

(An Autonomous Institute Affiliated to RTM Nagpur University)



## DEPARTMENT OF INFORMATION TECHNOLOGY M.Tech Artificial Intelligence & Machine Learning

# Structure & Curriculum

## From

# Academic Year 2021-22

### Vision of Institute

To emerge as a learning Center of Excellence in the National Ethos in domains of Science, Technology and Management

## **Mission of Institute**

[M1] To strive for rearing standard and stature of the students by practicing high standards of Professional ethics, transparency and accountability

[M2] To provide facilities and services to meet the challenges of Industry and Society

[M3] To facilitate socially responsive research, innovation and entrepreneurship

[M4] To ascertain holistic development of student and staff members by inculcating

knowledge and profession as work practices

### Vision of the Department

To contribute in the enhancement of capabilities of youth to face Information Technology challenges, by empowering them with innovative ideas.

### **Mission of the Department**

- To stimulate students to learn effectively and apply the knowledge in the field of Engineering and Technology.
- To undertake industry academic collaboration to enhance competency in graduates.
- > To foster innovative ideas amongst students for becoming leaders.
- > To create an environment of research culture.
- To impart social and ethical values for inculcating the culture of lifelong learning.

## **Program Education Objectives (PEO)**

- Acquire fundamental knowledge of mathematics, science and engineering to analyze, design and implement solutions to the Information Technology problems
- > Understand emerging concepts and trends in Information Technology.
- > Apply IT tools to develop innovative computational systems.
- The students are encouraged to develop the habit of lifelong learning to face the challenges.
- The students will be embedded as a responsible individual having ethical and social values to lead the society and to nurture team spirit.

## **Program Outcomes (PO)**

- **PO1:** An ability to independently carry out research /investigation and development work to solve practical problems.
- **PO2:** An ability to write and present a substantial technical report/document.
- **PO3:** Students should be able to demonstrate a degree of mastery over the area as per the specialization of the program. The mastery should be at a level higher than the requirements in the appropriate bachelor program

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#### **Scheme of Instructions**

Scheme of Instructions for First Year M. Tech. Program in Artificial Intelligence & Machine Learning

Semester - I (w.e.f.: AY 2021-22)

			Course Title	I.	т	Р	Contact	Credits		Ε	its Exam Scheme			
Sr.	Course Category	CourseCode	Course The				Hrs / week		CT - 1	CT – 2	TA / CA	ESE	TOTAL	
	Category			-			2	2	15	15	10	60	100	
1.	PCC	MAI1101	Artificial Intelligence	3	-•	-	3	3	15	15	10	60	100	
2.	PCC	MAI1102	Natural Language	3	-	-	3	3	15	15	10	00	100	
			Processing					-	15	15	10	60	100	
3	PCC	MAI1103	Probability & Statistics	3	-	-	3	3	15	15	10	00	50	
5.	100		Laboratery L(AD)	-	-	2	2	1	-	-	25	25	50	
4.	PCC	MAII104	Laboratory -1 (A1)			-	2	1		-	25	25	50	
5	PCC	MAI1105	Laboratory –II (NLP)	-	-	2	2	1	-		10	(0)	100	
	777	X 4 11 106 00*	Professional Elective – I	3	-	-	3	3	15	15	10	60	100	
6.	PEC	MAI1100-09*	FIOIESSIONAL Elective	-			2	3	15	15	10	60	100	
7	PEC	MAI1110-13*	Professional Elective - II	3	-	-	. 3	5	15	10				
	MCC	MATT1101	Pedagogy Studies	2	-	-	2	Audit	-	-	-	-		
8.	MCC	IVIAUTIUI	roungog, studies	1.7		4	21	17	75	75	100	350	600	
			Total	17	-	4	21	17	15	10		1		

L- Lecture

CT1- Class Test 1 P-Practical

CT2- Class Test 2

TA/CA- Teacher Assessment / Continuous AssessmentESE- End Semester

Examination (For Laboratory: End Semester Performance)

T-Tutorial

\* Indicates out of the four course codes each student has to select any one PEC from the list provided at the end of structure. PROGRESSIVE TOTAL CREDITS= 17

Chairman Head of Dept. (Information Technology) Tulsiramji Gaikwad-Patil College of Engineering & Technology, Nagpur.

Dean Academics Dean Academics Tulsiramji Gaikwad-Patil College Of Engineering and Technology, Nagpur

Principal Principal

Tulsiramji Galkwad - Patil College Of Engineering & Technology Nagpur

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#### Scheme of Instructions

Scheme of Instructions for First Year M. Tech. Program in Artificial Intelligence & Machine Learning

Semester - II (w.e.f.: AV 2021-22)

Sr.	Course Category	CourseCode	Course Title	L	T	Р	Contact Hrs / week	Credits			Exam Scheme		-
									<b>CT – 1</b>	CT- 2	TA / CA	ESE	TOTAL
1.	PCC	MAI1201	Machine Learning for Data Analysis	3	-	-	3	3	15	15	10	60	100
2.	PCC	MAI1202	Big Data Mining And Analytics	3	-	-	3	3	15	15	10	60	100
3.	PCC	MAI1203	Information & Cyber Security	3	-	-	3	3	15	15	10	60	100
4.	PCC	MAI1204	Laboratory –III (ML using Python)	-	-	2	2	1	-	-	25	25	50
5.	PCC	MAI1205	Laboratory -IV (BDMA)	-	-	2	2	1	-	-	25	25	50
6.	FC	MAI1206	Research Methodology#	2	-		2	2	-	-	25	25	50
7.	PEC	MAI1207-10*	Professional Elective - III	3	-	-	3	3	15	15	10	60	100
8	PEC	MAI1211-14*	Professional Elective - IV	3	-	-	3	3	15	15	10	60	100
9	MCC	MAU1202	Research Paper Writing	2	-	-	2	Audit	-	-	-	-	
	1.100		Total	19	-	4	23	19	75	75	125	375	650
L	Tarterial P-Practical CT1- Class Test 1 CT2- Class Test 2 TA/CA- Teacher Assessment / Continuous AssessmentESE- End												

L-Lecture Semester Examination (For Laboratory: End Semester Performance)

T-Tutorial

# Students is expected to complete it online by appearing NPTEL/Swayam Certification for 03 credits. Weekly 02 Hrs practical in which students are expected to work on mathematical modeling, Seminar on IPR, Patent filing, Removing Plagiarisms, etc. will be done.

Indicates out of the four course codes each student has to select any one PEC from the list provided at the end of structure.

### PROGRESSIVE TOTAL CREDITS= 17+19 = 36

**BoS** Chairman

Head of Dept. (Information Technology) Tulsiramij Galkwad-Patil College of Engineering & Technology, Nagpur

Dean Academics Dean Academics Tulsiramji Gaikwad-Patil College Of Engineering and Technology, Nagpur

rincipal Príncipal Tulsiramil Gaikwad - Patil College Of Engineering & Technology Nagpur

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### **Scheme of Instructions**

Scheme of Instructions for Second Year M. Tech. Program in Artificial Intelligence & Machine Learning

Semester - III (w.e.f.: AY 2021-22)

Sr.	Course	CourseCode	Course Title	L	Т	P	Contact	Credits		Exam Scheme			
	Category						Hrs / week		CT - 1	CT - 2	TA / CA	ESE	TOTAL
1	PROJ	MAI2301	Dissertation Phase-I	-	-	20	20	10	-	-	100	100	200
2	PEC	MAI2302	MOOC course (8-12)\$	-	-	-	-	3	-	-	-	-	-
3	OEC	M\$\$XX01-06#	Open Elective –I	3	-	-	3	3	15	15	10	60	100
			Total	3	-	20	23	16	-	-	110	160	300

ote:

1. MAI2301 will be decided by respective Guide in Consultation with Program Coordinator. Course is mandatory is for student and hisdissertation phase I will be considered incomplete without this Mandatory MOOC Course.

2. In Case, the course offered online are not completely relevant with the topic of dissertation then any course suggested by NASSCOM on recent technologies can be opted by candidate.

3. \$ Programme coordinator will provide list of 03 MOOC courses of minimum 08 weeks duration (as per availability). Students are expected to complete any one out of three courses in order to get the required credits.

#### # Indicates out of the 06 course codes each student has to select any one OEC except MCSXX01

L- Lecture	T-Tutorial	P-Practical
CT1- Class Test 1	TA/CA- Teacher Assessment	t/Continuous Assessment
CT2- Class Test 2	ESE- End Semester Examina	tion (For Laboratory End Semester performance)PROGRESSIVE

#### **TOTAL CREDITS= 36+16 = 52**

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### Scheme of Instructions

Scheme of Instructions for Second Year M. Tech. Program in Artificial Intelligence & Machine Learning

Semester - IV (w.e.f.: AV 2021-22)

٢	Sr	Course	Course	Course Title	1	т	P	Contact	Credits		Exam Scheme			
	.51.	Category	Code	Course Thie	L	•	· ·	Hrs / week		CT - 1	CT - 2	TA / CA	ESE	TOTAL
ł	1	PROI	MA12401	Dissertation Disco. II			32	12	16		-	100	200	300
ł	1.	FROJ	M/A12401	Dissertation Phase- II	-		12	32	16	-		100	200	300
1				Total	•			~~	1		k	1	L.	1

TA/CA- Teacher Assessment / Continuous Assessment

ESE- End Semester Examination (For Laboratory: End Sementer Performance)

#### PROGRESSIVE TOTAL CREDITS= 52+16 = 68

-BoS Chairman Head of Dept. (Information Technology) Tulsiramji Galkwad-Patil College of Engineering & Technology, Nagpur

Dean Academics Dean Academics fulsiramji Gaikwad-Patil College Of Engineering and Technology, Nagpur

Principal Principal Tutsiramji Gaikwad - Patil College Of Engineering & Technology Nagpur



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D		(An Autonomou	s Institute Affiliated to RTM Nagpur Unive	rsity, Nagpur	)				
Pro	rogram: M. Tech. Artificial Intelligence & Machine Learning								
Sem	nester	<b>II MAI1201</b> : M	achine Learning for Data Analysis						
	Tea	ching Scheme		Examinati	on Scheme				
	Theor	y 3 Hrs/week		CT-I	15 Marks				
]	Futoria	al -		CT-II	15 Marks				
Tot	tal Cre	dits 3		CA	10 Marks				
	Durati	on of ESE: 3Hrs		ESE	60 Marks				
Pre	-Requ	isites: Statistics, Line	ear Algebra, Calculus, Probability,	Total Marks	100 Marks				
Prog	gramm	ing Languages, Artifi	cial Intelligence						
	Stud	opt shall be able to ur	derstand the importance of Machine Learning						
1.	Stud	ent shall be able to up	derstand the importance of Machine Learning	ed Learning ?					
2.	Stud	ent shall be able to ur	derstand shout the Unsupervised Learning	eu Leannig-2	•				
J.	Stud	ent shall be able to ur	derstand the Design and Analysis of Machine	Leorning Ev	arimants				
4. 5	Stud	ent shall be able to ur	derstand the Design and Analysis of Machine		bernnents				
5.	Stud	ent shall be able to uf	derstand about the Advances in Machine Lea	ining .					
		Introduction to m	Course Contents	na Evamplas	of Mashina				
		Learning Application	actime learning. What is Machine Learning	lig, Examples	pervised and				
Ur	nit I	Unsupervised Learning, Reinforcement Learning, Generalization, Over-fitting, and Under-							
		fitting							
		Supervised Learning-1: k-Nearest Neighbors, linear Models, Naive Bayes Classifiers,							
TT	•4 11	Decision Trees, And Supervised Learning-2: Kernelized Support Vector Machines,							
Un	17 11	Uncertainty Estimates from Classifiers, The Decision Function, predicting Probabilities,							
		Uncertainty in Multiclass Classification, multivariate classification and regression.							
		Unsupervised Lea	rning k-Means Clustering Expectation	-Maximizatio	n Algorithm				
Uni	it III	Supervised Learnin	g after Clustering, Hierarchical Clustering,	Choosing th	e Number of				
		Clusters		U					
		Design and Analys	is of Machine Learning Experiments: Fact	ors. Response.	and Strategy				
		of Experimentation	, Randomization, Replication, and Blocking	g, Guidelines	for Machine				
Uni	it IV	Learning Experime	ents , Cross-Validation and Resampling	Methods, K	-Fold Cross-				
Validation, Bootstrapping, Measuring Classifier Performance, Hypothesis T				pothesis Testi	ng, Assessing				
	Advances in Machine Learning: Combining multiple learners, bagging and boosting								
Un	Jnit V introduction to learning using Neural networks, shallow and deep networks.								
Tex	ext Books								
Т	.1	Introduction to Mach	ine Learning, Second Edition by Ethem Alpay	dın, The MIT	Press				
Т	.2	Introduction to Mach Müller and Sarah Gu	ine Learning with Python, A Guide for Data S ido, ORIELLY	cientists by A	ndreas C.				
Ref	erence	Books							

R.1	Machine Learning, Tom M. Mitchel by McGraw Hill					
Useful L	Useful Links					
1	https://nptel.ac.in/courses/106/106/106106139/					
2	https://onlinecourses.nptel.ac.in/noc21_cs24/preview					
3	https://nptel.ac.in/courses/106/105/106105152/					

	Course Outcomes	PO/PSO	CL	Class Sessions
MAI1201.1	<b>Reviewing</b> the various models of supervised and unsupervised learning.	PO1,PO2,PO3	5	9
MAI1201.2	<b>Identify</b> appropriate learning paradigm to solve it.	PO1,PO2,PO3	4	9
MAI 1201.3	<b>Criticizing</b> the supervised learning for the given set of labeled samples and design the model to meet the desired output.	PO1,PO2,PO3	5	9
MAI 1201.4	<b>Validating</b> the unsupervised learning for the given set of samples, and design the model to meet the desired Output.	PO1,PO2,PO3	5	9
MAI 1201.5	Analyzing the advances in Machine Learning.	PO1,PO2,PO3	4	9



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- Due que		An Autonomous	institute Affinated to KTW Nagpur Unive	rsity, Nagpur	)					
Progra			Icial Intelligence & Machine Learnin	g						
Semeste	r-11	MAI1202: Big	Data Mining & Analytics							
Te	eaching	Scheme		Examination	ion Scheme					
Theo	ory	3 Hrs/week		CT-I	15 Marks					
Tutor	rial	-		CT-II	15 Marks					
Total C	redits	3		CA	10 Marks					
Dura	Duration of ESE: 3HrsESE60 Marks									
Pre-Req	uisites	Data Visualiza	tions, Big data, SQL, Data Mining, Public	Total Marks	100 Marks					
Clouds &	x nybri	a Clouds, Hadoo	p, Database Management Systems							
1. Stu	ident sh	all be able to un	derstand the Analytics Methods							
1. Stu 2. Stu	ident sh	all be able to un	derstand Relational Database.							
3. Stu	ident sh	all be able to un	derstand about the Clustering							
4. Stu	ident sh	all be able to un	derstand the ARIMA Model							
5. Stu	ident sh	all be able to un	derstand about the Analytics for Unstructured	data.						
			Course Contents							
	Dia	data avanviary	State of the prostice in Analytics Key roles	for now big d	ata accustom					
Unit I	Data	Analytics Life	cycle-Data analytics lifecycle overview- Di	scovery- Data	Preparation-					
	Mod	lel Planning-Mo	del Building-Communicate Results-operation	alize	i Troparation					
	Inte	aduction to D.	Evaluation Data Analytics Statistical mat	hada far ayalı	ation Hadoon					
Unit II	linu & N	Introduction to R: Exploratory Data Analytics-Statistical methods for evaluation Hadoop								
	Non	Non-Relational (NoSOL) DBs								
	Clus	stering: Ove	rview of Clustering-K-means, Association	n Rules-Ove	rview-Apriori					
	Algo	Algorithm-Evaluation of candidate rules-An Example: Transactions in grocerv Store-								
Unit III	Vali	Validation and Testing-Diagnostics, Regression-Linear Regression-Logistic Regression-								
	Reas	son to choose an	d Cautions-Additional Regression Models							
	Clas	ssification: De	ecision Trees-Naïve Bayes-Diagnostics	of Classifie	ers-Additional					
	class	sification metho	ds, Time series Analysis Overview of Tin	ne series ana	lysis-ARIMA					
Unit IV		lel-Additional n	nethods, Text Analysis-Text analysis steps	-A text analy	sis Example-					
	Coll	ecting raw	lext-Representing lext-lerm Freque	ency—Inverse	document					
	insi	frequency(TFIDF)-Categorizing documents by Topics-Determining Sentiments-Gaining								
	Analytics for Unstructured data: The Hadoon Ecosystem-NoSOL In-Database Analytics-									
Unit V	Unit V SOL Essentials-In-Database Text Analysis-Advanced SOL									
Text Bo	oks									
Т 1	EMC	Education Serv	ices, "Data Science and Big Data Analytics: I	Discovering, A	nalyzing,					
1.1	Visua	alizing and Prese	nting Data", Wiley publishers, 2015	<b>-</b>	-					
T.2	Simo	n Walkowiak, "I	Big Data Analytics with R" PackT Publishers	, 2016						
Keferen	eference Books									

<b>R</b> .1	Kim H. Pries and Robert Dunnigan, "Big Data Analytics: A Practical Guide for Managers" CRC Press, 2015.	
R2	Bart Baesens, "Analytics in a Big Data World: The Essential Guide to Data Science and its Applications", Wiley Publishers, 2015.	
Useful L	inks	Bart Appl
1	https://onlinecourses.nptel.ac.in/noc20_cs92/preview	
2	https://nptel.ac.in/courses/106/104/106104189/	
3	https://nptel.ac.in/noc/courses/noc19/SEM1/noc19-cs33/	

	Course Outcomes	PO/PSO	CL	Class Sessions
MAI1202.1	<b>Validating</b> big data and data analytics lifecycle	PO1,PO2,PO3	5	9
MAI1202.2	<b>Measuring</b> Basic Data analytic methods using R	PO2,PO3	5	9
MAI1202.3	<b>Reviewing</b> a knowledge on advanced analytical methods, technology and tools	PO1,PO2,PO3	5	9
MAI1202.4	<b>Apply</b> the Analytical methods, Technology and tools in the industry.	PO2,PO3	3	9
MAI1202.5	<b>Simulating</b> hadoop ecosystem and apply to solve real-life problems	PO2,PO3	6	9



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Pro	rogram: M. Tech. Artificial Intelligence & Machine Learning										
Sem	iester-	<b>II MAI1203</b> : In	formation and Cyber Security								
	Tea	ching Scheme	_	Examinat	ion Scheme						
,	Theory	y 3 Hrs/week		CT-I	15 Marks						
]	Futoria	al -		CT-II	15 Marks						
Tot	tal Cre	dits 3		CA	10 Marks						
	Durati	on of ESE: 3Hrs		ESE	60 Marks						
Pre	-Requ	isites:		Total Marks	100 Marks						
Cou	irse O	bjectives:									
1.	To u	nderstand the basics of	f computer, network and information security.								
2.	To st	udy operating system	security and malwares								
3.	To ac	equaint with security	ssues in internet protocols								
4.	To a	halyze the system for	vulnerabilities.								
5.	To ap	pply the scientific me	hod for security assessment								
			<b>Course Contents</b>								
Ur	nit I	Security Fundan Threats, Policy a Human Issues, Confidentiality, In	nentals: An Overview of Information Security nd Mechanism, Assumptions and Trust, Assu Security nomenclature. Access Control M tegrity, Availability Policies and Hybrid Policies	r: The Basic arance, Opera fatrix, Secur s, OS Security	Components, tional Issues, tity Policies:						
Un	it II	Modular Arithme Arithmetic Operat Cryptography : Cl Standard, Advance	etic and Cryptography Basics: Modular Arithmions, Euclid's method of finding GCD, The extensional encryption techniques, Block and Chain ed Encryption Standard, RC5	netic Notation ended Euclid's ciphers, Data	ns, Modular s algorithm. Encryption						
Uni	it III	Advanced Cryp Cryptography, D Arithmetic, Ellip Functions, MD5 a	<b>tography:</b> Chinese Remainder Theorem an iffie-Hellman key exchange algorithm, RS ic Curve Cryptography, Message Digest an nd SHA-1, Digital Signatures and Authentication	nd its impl SA algorithm nd Cryptogra n.	ication in a, Elgamal phic Hash						
Uni	Unit IVIssues in Security Management and Key Management: Overview, Risk identification, Risk Assessment, Risk Control Strategies, Quantitative vs. Qualitative Risk Control Practice Risk Management. Public Key Infrastructure(PKI), X.509 Certificate, Needham Schroede algorithm and Kerberos. IP Security: IPv6 and IPSec, Web Security: SSL, HTTPS, Ma Security: PGP, S/MIME										
Unit VAttacks, Malicious Logic and Countermeasures: Phishing, Password Cracking, Key-loggers and Spywares, Types of Virus, Worms, DoS and DDoS, SQL injection, Buffer Overflow, Spyware, Adware and Ransomware. Antivirus and other security measures Intrusion Detection System : IDS fundamentals, Different types of IDS. Intrusion Prevention											
Tex	t Bool	ζS									
T	.1	Ms. Monali R. Bora	ade, Sachin P. Godse, "Information & Cyber Se	ecurity "							

T.2	Identity management for Internet of things by ParikshitMahalle, River Publishers				
Reference	ee Books				
	Cyber Criminology: Exploring Internet Crimes and Criminal Behavior, Edited by K.				
<b>R</b> 1	Jaishankar, CRC Press, ISBN 978-1-4398-2949-3 2. Mark Merkow, "Information Security-				
	Principles and Practices", Pearson Ed., ISBN- 978-81-317-1288-7				
	Mark Merkow, "Information Security-Principles and Practices", Pearson Ed., ISBN- 978-81-				
<b>R</b> 2	317-1288-7				
Useful L	Useful Links				
1	https://nptel.ac.in/courses/106/105/106105173/				
2	https://onlinecourses.nptel.ac.in/noc20_cs17/preview				
3	https://nptel.ac.in/content/syllabus_pdf/106105173.pdf				

	Course Outcomes	PO/PSO	CL	Class Sessions
MAI1203.1	Use cryptographic techniques in secure application development.	PO1,PO2,PO3	4	9
MAI1203.2 Apply methods for authentication, access control, intrusion detection and prevention.		PO1,PO2,PO3	4	9
MAI12033	To apply the scientific method for security assessment	PO1,PO2,PO3	4	9
MAI1203.4	Use and apply advance cryptography technique	PO1,PO2,PO3	5	9
MAI1203.5	To develop computer forensics awareness	PO1,PO2,PO3	6	9



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Pro	ogran	n: M. Tech. Artif	icial Intelligence & Machine Learnin	g			
Sem	nester-	II MAI1207: Ele	ctive-III(Pattern Recognition)	I			
	Tea	ching Scheme		Examinati	on Scheme		
,	Theory	3 Hrs/week		CT-I	15 Marks		
]	Futoria	ıl -		CT-II	15 Marks		
Tot	tal Cre	dits 3		CA	10 Marks		
	Durati	on of ESE: 3Hrs		ESE	60 Marks		
Pre	-Requ	isites: Machine learr	ing ,Artificial Intelligence , Class-invariance	Total Marks	100 Marks		
,Dis	crete I	Aathematics					
Cou	irse O	bjectives:		• • •			
1.	Stud	ent shall be able to ur	derstand the Probability & Estimation minimu	im risk estima	tors.		
2.	Stud	ent shall be able to ur	Iderstand the Statistical Pattern Recognition.				
3.	Stud	ent shall be able to ur	derstand the Parameter Estimation Methods.				
4.	Stud	ent shall be able to ur	derstand the Non-Parameter methods.				
5.	Stud	ent shall be able to ur	derstand the Unsupervised learning and cluste	ering.			
			Course Contents				
		Introduction: Defin	ition, Applications, Datasets, Different parad	igms , Data st	ructures for		
Ur	nit I	distributions and d	n, introduction to probability, events ,r	andom varia	ndom variables, Joint		
		Representation of c	lusters, proximity measures, size of patterns,	Abstraction of	of Data set.		
		Feature extraction, H	Features election, Evaluation		,		
		Statistical Pattern	<b>Recognition:</b> Review of probabil	lity theory	, Gaussian		
Un	it II	distribution, Bayes of	lecision theory and Classifiers, Optimal sol	utions for min	imum error		
		and minimum risk c	riteria, Normal density and discriminate functi	ons, Decision	surfaces.		
		Parameter Estima	tion Methods: Maximum-Likelihood Esti	imation: Gau	ssian case.		
		Maximum Posteric	ri estimation, Bayesian estimation, Gaussing – Criterion functions for clustering Algorithms	sian case. Ui	stering K		
Uni	it III	Means, Hierarchical and other methods. Cluster validation Gaussian mixture models					
		Expectation-Maximization method for parameter estimation. Maximum entropy estimation,					
		Sequential Pattern	Recognition. Hidden Markov Models, Non p	parametric tecl	nniques for		
		density estimation.		•, ,• .•	D		
<b>Non-Parameter methods:</b> Non-parametric techniques for density estimation,				on, Parzen- ethod Non			
Unit IV		window method, K-NearestNeighbourmethod,Non- metricmethodsforpatternclassification Non-numeric data or nominal data Decision trees					
Concept of construction, splitting of nodes, choosing of attributes, over fitting, pruni				runing.			
		Unsupervised learn	ing and clustering: Unsupervised maximum	-likelihood est	imates,		
Un	it V	Unsupervised Bayes	ian learning, Criterion functions for clustering	, Algorithms f	or clustering:		
		Kmeans, Hierarchic	al and other methods, Cluster validation, Low-	-dimensional r	epresentation		
Tex	t Bool						
Т	1	 R.O.Duda,P.E.Hart a	ndD.G.Stork,PatternClassification,JohnWilev.	2001			
	.1	,	, <u> </u>				

T.2	S.TheodoridisandK.Koutroumbas,PatternRecognition,4thEd., AcademicPress,2009
T3	C.M.Bishop,PatternRecognitionandMachineLearning,Springer,2006
Reference	ce Books
R.1	DudaRO, HartPE, and StorkDG, Patternclassification, JohnWileyandSons, 2001.
R 2	Robert J. Schalkoff, Pattern Recognition : Statistical, Structural and Neural Approaches, John Wiley &Sons Inc., NewYork, 2007.
R 3	Ethem Alpaydin, "MachineLearning: The New AI", MIT Press,2016.
Useful L	inks
1	https://nptel.ac.in/courses/106/106/106106046/
2	https://www.geeksforgeeks.org/pattern-recognition-introduction/
3	https://nptel.ac.in/noc/courses/noc19/SEM2/noc19-ee56/

	Course Outcomes	PO/PSO	CL	Class Sessions
MAI1207(1).1	<b>Differentiate</b> a variety of pattern classification, structural pattern recognition and pattern classifier combination techniques.	PO1,PO2,PO3	5	9
MAI1207 (1).2Summarize the pattern recognition area verbally and in writing.		PO1,PO2,PO3	5	9
MAI1207(1).3 Apply performance evaluation methods for pattern recognition, and critique comparisons of techniques made in the research literature.		PO1,PO2,PO3	4	9
MAI1207(1).4Identify pattern recognition techniques to real-world problems such as document analysis and recognition.		PO1,PO2,PO3	5	9
MAI1207(1).5	<b>Implement</b> simple pattern classifiers, classifier combinations, and structural pattern recognizers.	PO1,PO2,PO3	3	9



Tulsiramji Gaikwad-Patil College of Engineering and Technology Wardna Road, Nagpur-441 108 NAAC Accredited with A+ Grade (An Autonomous Institute Affiliated to RTM Nagpur University, Nagpur)       Image: Colspan="2">Image: Colspan="2"       Image: Colspan="2"       Image: Colspan="2"       Image: Colspan="2"       Image: Colspan="2"       Image: Colspan="2"        Image: Colspan="2" <th colsp<="" th=""><th></th><th></th><th></th><th></th><th></th></th>	<th></th> <th></th> <th></th> <th></th> <th></th>							
Wardha Road, Nagpur-441 108 NAAC Accredited with A+ Grade (An Autonomous Institute Affiliated to RTM Nagpur University, Nagpur)           Program:         M. Tech. Artificial Intelligence & Machine Learning           Semester-II         MAI1208: Elective-III(Reinforcement Learning)           Teaching Scheme         Examination Scheme           Tutoriat         -         CT-I         15 Marks           Tutoriat         -         CT-II         15 Marks           Duration of ESE: 3Hrs         ESE         60 Marks           Duration of ESE: 3Hrs         ESE         60 Marks           Course Objectives:         I         Student shall be able to understand the reinforcement learning problem           3         Student shall be able to understand the function approximation         Student shall be able to understand the function approximation           5         Student shall be able to understand the function approximation         Student shall be able to understand the function approximation           5         Student shall be able to understand the function approximation         Torse Contents           Value iteration, policy iteration, approximation Sprioration schemes         Value functions, optimality and approximation           8         Evaluative feedback, non associative learning, Reavafs and returns, Markov Decision Processes, Value functions, optimality and approximation         Bandit Problems: Explore-exploit dilemma, Binary Bandits,		Tulsiramji Gaikwad-Patil College of Engineering and Technology						
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(An Autonomous Institute Affiliated to RTM Nagpur University, Nagpur)           Program: M. Tech. Artificial Intelligence & Machine Learning           Semester-II         MAI1208: Elective-III(Reinforcement Learning)           Teaching Scheme         Examination Scheme           Theory         3 His/week         CT-I         15 Marks           Tutorial         -         CT-II         15 Marks           Total Credits         3         CA         10 Marks           Digebra, calculus, Probability Theory         Total Marks         Total Marks         I00 Marks           Algebra, calculus, Probability Theory         Total Marks         10 Marks         10 Marks           Student shall be able to understand the reinforcement learning problem         .         .         .           Student shall be able to understand the function approximation         .         .         .         .           Student shall be able to understand the function approximation         .         .         .         .         .           Unit I         Evaluative feedback, non associative learning, Rewards and returns, Markov Decision Processes, Value functions, optimality and approximation Bandity Learning automata, exploration schemes         .         .           Unit II         Value iteration, policy iteration, asynchronous DP, generalized policy iteration Monte-Carlo		NAAC Accredited with A+ Grade						
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Pre-Requisites:     Supervised Learning , Search Methods in AI, Linear Algebra, calculus, Probability Theory     Total Marks     100 Marks       Algebra, calculus, Probability Theory     Image: Course Objective:     Image: Course Objective:     Image: Course Objective:       1     Student shall be able to understand the reinforcement learning problem     Image: Course Objective:     Image: Course Objective:       2     Student shall be able to understand the dynamic programming     Image: Course Ontents     Image: Course Contents       3     Student shall be able to understand the function approximation     Image: Course Contents     Image: Course Contents       Course Contents       Value functions, optimality and approximation Bandit Problems: Explore-exploit dilemma, Binary Bandits, Learning automata, exploration schemes       Value citeration, policy iteration, asynchronous DP, generalized policy iteration       Monte-Carlo methods: Policy evaluation, roll outs, on policy and off policy learning, importance sampling       TD prediction, Optimality of TD(0), SARSA, Q-learning, R-learning, Games and after states       ELIGIBILITY TRACES non-associative learning - REINFORCE algorithm, exact gradient methods, estimating gradient, approximate policy gradient algorithms, actor-critic methods       Value prediction, gradient descent methods, linear function approximation. Control algorithms, Fitted learning - REINFORCE algorithm, exact gradient methods, estimating gradients, approximate policy gradient algorithms, actor-critic methods </th <th>Durat</th> <td>ion of ESE: 3Hrs</td> <td></td> <td>ESE</td> <td>60 Marks</td>	Durat	ion of ESE: 3Hrs		ESE	60 Marks			
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Unit III       TD prediction, Optimality of TD(0), SARSA, Q-learning, R-learning, Games and after states         ELIGIBILITY TRACES       n-step TD prediction, TD(lambda), forward and backward views, Q(lambda), SARSA(lambda), replacing traces and accumulating traces.         Value       prediction, gradient descent methods, linear function approximation, Control algorithms, Fitted Iterative Methods         POLICY GRADIENT METHODS       non-associative learning - REINFORCE algorithm, exact gradient methods, estimating gradients, approximate policy gradient algorithms, actor-critic methods         MAXQ framework, Options framework, HAM framework, Option discovery algorithms         Case studies:         Elevator dispatching, Samuel's checker player, TD gammon, Acrobot, Helicopter piloting, Computational Neuroscience         T.1       R. S. Sutton and A. G. Barto. Reinforcement Learning - An Introduction. MIT Press. Second edition 2017.         T.2       K. S. Narendra and M. A. L. Thathachar. Learning Automata - An Introduction. Prentice-Hall, USA. 1989	0 1110 11	Policy evaluation, ro	oll outs, on policy and off policy learning, im	portance sampl	ing			
Unit III       File prediction, Optimizity of TD(0), SARSA, Q-tearining, Games and arter states         Unit III       ELIGIBILITY TRACES         n-step TD prediction, TD(lambda), forward and backward views, Q(lambda), SARSA(lambda), replacing traces and accumulating traces.         Value prediction, gradient descent methods, linear function approximation, Control algorithms, Fitted Iterative Methods         POLICY GRADIENT METHODS         non-associative learning - REINFORCE algorithm, exact gradient methods, estimating gradients, approximate policy gradient algorithms, actor-critic methods         MAXQ framework, Options framework, HAM framework, Option discovery algorithms         Case studies:         Elevator dispatching, Samuel's checker player, TD gammon, Acrobot, Helicopter piloting, Computational Neuroscience         T.1       R. S. Sutton and A. G. Barto. Reinforcement Learning - An Introduction. MIT Press. Second edition 2017.         T.2       K. S. Narendra and M. A. L. Thathachar. Learning Automata - An Introduction. Prentice-Hall, USA. 1989		TD prediction Opti	$\frac{1}{1}$	ning Games an	d after states			
Unit IIIInstant of Market and StressInstant of Market and StressInstant of Market and StressInstant and StressValue prediction, gradient descent methods, linear function approximation, Control algorithms, Fitted Iterative MethodsInit IVPOLICY GRADIENT METHODS non-associative learning - REINFORCE algorithm, exact gradient methods, estimating gradients, approximate policy gradient algorithms, actor-critic methodsInit IVMAXQ framework, Options framework, HAM framework, Option discovery algorithmsCase studies: Elevator dispatching, Samuel's checker player, TD gammon, Acrobot, Helicopter piloting, Computational NeuroscienceT.1R. S. Sutton and A. G. Barto. Reinforcement Learning - An Introduction. MIT Press. Second edition 2017.T.2K. S. Narendra and M. A. L. Thathachar. Learning Automata - An Introduction. Prentice-Hall, USA. 1989		ELIGIBILITY TR	ACES	ning, Games an	d arter states			
SARSA(lambda), replacing traces and accumulating traces.         Value prediction, gradient descent methods, linear function approximation, Control algorithms, Fitted Iterative Methods         POLICY GRADIENT METHODS         non-associative learning - REINFORCE algorithm, exact gradient methods, estimating gradients, approximate policy gradient algorithms, actor-critic methods         MAXQ framework, Options framework, HAM framework, Option discovery algorithms         Case studies:         Elevator dispatching, Samuel's checker player, TD gammon, Acrobot, Helicopter piloting, Computational Neuroscience         T.1       R. S. Sutton and A. G. Barto. Reinforcement Learning - An Introduction. MIT Press. Second edition 2017.         T.2       K. S. Narendra and M. A. L. Thathachar. Learning Automata - An Introduction. Prentice-Hall, USA. 1989	Unit III	n-step TD prediction, TD(lambda), forward and backward views, O(lambda).						
Unit IVValue prediction, gradient descent methods, linear function approximation, Control algorithms, Fitted Iterative MethodsUnit IVPOLICY GRADIENT METHODS non-associative learning - REINFORCE algorithm, exact gradient methods, estimating gradients, approximate policy gradient algorithms, actor-critic methodsUnit VMAXQ framework, Options framework, HAM framework, Option discovery algorithms Case studies: Elevator dispatching, Samuel's checker player, TD gammon, Acrobot, Helicopter piloting, Computational NeuroscienceT.1R. S. Sutton and A. G. Barto. Reinforcement Learning - An Introduction. MIT Press. Second 		SARSA(lambda), replacing traces and accumulating traces.						
Unit IValgorithms, Fitted Iterative MethodsPOLICY GRADIENT METHODS non-associative learning - REINFORCE algorithm, exact gradient methods, estimating gradients, approximate policy gradient algorithms, actor-critic methodsUnit VMAXQ framework, Options framework, HAM framework, Option discovery algorithms Case studies: Elevator dispatching, Samuel's checker player, TD gammon, Acrobot, Helicopter piloting, Computational NeuroscienceT.1R. S. Sutton and A. G. Barto. Reinforcement Learning - An Introduction. MIT Press. Second edition 2017.T.2K. S. Narendra and M. A. L. Thathachar. Learning Automata - An Introduction. Prentice-Hall, USA. 1989		Value prediction,	gradient descent methods, linear function	on approxima	tion, Control			
Unit IVPOLICY GRADIENT METHODS non-associative learning - REINFORCE algorithm, exact gradient methods, estimating gradients, approximate policy gradient algorithms, actor-critic methodsUnit VMAXQ framework, Options framework, HAM framework, Option discovery algorithms Case studies: Elevator dispatching, Samuel's checker player, TD gammon, Acrobot, Helicopter piloting, Computational NeuroscienceT.1R. S. Sutton and A. G. Barto. Reinforcement Learning - An Introduction. MIT Press. Second edition 2017.T.2K. S. Narendra and M. A. L. Thathachar. Learning Automata - An Introduction. Prentice-Hall, USA. 1989		algorithms, Fitted Iterative Methods						
Inon-associative learning - REINFORCE algorithm, exact gradient methods, estimating gradients, approximate policy gradient algorithms, actor-critic methodsUnit VMAXQ framework, Options framework, HAM framework, Option discovery algorithms Case studies: Elevator dispatching, Samuel's checker player, TD gammon, Acrobot, Helicopter piloting, Computational NeuroscienceText BooksT.1R. S. Sutton and A. G. Barto. Reinforcement Learning - An Introduction. MIT Press. Second edition 2017.T.2K. S. Narendra and M. A. L. Thathachar. Learning Automata - An Introduction. Prentice-Hall, USA. 1989	Unit IV	POLICY GRADIENT METHODS						
Image: statistic state		non-associative learning - REINFORCE algorithm, exact gradient methods, estimating						
Unit V       MAAQ framework, Options framework, HAM framework, Option discovery algorithms         Case studies:       Elevator dispatching, Samuel's checker player, TD gammon, Acrobot, Helicopter piloting, Computational Neuroscience         Text Books       R. S. Sutton and A. G. Barto. Reinforcement Learning - An Introduction. MIT Press. Second edition 2017.         T.2       K. S. Narendra and M. A. L. Thathachar. Learning Automata - An Introduction. Prentice-Hall, USA. 1989	gradients, approximate policy gradient algorithms, actor-critic methods							
Unit V       Case studies.         Elevator dispatching, Samuel's checker player, TD gammon, Acrobot, Helicopter piloting, Computational Neuroscience         Text Books         T.1       R. S. Sutton and A. G. Barto. Reinforcement Learning - An Introduction. MIT Press. Second edition 2017.         T.2       K. S. Narendra and M. A. L. Thathachar. Learning Automata - An Introduction. Prentice-Hall, USA. 1989		MAAQ Iramework,	Options framework, HAM framework, Opti	on discovery alg	gorunms			
Text Books         T.1       R. S. Sutton and A. G. Barto. Reinforcement Learning - An Introduction. MIT Press. Second edition 2017.         T.2       K. S. Narendra and M. A. L. Thathachar. Learning Automata - An Introduction. Prentice-Hall, USA. 1989	Unit V	<b>Case studies:</b> Elevator dispatching Samuel's checker player TD gammon Acrobot Helicopter piloting						
Text Books         T.1       R. S. Sutton and A. G. Barto. Reinforcement Learning - An Introduction. MIT Press. Second edition 2017.         T.2       K. S. Narendra and M. A. L. Thathachar. Learning Automata - An Introduction. Prentice-Hall, USA. 1989	Computational Neuroscience							
T.1R. S. Sutton and A. G. Barto. Reinforcement Learning - An Introduction. MIT Press. Second edition 2017.T.2K. S. Narendra and M. A. L. Thathachar. Learning Automata - An Introduction. Prentice-Hall, USA. 1989	Text Boo	ks						
1.1edition 2017.T.2K. S. Narendra and M. A. L. Thathachar. Learning Automata - An Introduction. Prentice-Hall, USA. 1989	T 1	R. S. Sutton and A.	G. Barto. Reinforcement Learning - An Intr	oduction. MIT	Press. Second			
T.2 K. S. Narendra and M. A. L. Thathachar. Learning Automata - An Introduction. Prentice-Hall, USA. 1989	1.1	edition 2017.	· · · · · · · · · · · · · · · · · · ·					
<sup>1.2</sup> USA. 1989	т 2	K. S. Narendra and M	I. A. L. Thathachar. Learning Automata - A	n Introduction.	Prentice-Hall,			
	1.2	USA. 1989						

Т3	D. P. Bertsikas and J. N. Tsitsiklis. Neuro-dynamic programming. Athena Scientific. 1996.					
Reference	ee Books					
R.1	A. G. Barto and S. Mahadevan, Recent Advances in Hierarchical Reinforcement Learning, Discrete Event Systems Journal, Volume 13, Special Issue on Reinforcement Learning, pp. 41-77. 2003.					
R 2	R. J. Williams, Simple Statistical Gradient-following algorithms for Connectionist Reinforcement Learning, Machine Learning, 8:229-256. 1992					
R 3	J. Baxter, P. L. Bartlett, Infinite-Horizon Gradient-Based Policy Search, Journal of Artificial Intelligence Research, 15: 319-350, 2001.					
Useful L	Useful Links					
1	https://www.guru99.com/reinforcement-learning-tutorial.html					
2	https://neptune.ai/blog/best-reinforcement-learning-tutorials-examples-projects-and-courses					
3	https://nptel.ac.in/content/syllabus_pdf/106106143.pdf					

	Course Outcomes	PO/PSO	CL	Class Sessions
MAI1208(2).1	<b>Analyze</b> the reward function and Markov Decision Process	PO1,PO2,PO3	4	9
MAI1208(2).2	<b>Solve</b> problems using Dynamic Programming.	PO1,PO2,PO3	5	9
MAI1208(2).3	<b>Evaluate</b> temporal difference (TD) learning method for reinforcement learning problem	PO1,PO2,PO3	5	9
MAI1208(2).4	Criticize Gradient methods for Reinforcement Learning	PO1,PO2,PO3	5	9
MAI1208(2).5	<b>Implement</b> Hierarchical Reinforcement Learning Algorithms	PO1,PO2,PO3	3	9



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3	NAAC Accredited with A+ Grade						
	(An Autonomous Institute Affiliated to RTM Nagpur University, Nagpur)						
Pro	gran	n: M. Tech. Artif	ficial Intelli	gence & Machine Learnin	g		
Sem	lester	-II MAI1209: Ele	ective-III (Opt	timization Techniques)	1		
	Tea	ching Scheme			Examinat	ion Scheme	
,	Theor	y 3 Hrs/week			CT-I	15 Marks	
ſ	<b>Futori</b>	al -			CT-II	15 Marks	
Tot	al Cre	edits 3			CA	10 Marks	
	Durat	ion of ESE: 3Hrs			ESE	60 Marks	
Pre	Requ	isites: Compile Time	e Evaluation,	Requirements Selection ,	Total Marks	100 Marks	
Basi	cs of	Linear Programming	& Non Linea	r Programming			
Cou	rse O	bjectives:	1 ( 1.1				
1.	Stud	lent shall be able to up	nderstand the	Linear Programming			
2.	Stud	lent shall be able to up	adorstand the	Duality and Sansitivity Analysi	0		
5.	Stud	lent shall be able to up	iderstand the	Non linear Drogramming	8		
4.	Stud			Non-Intear Programming			
5.	Stud	lent shall be able to ur	nderstand the	Dynamic programming			
		T. D	· · · · · · · · · · · · · · · · · · ·	ourse Contents		• 1 •	
		formulating linear r	<b>ing</b> : introduc	ction and need for optimization	n in engineer	ang design,	
Ur	nit I	programming.	nograms, graj	incar solution of intear program	lis, special cas	es of fifical	
		The Simplex Meth	od: Converti	ng a problem to standard form,	the theory of	the simplex	
Un	it II	method, the simplex	k algorithm, sj	pecial situations in the simplex a	lgorithm, obta	ining initial	
		feasible solution.					
		Duality and Sensit	tivity Analys	is: Sensitivity analysis, shadow	prices, dual of	of a normal	
Uni	t III	linear program, duality theorems, dual simplex method. Integer Programming: Formulating					
		integer programming problems, the branch-and-bound algorithm for pure integer programs, the branch and bound algorithm for mixed integer programs					
		Non-linearProgram	nming:Introd	uctiontonon-			
		linearprogramming(	(NLP),Convex	andconcave functions, NLP	with one var	iable, Line	
Uni	it IV	search algorithms, Multivariable unconstrained problems, constrained problems, Lagrange					
		Multiplier, The Ka	rush-Kuhn-Tu method pen	icker (KKT) conditions, the malty function Quadratic program	ethod of steep	pest ascent,	
	• • • •	Dynamic program	ming: Evoluti	onary algorithms: Genetic Algor	rithm. concept	s of multi	
Un	it V	objective optimizati	on, Markov P	rocess, Queuing Models.	, • • • • • • • • • • • • • • • • •		
Tex	t Boo	ks					
Т	.1	S.S. Rao, Engineerin	g Optimizatio	n: Theory and Practice, Wiley &	Sons, New Je	rsey, 2009.	
Т	.2	F.H. Hillerand G.J. L	liberman, Intr	oductionto Operations Research,	Tata-McGraw	-Hill,2010.	
		K.Deb,Multi-Objecti	ve Optimizati	on using evolutionary algorithm	s, John Wileya	and	
T	3	Sons,2009					
Ref	erence	e Books					
mul							

R.1	W.L.Winston,Operations Research: ApplicationsandAlgorithm,4thEdition,CengageLearning,1994.
R 2	K.Deb,OptimizationforEngineeringDesign,PrenticeHall,2013.
R 3	M.C.JoshiandK.M.Moudgalay,Optimization:TheoryandPractice,Narosa,2004.
Useful L	inks
1	https://nptel.ac.in/courses/105/108/105108127/
2	https://nptel.ac.in/courses/111/105/111105039/
3	https://nptel.ac.in/courses/108/103/108103108/

	Course Outcomes	PO/PSO	CL	Class Sessions
MAI1203(3).1	Illustrate the importance of optimization of industrial process management	PO1,PO2,PO3	5	9
MAI1203(3).2	Implement the basic concept of mathematics to formulate an optimization problem	PO1,PO2,PO3	5	9
MAI1203(3).3	Analyze and Appreciate variety of performance measures for various optimization problems	PO1,PO2,PO3	4	9
MAI1203(3).4	Design the model engineering minima/maxima problems as optimization problems	PO1,PO2,PO3	5	9
MAI1203(3).5	Apply Dynamic programming techniques	PO1,PO2,PO3	3	9



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	(An Autonomous Institute Affiliated to RTM Nagpur University, Nagpur)						
Pro	gran	n: M	I. Tech. Artifi	cial Intelligen	ce & Machine Learning	g	
Sem	ester	-II	MAI1210: Ele	ctive-III Artificia	l Neural Network(Deep Lear	ming)	
	Tea	ching	Scheme			Examinati	ion Scheme
]	Theor	У	3 Hrs/week			CT-I	15 Marks
Т	lutori	al	-			CT-II	15 Marks
Tot	al Cro	edits	3			CA	10 Marks
	Durat	ion of	ESE: 3Hrs			ESE	60 Marks
Pre-	Requ	isites	Machine Learn	ing, Mathematic	s, Statistics, Probability,	Total Marks	100 Marks
Line	ar Al	gebra,	Calculus, Prog	amming Langua	ges.		
	rse U	ojecu lont ch	ives:	larstand the Dair	forcement learning problem		
1.	Stud	lent sh	all be able to un	lerstand the Dun	amia neo anomina	•	
2.	Stud	lent sh	all be able to un	lerstand the Dyn	anne programming.		
J.	Stud	lont sh	all be able to un	lerstand the Fun			
4.	Stud	lent sh	all be able to un	lerstand the Hier			
5.	Stuc	lent sn			archical KL.		
		T	1	Cour	se Contents		
∐n	it T	logis	stic regression),	Introduction to machina	Neural Nets: What a shall	(SVMs and F llow network	computes-
		Train Neur	ning a network ral networks as u	loss functions, niversal functior	back propagation and stor approximates.	chastic gradie	nt descent-
		Con	Convolutional Neural Networks				
Uni	it II	CNN	N Architectures,	Convolution Poc	oling Layers, Transfer Learn	ing, Image Cl	assification
		using Transfer Learning, Recurrent and Recursive Nets, Recurrent Neural Networks, Deep Recurrent Networks, Recursive Neural Networks, Applications					
		Dim	ensionality Re	luction: Linear	(PCA, LDA) and manifold	ls, metric lear	ning, Auto
Uni	t III	encoders and dimensionality reduction in networks, Introduction to Convent, Architectures,					
Cim		Alex Net, VGG, Inception, Res Net- Training a Convent: weights initialization, batch					
		norn	nalization, hyper	parameter optim	ization.		
		Opti	imization and	Generalization	Stochastic Optimization (	learning– No	in nourol
Uni	t IV	optimization for deep networks- Stochastic Optimization Generalization in neural networks- Spatial Transformer Networks-Case Study of Image net Detection Audio Waye					
Net.							
		Recu	urrent Neural	Network: Recu	urrent networks, LSTM - 1	Recurrent Ne	ural Network
Unit V		Lang	guage Models-	Vord-Level RN	Ns & Deep Reinforcement I	Learning, Con	nputational &
		Artificial Neuro science Case study on Natural Language ProcessingWord2Vec, Joint					
Toy	Detection Bio informatics, Face Recognition.						
ICA		R S	Sutton and A	Barto Reinfor	cement Learning - An Introd	duction MIT	Press Second
Τ.	1	editio	on 2017.	. Durto, Romfor	Coment Dearning 7 th Introt		ress. Second
T.	.2	K. S. Narendra and M. A. L. Thathachar. Learning Automata - An Introduction. Prentice-Hall, USA. 1989					
Т	3	D. P.	Bertsikas and J.	N. Tsitsiklis. Ne	uro-dynamic programming.	Athena Scienti	fic. 1996.

Reference	Reference Books					
R.1	A. G. Barto and S. Mahadevan, Recent Advances in Hierarchical Reinforcement Learning, Discrete Event Systems Journal, Volume 13, Special Issue on Reinforcement Learning, pp. 41-77. 2003.					
R 2	R. J. Williams, Simple Statistical Gradient-following algorithms for Connectionist Reinforcement Learning, Machine Learning, 8:229-256. 1992					
R 3	J. Baxter, P. L. Bartlett, Infinite-Horizon Gradient-Based Policy Search, Journal of Artificial Intelligence Research, 15: 319-350. 2001.					
Useful L	Useful Links					
1	https://www.guru99.com/reinforcement-learning-tutorial.html					
2	https://neptune.ai/blog/best-reinforcement-learning-tutorials-examples-projects-and-courses					
3	https://nptel.ac.in/courses/108/105/108105103/					

	Course Outcomes	PO/PSO	CL	Class Sessions
MAI1210(4).1	Analyze the reward function and Markov Decision Process	PO1,PO2,PO3	4	9
MAI1210(4).2	<b>Solve</b> problems using Dynamic Programming.	PO1,PO2,PO3	5	9
MAI1210(4).3	<b>Evaluate</b> temporal difference (TD) learning method for reinforcement learning problem	PO1,PO2,PO3	5	9
MAI1210(4).4	Criticize Gradient methods for Reinforcement Learning	PO1,PO2,PO3	5	9
MAI1210(4).5	<b>Implement</b> Hierarchical Reinforcement Learning Algorithms	PO1,PO2,PO3	3	9



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3		(An Autonomo	NAAC Accredited with A+ Grade	reity Noonur				
Pro	Program: M. Tech. Artificial Intelligence & Machine Learning							
Sem	ester	-II MAI1211: E	lective – IV (Computer Vision)					
	Tea	ching Scheme		Examinati	ion Scheme			
J	Theor	y 3 Hrs/week		CT-I	15 Marks			
Т	utoria	al -		CT-II	15 Marks			
Tota	al Cre	edits 3		CA	10 Marks			
]	Durat	ion of ESE: 3Hrs		ESE	60 Marks			
Pre-	Requ	isites: Deep Learni	ng, Fundamental Convolution Networks, 3D	Total Marks	100 Marks			
Geor	metry	, Convolution Neur	al Networks					
1.	Stud	ent shall be able to u	understand the Computer Vision & Image analy	sis.				
2.	Stud	ent shall be able to u	inderstand the Image Formation Models.					
3.	Stud	ent shall be able to u	nderstand the Object Recognisition and Tracki	ng.				
4.	Stud	ent shall be able to u	nderstand the Visual surveillance.					
5.	Stud	ent shall be able to u	nderstand the 3D Vision.					
			<b>Course Contents</b>					
		Introduction: Pur	pose of computer vision, State-of-the-art, his	tory of comp	uter vision,			
Un	it I	some typical appli	cations of computer vision in surveillance, co	mputer imagir	ng systems,			
		lenses, Image for	nation and sensing, Image analysis, pre-proce	essing and Bi	nary image			
		Image Formatio	<b>Models:</b> Monocular imaging system of	rthographic &	nerspective			
		projection, camera model and camera calibration, binocular imaging systems, Image						
Uni	it II	Processing and Feature Extraction, Image representations color representations, edge						
		detection, some important texture representation, Motion Estimation, Regularization theory,						
		optical flow computation, stereo vision, motion estimation, structure from motion.						
		Object Recognit	on and Tracking: Shape representation,	shape descri	ptors, object			
Unit	t III	localization, object representation using low level and high level features; Object Tracking:						
		Basics of object tracking, single object tracking, multiple object tracking, slow moving and fast moving objects and related algorithms, object trajectory analysis						
		Tast moving object	s and related argorithms, object trajectory analy	515				
Unit	<b>4 TX</b> 7	Visual Surveillan	ce: Basics of surveillance, single camera bas	ed surveillanc	e, multiple			
UIII	ιιν	health care surveill	ance.	public place s	urvennance,			
		2D Vision Ducia	tive geometry single perspective compare sta	roopsis the f	undomantal			
		matrix –its estimat	ion from image point correspondences, applica-	tions of epipol	argeometry			
Uni	it V	in vision, correlati	on based and feature based stereo corresponde	ence, shape from	om motion,			
	D '	optical flow.						
Text	: <b>R00</b>	KS Computer Vision	Modern Approach by D. A. Forsyth and I. Do	nce Dearson	Ind adition			
Τ.	1	2012		1100, 1°0018011, 2				
Τ.	2	Schalkoff, John Wi	ey and Sons, "Digital Image Processing &Com	puter Vision",	1989, John			

	Wiley and Sons.				
Reference	Reference Books				
R.1	Sonka, Hlavac and Boyle Brooks/Cole, "Image Processing, Analysis, and Machine Vision", 1999, Thomson Asia Pte Ltd Singapore.				
R 2	Jain and Rangachar, "Machine Vision", 1999, McGraw Hill International Edition.				
Useful L	inks				
1	https://onlinecourses.nptel.ac.in/noc21_ee23/preview				
2	https://nptel.ac.in/courses/106/105/106105216/				
3	https://nptel.ac.in/content/syllabus_pdf/106105216.pdf				

	Course Outcomes	PO/PSO	CL	Class Sessions
MAI1211(1).1	<b>Identify</b> basic concepts, terminology, theories, models and methods in the field of computer vision.	PO1,PO2,PO3	5	9
MAI1211(1).2	<b>Discriminate</b> the basic methods of computer vision related to multi-scale representation, edge detection and detection of other primitives, stereo, motion and object recognition.	PO1,PO2,PO3	5	9
MAI1211(1).3	<b>Analyze</b> and demonstrate various image segmentation techniques.	PO1,PO2,PO3	4	9
MAI1211(1).4	<b>Distinguish</b> the methods to use for solving a given problem, and analyze the accuracy	PO1,PO2,PO3	4	9
MAI1211(1).5	<b>Utilize</b> the techniques, skills and modern computer Engineering tools, Software and techniques necessary for Engineering practice.	PO1,PO2,PO3	4	9



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Pro	ogran	n: M. Tech. Artif	icial Intelligence & Machine Learnin	g		
Sen	iester-	II MAI1212: Ele	ctive – IV (Data Visualization Techniques)	1		
	Tea	ching Scheme		Examinati	ion Scheme	
	Theory	3 Hrs/week		CT-I	15 Marks	
]	Futoria	ıl -		CT-II	15 Marks	
Tot	tal Cre	dits 3		CA	10 Marks	
	Durati	on of ESE: 3Hrs		ESE	60 Marks	
Pre	-Requ	isites: Big Data, data	visualization tools and technologies,	Total Marks	100 Marks	
	ogram	Plot, Box and whisk	er Plot for Large Data.			
1.	Stud	ent shall be able to un	derstand the Data-Visualization-Design.			
2.	Stud	ent shall be able to un	derstand the Data-Driven documents (D3).			
3.	Stud	ent shall be able to un	derstand the Design Studio & Text visualization	on.		
4.	Stud	ent shall be able to un	derstand the Color processing.			
5.	Stud	ent shall be able to un	derstand the Data visualization system.			
	1		<b>Course Contents</b>			
Ur	nit I	Introduction: Data Data, Scivis and Inf & Scales.	Visualization-Design, Data & Tasks-Data Ty ovis, Graphic Design, Graphical Integrity, Da	pes, Dataset T ta-Ink Ratio, 2	Гуреs, Spatial Aspect Ratios	
Un	it II	Data-Driven docu Luminance Percepti Sketching, Data Typ Queries. Brushing & Linear Layouts, Map Maps.	<b>ments (D3):</b> Introduction to D3-Relative on-D3 Key Features-Concepts Visualization bes. Statistical Graphs. Interaction Design. Ov & Linking, Animation, Trees & Networks, F os, Choropleth Maps, Cartograms, Symbol Ma	vs. Absolute Process. Desi verview & De Radial Layouts aps, Flow Maj	e Judgments- ign Iterations. tail, Dynamic s. Tree maps, ps, Real-Time	
Uni	<ul> <li>Design Studio &amp;Text visualization: Design Studio High-Dimensional Data Filtering. Parallel Coordinates, Glyphs, Aggregation, Text Visualization, Document Visualization,</li> <li>Unit III Images &amp; Video, Maps. Choropleth Maps, Cartogram, Symbol Maps, Flow Maps. Real-Time Maps, Perception, Visual Channels. Weber's Law, Pre-attentive Processing, Visual Channel Rankings.</li> </ul>					
Uni	it IV	<b>Color processing:</b> Color Spaces. Color Aesthetics. Colors for Visualization Cognition. <b>t IV</b> Looking vs Seeing, Image Gist, Gestalt Principles, Visual Attention, Visual Working & Long-Term Memory.				
Un	iit V	Data visualization system: Visual Story Telling, Messaging. Effective Presentations. Design for Information Visualization and Arts, Visualization Systems, Database Visualization, Visualization of volumetric data, vector fields, processes and simulations, Visualization of maps, geographic information, GIS systems, collaborative visualizations, evaluating visualizations.				

Text Boo	bks
Т 1	BenFry "Visualizing Data: Exploring and Explaining Data with the Processing Environment"
1.1	O'Reilly Media, 2007.
т 2	Ward, Grinstein Keim, Interactive Data Visualization: Foundations, Techniques, and
1.2	Applications. Natick: A K Peters, Ltd
Reference	e Books
<b>R</b> .1	Edward Tufte "The Visual Display of Quantitative Information" 2001.
R 2	Colin Ware, "Visual Thinking for Design", Morgan Kaufman Series, 2008.
Useful L	inks
1	https://nptel.ac.in/courses/110/107/110107092/
2	https://onlinecourses.nptel.ac.in/noc20_mg24/preview
3	https://nptel.ac.in/courses/106/106/106106179/

	<b>Course Outcomes</b>	PO/PSO	CL	Class Sessions
MAI1212(2).1	<b>Design and create</b> data visualizations and Conduct exploratory data analysis using visualization.	PO1,PO2,PO3	4	9
MAI1212(2).2	<b>Modify</b> existing visualizations based on data visualization theory and principles.	PO1,PO2,PO3	5	9
MAI1212(2).3	<b>Demonstrate</b> knowledge of perception and cognition to evaluate visualization design alternatives.	PO1,PO2,PO3	4	9
MAI1212(2).4	<b>Design</b> opportunities for application of data visualization in various domains.	PO1,PO2,PO3	4	9
MAI1212(2).5	<b>Develop</b> the appropriate data visualization technique.	PO1,PO2,PO3	4	9



Ľ	Tulsiramji Gaikwad-Patil College of Engineering and Technology Wardha Road, Nagpur-441 108 NAAC Accredited with A+ Grade (An Autonomous Institute Affiliated to RTM Nagpur University, Nagpur)						
Pro	ogran	n: M	. Tech. Artifi	cial Intelligence & Mach	ine Learnin	g	
Sem	nester	-II	MAI1213: Ele	tive – IV (Block chain Technol	ology)		
	Tea	ching	Scheme			Examinati	ion Scheme
, 	Theor	y	3 Hrs/week			CT-I	15 Marks
]	Futori	al	-			CT-II	15 Marks
Tot	tal Cro	edits	3			CA	10 Marks
	Durat	ion of	ESE: 3Hrs			ESE	60 Marks
Pre-	-Requ	isites	Fundamental sl	ill and Knowledge in Technica	l Field,	Total Marks	100 Marks
Dist	ribute	d syste	ems and Network	ng, Cryptography, Data Structu	ires		
1.	Stud	lent sh	all be able to un	lerstand the Basic Cryptograp	hic primitives u	used in Block of	chain.
2.	Stud	lent sh	all be able to un	lerstand the technologies borr	owed in Block	chain.	
3.	Stud	lent sh	all be able to un	lerstand the Abstract Models I	For Block chair	1.	
4.	Stud	lent sh	all be able to un	lerstand the Ethereum.			
5.	Stud	lent sh	all be able to un	lerstand the Block chain appli	cation develop	ment.	
	1			<b>Course Contents</b>			
Un	nit I	Intro resis syste Gene	oduction: Basic tant hash functi ems. Need for D erals problem, ( e up with Block	Cryptographic primitives ons, digital signature, public stributed Record Keeping, M Consensus algorithms and th chain based crypto currency?	used in Block key cryptosyst lodelling faults eir scalability	c chain –Secu ems, zero-kno and adversari problems, Wl	rre, Collison- wledge proof es, Byzantine hy Nakamoto
Un	it II	Tecl fault hard ,mat	tolerance, diginess of minin hematical analys	wed in Block chain: hash p al cash etc.Bitcoin block ch g,transaction verifiability , s of properties of Bitcoin. Bit	pointers, Conse aain - Wallet anonymity , coin, the challe	ensus, Byzanti Blocks - Me forks , doul enges, and solu	ne Models of erkley Tree - ole spending tions.
Uni	it III	Abs rand base	tract Models Food om oracle, form d Chains, Hybrid	<b>r Block chain:</b> GARAY model treatment of consistency, li models (PoW + PoS), Bitcoir	del, RLA Mode veness and fair a scripting lange	el, Proof of W ness - Proof o uage and their	fork (PoW) as f Stake (PoS) use.
Uni	Unit IVEthereum: Ethereum Virtual Machine, Wallets for Ethereum, Solidity -Smart Contracts, The Turing Completeness of Smart Contract Languages and verification challenges, using smart contracts toe nforce legal contracts, comparing Bitcoin scripting vs. Ethereum Smart Contracts. Some attacks on smart contracts.						
Un	<b>Unit V</b> Block chain application development: Hyper ledger Fabric-Architecture, Identities and Policies, Membership and Access Control, Channels, Transaction Validation, Writing smart contract using Hyper ledger Fabric, Writing smart contract using Ethereum, Overview of Ripple and Corda.						
Tex	t Boo	ks					
T.	.1	Block	chain: Blueprin	for a New Economyby Melar	nie Swan, O "R	eilly, 2015	
T.	.2	Block S. Ve	chain Technolo nkatesan, Oxfor	y: Cryptocurrency and Applic University Press, 2019.	cations, S. Shul	kla, M. Dhawa	n, S. Sharma,
Т	3	Block	chain Basicsby	Daniel Drescher, Apress; 1stee	dition, 2017		

Reference	Reference Books				
R.1	Research perspectives and challenges for Bitcoin and cryptocurrency Joseph Bonneauet al, SoKIEEE Symposium on security and Privacy2015.				
R 2	R 2 The bitcoin backbone protocol -analysis and applicationsJ.A.Garay et al, EUROCRYPT LNCS VOI 9057, (VOLII), pp 281-3102015				
Useful L	inks				
1	https://nptel.ac.in/courses/106/105/106105184/				
2	https://nptel.ac.in/courses/106/104/106104220/				
3	https://onlinecourses.nptel.ac.in/noc20_cs01/preview				

	Course Outcomes	PO/PSO	CL	Class Sessions
MAI1213(3).1	Analyze the clustering applications like Market segmentation and Social network analysis	lustering applications like ntation and Social network PO1,PO2		9
MAI1213(3).2	<b>Discriminate</b> between clustering and classification problems.	PO1,PO3	4	9
MAI1213(3).3	<b>Evaluate</b> data reduction and data pre- processing techniques for clustering	PO1,PO2,PO3	5	9
MAI1213(3).4	<b>Appraise</b> feature extraction methods and identify the suitable method for a given problem	PO1,PO2,PO3	4	9
MAI1213(3).5	<b>Demonstrate</b> the Block chain application development	PO1,PO2,PO3	4	9



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3	NAAC Accredited with A+ Grade							
	(An Autonomous Institute Affiliated to RTM Nagpur University, Nagpur)							
Pro	ogran	n: M	I. Tech. Artif	cial Intelligence &	& Machine Learnin	g		
Sen	nester	II	MAI1214: Ele	ctive-IV(Advance Dat	ta Mining)	1		
	Tea	ching	Scheme			Examinat	ion Scheme	
	Theor	y	3 Hrs/week			CT-I	15 Marks	
	Futoria	al	-			CT-II	15 Marks	
Tot	tal Cre	dits	3			CA	10 Marks	
	Durati	on of	ESE: 3Hrs			ESE	60 Marks	
Pre	-Requ	isites	: Learn R and P	ython, data analysis to	ools, especially SQL,	Total Marks	100 Marks	
Nos	SQL, S	AS, a	nd Hadoop, Jav	, Python, and Perl, Ll	NUX			
Cou	irse O	bjecti	ives:					
1.	Stud	ent sh	all be able to un	derstand the data mini	ing and preprocessing.			
2.	stude	ent sha	all be able to un	lerstand the classifica	ation algorithms			
3.	stude	ent sh	all be able to un	lerstand the Bayesian	belief networks			
4.	stude	ent sh	all be able to un	lerstand the clustering	g			
5.	stude	ent sh	all be able to un	lerstand the outlier de	etection			
				Course C	ontents			
		INT	<b>RODUCTION</b>	O DATA MINING A	ND PREPROCESSING	G		
<b>T</b> 7	• 4 -	Data	mining - Relate	l technologies - Machi	ne Learning, DBMS, OI	LAP, Statistics	- Data Mining	
U	nit I	Goals - Stages of the Data Mining Process - Data Mining Techniques - Knowledge						
		trans	sformation - Data	reduction - Discretizat	ion and generating conce	ept hierarchies	eaning- Data	
		CLA	SSIFICATION	ALGORITHMS	ton and generating conec			
		Association rules: Basic idea: item sets - Generating item sets and rules efficiently - Correlation						
Un	it II	analysis						
		Classification: Basic learning/mining tasks - Inferring rudimentary rules: 1R algorithm -						
		Decision trees - Bayes Classification Methods - Rule-Based Classification - Model Evaluation and Selection - Techniques to Improve Classification Accuracy						
<u> </u>		CLA	SSIFICATION	ALGORITHMS				
		Bayesian Belief Networks - Classification by Back propagation - Support Vector Machines -						
Uni	it III	Classification Using Frequent Patterns - k-Nearest-Neighbor Classifiers - Case-Based						
		Reasoning- Multiclass Classification - Semi-Supervised Classification- Mining Time series						
			STEDINC	iysis ioi unite fetated so	yuthet uala			
<b>.</b>	• / • • •	<b>ULUDIEKING</b> Basic issues in clustering - First conceptual clustering system: Cluster/2 - Partitioning methods:						
Un	it IV	k-means, expectation maximization (EM) - Hierarchical methods: distance-based						
		agglomerative and divisible clustering - Conceptual clustering: Cobweb						
		OUT	<b>FLIER DETEC</b>	TION				
Unit V	nit V	Outl	iers and Outlier	Analysis, Outlier De	tection Methods, Statist	ical Approach	es, Proximity-	
		Base Cont	textual and Colle	Clustering-Based Approximation Appr	Droacnes, Classification-	Based Approa	acnes, Mining	
Tex	t Bool			Surve Outliers, Outlier I	Second in mgn-Dillen			
		Ian H	. Witten and Eil	e Frank, Data Mining	: Practical Machine Lea	rning Tools a	nd	
	.1	Techniques (Fourth Edition), Morgan Kaufmann, 2016						
	1							

	Techniques (Fourth Edition), Morgan Kaufmann, 2016			
T.2	Jiawei Han, MichelineKamber, Jian Pei, "Data Mining Concepts and Techniques", Morgan Kaufman Publications, Third Edition, 2011.			
T 3	Pang-NingTan, Michael Steinbach, Vipin Kumar," Introduction to Data Mining" Progress 2016			
Refere	rce Books			
R.1	Introduction to Data Mining – Tan, Steinbach, Vipin Kumar, Pearson Education. Fundamentals of Data Warehouses, Jarke, Vassiliou, 2nd Edition, Springer			
R 2				
R 3	Data Warehousing - Paulraj Ponniah			
Useful	Links			
1	https://ocw.mit.edu/courses/sloan-school-of-management/15-062-data-mining-spring-2003/lecture-notes/			
2	https://nptel.ac.in/courses/106/105/106105174/			
3	https://onlinecourses.nptel.ac.in/noc20_cs12/preview			

	Course Outcomes	PO/PSO	CL	Class Sessions
MAI1204(4).1	<b>Explain</b> the techniques for data pre processing	PO1,PO2,PO3	3	9
MAI1204(4).2	<b>Demonstrate</b> association rules algorithm for correlation analysis	PO1,PO2,PO3	5	9
MAI1204(4).3	<b>Discuss</b> decision tree algorithm for classification	PO1,PO2,PO3	4	9
MAI1204(4).4	<b>Evaluate</b> Bayesian networks algorithm for classification	PO1,PO2,PO3	5	9
MAI1204(4).5	<b>Estimate</b> the classifier accuracy with training, testing and cross validation datasets	PO1,PO2,PO3	5	9

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