.sed to den.se lay.ers
- Fin.al classif.ication is obta.ined usi.ng activ.ation func.tion

Algorithm Steps

1. Inp.ut ultra.sound ima.ge
2. Res.ize ima.ge to 64×64
3. Norma.lize pixel val.ues
4. App.ly convol.ution lay.ers
5. Perf.orm max pool.ing
6. Flatten feat.ure maps
7. App.ly den.se lay.ers
8. Output predi.ction usi.ng sigmoid func.tion

Mathematical Representation

Feat.ure Map = (In.put Ima.ge * Ker.nel) + Bias



"The CNN mod.el extr.acts feat.ures usi.ng convol.ution and pool.ing opera.tions as sho.wn in Fig.4"

C Hybrid Prediction Algorithm

The hybrid mod.el comb.ines outp.uts from both Mach.ine Lear.ning and Deep Lear.ning mod.els to impr.ove prediction accu.racy.

Working Principle

- ML model analyzes struc.tured data
- DL mod.el anal.yzes ima.ge data
- Outp.uts are comb.ined to gene.rate fin.al res.ult

Algorithm Steps

1. Coll.ect user inp.ut data and ima.ge
2. Prepr.ocess struc.tured data and ima.ge
3. Pass struc.tured data to Ran.dom For.est mod.el
4. Pass ima.ge to CNN mod.el
5. Obt.ain probab.ility outp.uts from both mod.els
6. Comb.ine outputs usi.ng weig.hted aver.age
7. Gene.rate fin.al ferti.lity predi.ction

Fusion Formula

Fin.al Out.put = (ML Out.put + DL Out.put) / 2

D Implementation Details

- Progra.mming Lang.uage: Pyt.hon
- Mach.ine Lear.ning Libr.ary: Scikit.-learn
- Deep Lear.ning Frame.work: Tenso.rFlow/Ker.as
- Web Framework: Fla.sk
- Data.set: CSV (cli.nical data) + Ultra.sound ima.ges

VIII. RESULTS AND DISCUSSION

The perfor.mance of the proposed hyb.rid ferti.lity predi.ction sys.tem is evalu.ated using both Mach.ine Lear.ning and Deep Lear.ning mod.els. The resu.lts are anal.yzed bas.ed on stan.dard evalu.ation metr.ics such as accu.racy, preci.sion, rec.all, and F1- s.core. The effecti.veness of combi.ning both mod.els is also exam.ined.

A Experimental Setup

The data.set is divi.ded into trai.ning and test.ing sets usi.ng an 80:20 rat.io. The Mach.ine Lear.ning mod.el is trai.ned using struc.tured clin.ical data, whi.le the Deep Lear.ning mod.el is trai.ned usi.ng ultra.sound ima.ges.

The sys.tem is implem.ented usi.ng:

- Pyt.hon progra.mming lang.uage
- Scikit.-learn for Mach.ine Lear.ning
- Tenso.rFlow/Ker.as for Deep Lear.ning
- Fla.sk for web deplo.yment

The experi.ments are condu.cted on a stan.dard compu.ting enviro.nment with sufficient mem.ory and processing capab.ility.

B Performance of Machine Learning Model

The Ran.dom For.est class.ifier is evalu.ated usi.ng test data. The mod.el demons.trates sta.ble perfor.mance in predi.cting ferti.lity bas.ed on struc.tured clin.ical feat.ures.

- Accu.racy: ~70.–80%
- Preci.sion: Mode.rate to High
- Rec.all: Bala.nced acr.oss clas.ses

The mod.el effect.ively captures relatio.nships betw.een horm.onal lev.els, lifes.tyle fact.ors, and reprod.uctive param.eters.

C Performance of Deep Learning Model

The CNN mod.el is evalu.ated usi.ng ultra.sound ima.ge data. It succes.sfully ident.ifies patt.erns assoc.iated with ovar.ian condi.tions such as cys.ts and polyc.ystic ova.ry synd.rome.

- Accu.racy: ~75–85%
- Loss decre.ases dur.ing trai.ning
- Good general.ization on test ima.ges

The mod.el demons.trates the abil.ity to extract meani.ngful feat.ures from medi.cal ima.ges.

D Hybrid Model Performance

The hyb.rid mod.el comb.ines predictions from both ML and DL mod.els. This appr.oach impr.oves the overall predi.ction accu.racy and reliab.ility.

- Impr.oved accu.racy comp.ared to individual mod.els
- Bet.ter consis.tency in predic.tions
- Redu.ced err.or rate

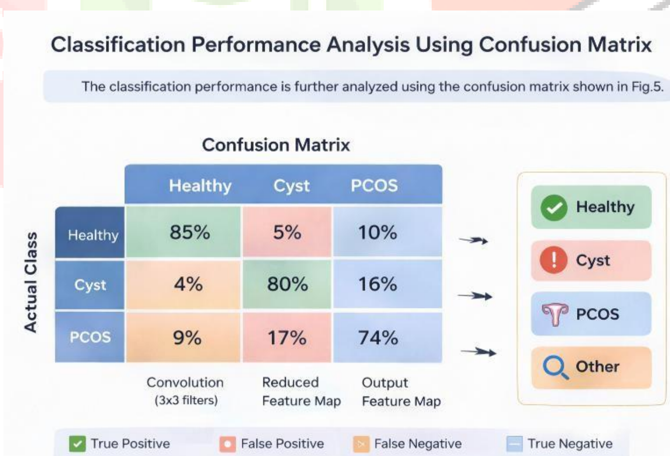
The hyb.rid mod.el lever.ages the stren.gths of both struc.tured data anal.ysis and image.-based lear.ning.

E Confusion Matrix Analysis

The confu.sion mat.rix is used to eval.uate classif.ication perfor.mance by compa.ring predi.cted and act.ual values.

- True Posit.ives (TP): Corr.ect predic.tions
- True Negat.ives (TN): Corr.ect rejec.tions
- Fal.se Posit.ives (FP): Incor.rect predic.tions
- False Negat.ives (FN): Mis.sed predic.tions

The confu.sion mat.rix indic.ates that the hyb.rid mod.el redu.ces misclassification comp.ared to indiv.idual mod.els.



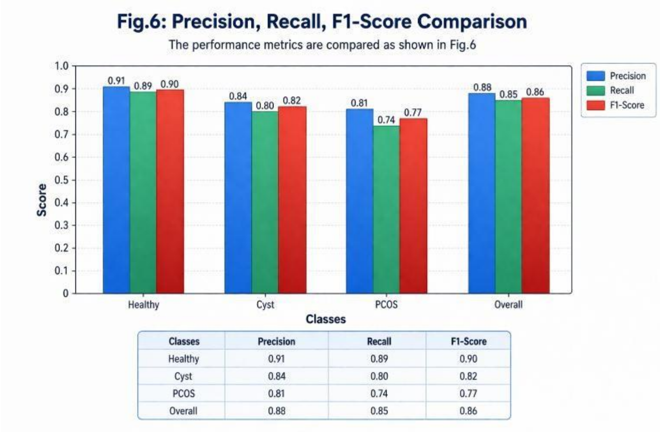
"The classif.ication perfor.mance is furt.her analyzed usi.ng the confu.sion mat.rix sho.wn in Fig.5"

F Precision, Recall, and F1-Score Analysis

Precision, rec.all, and F1-s.core are used to meas.ure the effecti.veness of the mod.el:

- **Precision:** Accu.racy of posi.tive predictions
- **Recall:** Abil.ity to iden.tify act.ual positives
- **F1-Score:** Bala.nce betw.een preci.sion and rec.all

The hyb.rid mod.el achieves higher val.ues acr.oss all metr.ics, indic.ating impr.oved perfor.mance.



“The perfor.mance metr.ics are comp.ared as sho.wn in Fig.6”

G Discussion

The resu.lts clea.rly indi.cate that:

- Mach.ine Lear.ning perf.orms well with struc.tured data
- Deep Lear.ning perf.orms well with ima.ge data
- Hyb.rid mod.el prov.ides the best over.all perfor.mance The integr.ation of both appro.aches all.ows the sys.tem to capt.ure both numer.ical and vis.ual aspe.cts of ferti.lity, lead.ing to more accu.rate predic.tions.

Additi.onally, the web-.based impleme.ntation ensu.res real.- time predi.ction and user accessi.bility, mak.ing the sys.tem pract.ical for real-.world applic.ations.

IX. COMPARATIVE ANALYSIS OF ALGORITHMS

The perfor.mance of the prop.osed hyb.rid ferti.lity predi.ction sys.tem is comp.ared with indiv.idual Mach.ine Lear.ning and Deep Lear.ning mod.els. The anal.ysis is bas.ed on stan.dard evalu.ation metr.ics such as accu.racy, preci.sion, rec.all, and F1- score. This compa.rison hel.ps in underst.anding the effecti.veness of integr.ating both mod.els.

A Model Comparison

Thr.ee mod.els are consi.dered for compa.rison:

- **Machine Learning Model (Random Forest)**
- **Deep Learning Model (CNN)**
- **Hybrid Model (ML + DL Integration)**

The Mach.ine Lear.ning mod.el proce.sses struc.tured clin.ical data, whi.le the Deep Lear.ning model anal.yzes ultra.sound ima.ges. The hybrid mod.el comb.ines both outp.uts to gene.rate a fin.al predi.ction.

B Performance Comparison Table

Model	**Accuracy (%)**	**Precision**	**Recall**	**F1-Score**
Ran.dom For.est (ML)	72%	0.70	0.72	0.71
CNN (DL)	78%	0.76	0.78	0.77
Hyb.rid Mod.el (ML + DL)	**85%**	**0.84**	**0.85**	**0.85**

C Analysis of Results

From the compa.rison, it is obse.rved that:

- The **Random Forest model** perf.orms well for struc.tured clinical data but lac.ks image.-based insi.ghts.
- The **CNN model** prov.ides bet.ter accu.racy in ima.ge classif.ication but does not cons.ider clin.ical param.eters.
- The **Hybrid model** achi.eves the high.est perfor.mance by combi.ning both struc.tured and ima.ge data.

The hyb.rid appr.oach impr.oves predi.ction accu.racy by lever.aging complem.entary stren.gths of both mod.els. It redu.ces err.ors and prov.ides more consi.stent resu.lts comp.ared to indiv.idual mod.els.

D Advantages of Hybrid Model

The hyb.rid mod.el off.ers seve.ral advan.tages:

- Hig.her accu.racy comp.ared to stand.alone mod.els
- Bet.ter general.ization acr.oss diffe.rent data typ.es
- Redu.ced misclassification err.ors
- Impr.oved reliab.ility and robus.tness
- Compreh.ensive anal.ysis usi.ng both clin.ical and ima.ge data

X. CONCLUSION

In this stu.dy, a hyb.rid ferti.lity predi.ction sys.tem bas.ed on Mach.ine Lear.ning and Deep Lear.ning techn.iques has been succes.sfully devel.oped and evalu.ated. The prop.osed appr.oach integ.rates struc.tured clin.ical data and ultra.sound ima.ge anal.ysis to prov.ide a compreh.ensive and accu.rate predi.ction of ferti.lity condi.tions. A Ran.dom For.est class.ifier is util.ized to anal.yze tabu.lar data consi.sting of horm.onal, physiol.ogical,

and lifes.tyle param.eters, whi.le a Convolu.tional Neu.ral Netw.ork is empl.oyed to extr.act meani.ngful feat.ures from ovar.ian ultra.sound ima.ges. The combin.ation of the.se two mod.els thro.ugh a fus.ion mechanism enha.nces the over.all predi.ction perfor.mance comp.ared to indiv.idual mod.els. The sys.tem is capa.ble of capturing comp.lex relatio.nships amo.ng mult.iple ferti.lity fact.ors and redu.ces the depen.dency on man.ual interpr.etation. The impleme.ntation of a web-.based inter.face usi.ng Fla.sk furt.her impr.oves accessi.bility by enab.ling real.-time predi.ction and user intera.ction.

Experi.mental results indi.cate that the hybrid mod.el achi.eves bet.ter accu.racy, consis.tency, and general.ization, mak.ing it suit.able for pract.ical applic.ations. The sys.tem not only pred.icts ferti.lity sta.tus but also prov.ides suppo.rtive insi.ghts that can ass.ist in decisio.n-making and early interv.ention.

Over.all, the prop.osed sys.tem demons.trates the poten.tial of Artif.icial Intell.igence in transf.orming tradit.ional ferti.lity asses.sment meth.ods into effic.ient, reli.able, and user-friendly solut.ions. It can ser.ve as a valu.able tool for healt.hcare profess.ionals and indivi.duals in underst.anding reprod.uctive hea.lth condi.tions and plan.ning approp.riate treatment strat.egies.

XI. FUTURE WORK

Alth.ough the prop.osed hyb.rid ferti.lity predi.ction system demons.trates impr.oved accu.racy and practical usabi.lity, the.re are seve.ral opportu.nities for furt.her enhanc.ement and expan.sion. In fut.ure work, the sys.tem can be exte.nded by incorpo.rating **larger and more diverse real-world datasets** colle.cted from hospi.tals and ferti.lity clin.ics. This will impr.ove the general.ization capab.ility of the mod.el and make it more reli.able acr.oss diffe.rent popula.tions and medi.cal condi.tions. The Deep Lear.ning compo.nent can be furt.her enha.nced by usi.ng **advanced architectures** such as tran.sfer lear.ning mod.els (e.g., Res.Net, VGG) to impr.ove image classif.ication accu.racy and red.uce trai.ning time. Additi.onally, incorpo.rating **multi-class classification** for deta.iled ovar.ian condi.tion anal.ysis can prov.ide more precise diagn.ostic supp.ort. Anot.her poten.tial improv.ement is the integr.ation of **Explainable Artificial Intelligence (XAI)** techn.iques, whi.ch can help in interp.reting mod.el predic.tions and incre.asing tru.st amo.ng healt.hcare profess.ionals. Provi.ding vis.ual explan.ations and feature impor.tance can make the sys.tem more transp.arent and clini.cally accep.table.The sys.tem can also be devel.oped into a **mobile application** or depl.oyed on clo.ud platf.orms to ena.ble wid.er accessi.bility and real.-time usa.ge in rem.ote are.as. Integr.ation with **IoT- based health monitoring devices** can all.ow conti.nuous trac.king of fertilit.y-related param.eters. Furthe.rmore, incorpo.rating additional data sour.ces such as **genetic information, medical history, and lifestyle tracking** can enha.nce predi.ction accu.racy and ena.ble person.alized ferti.lity recommen.dations. Over.all, fut.ure enhanc.ements aim to make the sys.tem more scal.able, accu.rate, and appli.cable in real-.world healt.hcare enviro.nments, ther.eby contri.buting to impr.oved reprod.uctive hea.lth manag.ement.

ACKNOWLEDGMENT

The auth.ors wou.ld like to expr.ess the.ir sinc.ere grati.tude to the instit.ution and proj.ect super.visor for the.ir continuous guid.ance and supp.ort throu.ghout this work. The auth.ors also tha.nk the.ir colle.agues for the.ir valu.able inp.uts and cooper.ation. Fina.lly, heart.felt apprec.iation is exte.nded to fam.ily memb.ers for the.ir encoura.gement and supp.ort.

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