2nd Semester

Total N	code: 1	ACSEC	CAL224						Exan	ninatio	n Scheme	
	mber	of Lect	ure Hou	rs: 40					Extern	al	72	
			1			-			Interna	al	28	1.
Lecture	(L)	4	Pra	ctical (P) 0	Ti	itorial ((1)	0	Total	Credits	4
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comp	utation	ai moae	Cou	rse Con	tent				No.	of Tea	ching Hou	irs
			cou	UNIT 1						10	Hrs	
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Course Title: Soft Comput	ing			Examinat	ion Scheme	
Total Number of Lecture	Hours: 56			External	72	
rotal Number of Lecture	nours. 30			Internal	28	
Lecture (L) 4	Practical (P)	0	Tutorial (T)	0 Tot	al Credits	4
 Course Objectives: To introduce sof appropriate tech To implement so To give students networks, fuzzy To provide stude 	t computing conce inique for a given s oft computing base knowledge of nom sets, fuzzy logic, ge ents a hand-on exp	epts and scenario ed solutio entraditic enetic al perience	techniques and fos ons for real-world onal technologies a gorithms. on MATLAB/Pytho	ter their abilitie problems. nd fundamental on to implement	s in design s of artifici various st	ing al neural rategies.
LECTURE WITH BREAD	KUP				Ġ.	NO. OF LECTURES
Unit 1 SOFT COMPUTING and on Fuzzy Sets, Fuzzy Rel Fuzzy Inference Systems	FUZZY LOGIC: So ations, Membersh s, Fuzzy Expert Sys	oft Comp ip Funct stems, Fu	uting Constituents ions: Fuzzy Rules a uzzy Decision Maki	, Fuzzy Sets, Op and Fuzzy Reasc ng.	erations oning,	14
Unit 2 NEURAL NETWORKS: forward Networks, Sup Unsupervised Learning	Machine Learning ervised Learning N Neural Networks,	Using N Neural N	leural Network, Ad etworks, Radial Ba	laptive Networl sis Function Ne	ks, Feed tworks,	14
Unit 3 DEEP LEARNING and Classifiers. Introduction Implementation of rece	GENETIC ALGORI n to Genetic Algorit ently proposed soft	THMS: R thms (GA comput	ecent Trends in de), Applications of G ing techniques.	ep learning, vari A in Machine Le	ous earning.	14
Unit 4 Matlab/Python Lib: In and Files, Study of implementation of mac	troduction to Matl f machine learn hine learning/soft	ab/Pyth ning/soft comput	on, Arrays and arra t computing too ing techniques.	ay operations, Fu lbox/libraries,	inctions Simple	14
COURSE OUTCOMES						
After completion of cou	rse, students woul	d be abl	e to:			
Identify and desc	cribe soft computin	ng techn	iques and their rol	es in building in	telligent m	achines
□ Apply fuzzy logic a	nd reasoning to ha	andle un	certainty and solve	various engine	ering probl	ems.
Apply genetic algor	rithms to combina	torial or	timization probler	ns.		
D Evaluate and comm	are solutions by y	arious	oft computing appr	oaches for a giv	en problem	1
eferences			Bankanbh		- problem	-
1. Jyh:Shing Roger J India, 2003.	ang, Chuen:Tsai Su	ın, EijiM	izutani, Neuro:Fuz	zy and Soft Com	puting, Pre	entice:Hall of
 George J. Kir and MATLAB Toolkit 	во ruan, ruzzy Se Manual	ets and F	uzzy Logic: Theory	and Application	ns , Prentico	e nall, 1995.
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4	3	2	2	4	5			100				

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Cours	Coda	MCOD	CROAA	Course 7	litle: Mi	ni Pro	ject with S	eminar				
Total	Vumber	MCSE	CPS224						Exa	aminati	on Schem	e
- orall	umber	of Lect	ure Hou	irs: 30					Exter	nal	36	
Loo	tores (T		1						Inter	nal	14	
Course	ture (L) 0	Pra	actical (P)) 4		Tutorial (T	Γ)	0	Total	Credits	2
1 T	e Objec	uves										
2 T	o aevelo	p techni	cal prese	entation a	nd resea	rch co	mmunicatio	n skills.				
2. 1	o ennan	ce the at	pility to r	eview lite	rature a	nd iden	tify relevan	t resea	rch are	as.		
J. 10	o design	and imp	plement d	a mini pro	oject add	ressing	, a real-wor	ld or re	search	-based p	roblem.	
7. 1	o encou	rage inn	ovation d	and applic	cation of	theore	tical knowle	edge to	practic	al probl	ems.	
]	Descriptio	on				N	o, of Tes	ching H	ure
Litera	ture Su	rvey &]	Problem	Identific	ation						tening IIt	Juis
Ide	entifying	g a doma	in of inte	erest								
Su	rveying	recent re	esearch p	apers, pat	tents, and	d open	problems					
De	fining s	cope and	l signific	ance of th	e proble	m						
Fra	aming pr	roject ob	jectives	and delive	erables							
Design	and In	nplemen	tation									
Sy	stem arc	chitecture	e/design	models								
Ch	oice of	tools, alg	gorithms.	, datasets,	or simul	ations						
Im	plement	ation ph	ases: coo	ling, testin	ng, mode	ling						
Ite	rative de	evelopm	ent and t	esting stra	ategies	-						
Docun	ientatio	n & Rej	port Wr	iting								
le	chnical	writing s	standards	and struc	cture							
Pre	eparation	n of inter	rim and f	final repor	rts							
Ci	ing refe	rences (]	EEE/AF	PA style)								
Pla C.	giarism	checkin	g and eth	nics in res	earch							
Semin	ar & Pr	esentati	on									
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J. Pl	ollahors	chnical i	content e	effectively	in oral d	ind wri	itten form.	-				
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PROGRAM ELECTIVE-III & IV

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Course Codes Moor	T I DAAL	and Security & Meeess	E	an	ion Sahan	
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			Int	ernal	14	
Lecture (L) 0	Practical (P)	4 Tutorial (T)	0	Total	Credits	2
	I	List of Experiments				
 2) Implement simple ad requests. 3) Simulate Attribute-E traditional ACL method 4) Analyse a real-world brief report on its effec 5) Develop a basic Rol- using Python. 6) Extend the RBAC sy access management. 7) Compare the behavior discuss their respective 8) Review a case study document its key feature 9) Simulate Biba's inte 10) Simulate the Clark- *This is only a suggest students with additional 	andatory Access Co ccess control policio Based Access Control ds. d access control imp tiveness. e-Based Access Con ystem to include rol our of RBAC, DAC strengths and weak of a real-world RB res in a report. grity model in Pyth Wilson security mo ted list of experimen- al relevant exercise.	ontrol (MAC). es using Python scripts, an ol (ABAC) using user attri olementation (e.g., in healt ntrol (RBAC) system by n e hierarchies and permission c, and MAC models throug chesses. AC implementation (e.g., on. odel using Python nts/simulations. The instru- s.	d test them ibutes in Py hcare or go napping use on inheritar sh simple P in a bankin	with sim with sim wernment ers, roles, nce for m ython sim g environ	ulated user d compare i and prepa and permis ore efficien nulations an ment) and <i>to familiar</i> .	t wit Ire a sion: t d

- Operating Systems: Windows, Linux (e.g., Ubuntu) .
- .
- Programming Language: Python Virtualization Tools (Optional): VirtualBox or Docker .

C 0 9 un 1

Lecture Course 1. To in stand 2. To en	unner	The	LAEZZA			_			Exa	minatio	on Schen	ne
Lecture Course 1. To in stand 2. To er		of Lee	cture H	ours: 3	0				Exter	nal	36	;
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2. To er	lord to		il skills	for coll	ecting,	analyzir	ig, and	interpre	eting we	eb data	using ind	lusi
10 01	ables	ois ana	techniq	jues.								
user	hehavi	iudenis	to impl	ement	web trac	cking m	echanis	ms like	cookies	, session	n trackin	g, c
3. To th	rain c	tudents	in us		alution	.1.10		0				
actio	nable i	insights	from u	sor into	raction	blaijorn data	is such	a as Ge	pogle /	Analytic.	s for de	riv
4. To d	levelop	hand	s-on ex	nertise	in cree	adia. Itina di	schhoar	de and	Fanor	for a		
perfo	rmanc	e and s	upporti	ng data	-driven	decision	isnoour ne	us unu	report	s jor e	valuating	g v
			11	- <u>6</u> uuru	List of	f Exper	iments			_		-
1. (Create	a basic	respons	ive we	bsite usi	ng HTN	AL CSS	S and L	vaSori	nt	_	-
2. I	mplem	nent for	m valid	ation at	nd intere	ctivity	with Ion	vaScript	avaSCII	р г.		
3. I	Develo	p a sim	ple web	applic	ation us	ing a ha	ckend f	ramewo	rk (Nov	le ic/DU	P)	
4. (Connec	t a web	applica	ation to	a datah	ase and	retrieve	data	11 (110)		.).	
5. 8	Set up	Google	Analyt	ics for a	a test we	bsite.		- until.				
6. 1	Frack v	vebsite	traffic,	bounce	rate, an	d user f	low.					
7. 5	Set goa	ls, crea	te dashl	boards,	and inte	rpret an	alytics	data.				
8. F	Perform	n A/B t	esting u	ising Go	oogle O	ptimize.						
9. <i>I</i>	Analyz	e SEO	perform	ance us	sing God	ogle Sea	irch Con	nsole.				
10. 1	Visuali	ze web	traffic	using h	eatmap	tools (e.	g., Hotj	ar/Clari	ty).			
Course 1. 1 2. 1 3. A 4. H	Outco Develop Integrat Analyze Perform	mes: and de de Goog web tra testing	ploy dyn le Analy affic data and opt	namic an tics and a and int imizatio	nd respon other too terpret re on for imp	nsive wel ols for we ports. proving v	o applica eb tracki vebsite p	ations. ing. performa	nce.	1		
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	unite	TOLL	ecture H	lours: 30				_	Ext	ernal	-	36
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Cours	e Obio	otinua	Pract	ical (P)	4	Tutor	ial (T)		0	Total	Credits	2
2. To 3. To 4. To	o implen o apply a o develo	nent and associat p and pi	l evaluate ion rule i resent a c	ssing lech classifica mining on complete k	niques ation ai transa mowled	on real-w nd cluster ctional da lge discov	vorld dd ring alg atasets. very pip	ntasets. corithms. veline.				
					List of	f Experi	iments					
1. D	ata clear	ning and	preproc	essing usir	ng Pyth	on or R.						
2. In	nplemen	tation o	fclassifi	cation algo	orithms	(e.g., De	ecision '	Tree. Na	ive Ba	ves)		
3. In	nplemen	tation o	f clusteri	ng algorith	hms (e	g. K-Me	ans DF	SCAN		,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,		
4. A	ssociatio	on rule n	nining us	ing Aprice	ri and I	D Croud	4h	JOCAN	•			
5 W	when and a	out min	inning us	ang Aprilo	n anu i	-F-Orowi	un.					
5. W		ext mm	ing using	g open-sou	irce too	ls.						
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Course Code:	MCSELAG22	.4				Exa	minatio	on Sche	me
Total Numbe	r of Lecture H	Iours: 30				Exter	nal	3	6
						Inter	nal	1	4
Lecture (L)	0 Pract	ical (P)	4 Tuto	rial (T)		0	Total C	redits	2
Course Object	tives								
To enable stu	dents with bot	h theoretica	al understa	nding ar	nd prac	tical in	nplemen	tation s	skills
modern neura	l network arch	itectures, bu	uilding a sin	ngle-laye	er perce	ptron f	rom scra	atch for	bina
classification,	and implement	ting a basic	Artificial N	Veural N	etwork	(ANN)	using To	ensorFl	'ow a
Keras for task	s like handwri	tten digit red	cognition w	ith the M	INIST a	lataset.			
		Li	st of Expen	riments			_		
1. Design a	single unit p	erceptron fo	or classific	ation of	a line	arly se	parable	binary	datas
without u	sing pre-define	d models.							
2. Design ar	d implement a	basic Artif	icial Neural	l Networ	k (ANI	N) using	g Tensor	Flow 8	k Ker
for a simp	le classificatio	n task (e.g.,	handwritte	n digit re	ecogniti	on usin	g MNIS	T datas	set).
3. Build an	Artificial Neur	al Network	by impleme	enting the	e Backr	oropaga	tion algo	orithm a	and te
the same	using appropri-	ate data sets							
4. Design ar	nd implement	an Image cl	assification	model	to class	ify a d	ataset of	f image	s usi
Deep Fee	d Forward NN	I. Record th	e accuracy	correspo	onding	to the n	umber o	of epocl	hs. U
the MNIS	T datasets.							8777	
5. Design ar	nd implement :	a CNN mod	lel to classi	fy multi	catego	ry imag	e datase	ets. Rec	ord t
accuracy	corresponding	to the numb	er of epoch	s. Use th	e MNI	ST, CIF	AR-10	datasets	5.
6. Use the c	oncept of Data	Augmentati	ion to increa	ase the d	ata size	from a	single i	mage.	
7. Implemen	it the standard	VGG-16 &	2 19 CNN a	architect	ure mo	del to c	lassify	multi ca	atego
image dat	aset and check	the accurac	y.						
8. Implemen	t RNN for sen	timent analy	sis on mov	ie review	VS				
9. Implemen	t Bi-directiona	al LSTM for	sentiment a	analysis	on mov	ie revie	ws.		
10. Implement	it Auto encode	rs for image	denoising	on MNIS	T datas	set.			
*This is only a students with a	suggested list dditional releva	of experiment of exercises.	nts/simulatio	ons. The	instruct	or is en	courage	d to fan	niliar
*This is only a students with a Course Outco	suggested list dditional releva	of experiment of exercises.	nts/simulatio	ons. The	instruct	or is en	courage	d to fan	niliar
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4	2	2	2	2	3	2	1	1	1	1	1	2
3	2	3	2	2	2	2	1	1	1	1	1	2
4	3	2	3	3	3	2	1	1	1	1	1	2
	3	3	3	3	5	2	2	1	1	1		1

hard