Syllabus for Multi-Disciplinary Minor Degree
in
Machine Learning and Artificial Intelligence

Under the National Education Policy (NEP 2020)
in
(2023-2024)

Offered by

DEPARTMENT OF MATHEMATICS

INSTITUTE OF CHEMICAL TECHNOLOGY

(University Under Section-3 of UGC Act, 1956)

Elite Status and Center for Excellence

Government of Maharashtra

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A. Preamble:

Artificial Intelligence (AI) and Machine Learning (ML) have emerged as transformative forces in many industries, including engineering as we navigate the ever-evolving landscape of technology. These technologies can revolutionize the way we solve problems, design products, and innovate. The implementation of AI and ML in engineering education is therefore crucial to preparing future engineers and technocrats for the challenges that lie ahead.

Under the aegis of New Education Policy (NEP 2020), the Department of Mathematics, Institute of Chemical Technology (ICT), Mumbai is aimed at creating professionals with a sound background in theoretical and applied understanding of AI and ML. To achieve this, the department is offering the Multi-Disciplinary Minor (MDM) course on Machine Learning and Artificial Intelligence for the Undergraduate students who are enrolled in various undergraduate engineering programs in ICT Mumbai. Some of the salient features of the program is listed below:

Industry Relevance: In many engineering disciplines, such as robotics, automation, data analysis, and predictive modeling, Artificial Intelligence and Machine Learning have become integral components. Students develop the skills and knowledge they need to thrive in their future careers when these concepts are introduced in engineering education.

Enhancing Data-driven Problem-Solving abilities: Data-driven decisions can be made by using AI-ML techniques to analyze complex systems and identify patterns. By integrating these technologies into engineering curriculums, students can overcome intricate engineering challenges more efficiently and effectively.

Innovation and Design: The use of AI and ML enables engineers to create innovative solutions and optimize designs. Engineering students can develop groundbreaking ideas, improve efficiency, and deliver innovative solutions through the understanding and application of these technologies.

Fostering Interdisciplinary Collaboration: In addition to engineering, AI and ML intersect with other disciplines, including mathematics, statistics, and computer science. Incorporating AI and ML into engineering education encourages interdisciplinary collaboration, fostering a comprehensive approach to problem-solving and opening doors to new possibilities.

Addressing Ethical and Societal Implications: AI and ML raise important ethical and societal concerns that need to be addressed by future engineers. By incorporating these topics into engineering education, students can develop a comprehensive understanding of the ethical implications of AI and ML technologies and learn how to design and deploy them responsibly.

B. Programme Specific Outcomes:

Program Specific Outcomes (PSOs) for MDM in Machine Learning and Artificial Intelligence

PSO1	Foundation of Mathematics: Strong foundation of Applied Mathematics which is directly connected to solving real life problems in different domains by means of mathematical

	modelling and analysis.
PSO2	Foundation of Statistics and Data Science: Strong foundation of Mathematics and Statistics of Data science and good hold on various statistical methodologies including probability theory, estimation, and testing of hypothesis etc.
PSO3	Foundation of Computer Programming: Understand and employ modern computational methods of Machine Learning, Deep Learning and Artificial Intelligence and use them effectively using free and proprietary advanced computational platforms for solving large scale problems arising from different research areas.
PSO4	Conduct investigations of complex problems using AI: Use research-based knowledge in machine learning and artificial intelligence and research methods including design of experiments, analysis, and interpretation of data to unfold complex problems from industry and academia and provide intelligent solutions.
PSO5	Project based Teaching Learning: Function effectively as an individual, and as a member in large scale data science projects in multidisciplinary settings involving both academic and industrial research.
PSO6	Societal Applications of AI and ML: Apply reasoning informed by the existing knowledge pool and address various societal issues using Machine Learning and AI tools.

C. **Intake:** Minimum **15**; Maximum **35**

D. Eligibility criteria:

a. CGPA of the first two semesters.

b. In case the results of the 2nd semester are not available, eligibility will be based on CGPA of the 1st Semester (50% weightage) and CET/JEE score (converted into percentile based on admitted students, 50% weightage).

c. If the number of interested students is more than the maximum intake capacity, marks obtained in the Engineering Mathematics – I (MAT1205) (for Bachelor of Technology students) and Applied Mathematics – I (MAT1101) (for Bachelor of Chemical Engineering students).

E. Prerequisites:

a. Engineering Mathematics (MAT1205) (For Bachelor of Technology)

b. Applied Mathematics – I (MAT1101) (For Bachelor of Chemical Engineering)

F. Pedagogy/Teaching method

In all the courses, the teaching learning process will use the S^{3}MART concepts. (S – Start with action-oriented verb, Student oriented and Specific; M – Measurable; A – Achievable (within a given time); R – Realistic; T – Time-bound).

a. Lecture and tutorial: All the theory courses (codes starting with MAT1501 and MAT1601) will be taught in classroom using blackboard/presentations and the discussions will be led by the instructor. Tutorials will be provided, and separate sessions will be allocated for solving tutorial problems. These two courses will build the foundation of Mathematics and Statistics which will be required to delve deeply into the Applications of Machine Learning and Artificial Intelligence. A basic introduction to data analysis tools will also be provided.

b. Integrative approach: The courses MAP1601, MAP1602, and MAP1603 will be taught in an integrated approach which will utilize the theoretical knowledge learned from the previous semester. It will be partly instructor based which will dictate how the learned theoretical knowledge is being implemented in Machine Learning using software tools (R/Python). A collaborative approach will be adopted to give the students to solve real-world problems through assignments and case studies. This will be executed through group projects which will be evaluated through presentations and report.

c. **Inquiry based approach:** The course MAP1604 (AI Project) will be designed to engage students in research and investigations of real-world problems and how to address them through ML and AI. Case studies from various domains will be considered. This will also be a combination of problem-centred approaches and collaborative approaches.

G. Structure of the MDM course:

Subject Code	Semester	Subject	Credits	Hours/ Week			Marks for various Exams			
				L	T	P	CA	MS	ES	Total
MAT 1501	III	Statistical Computing	2	2	0	0	20	30	50	100
MAP 1601	IV	Data Analytics with R/Python	2	0	0	4	20	30	50	100
MAT 1502	V	Mathematical Methods in AI and ML	4	4	0	0	0	50	50	100
MAP 1602	VI	Machine Learning	2	0	0	4	20	30	50	100
MAP 1603	VII	Deep Learning	2	0	0	4	20	30	50	100
MAP 1604	VIII	AI Project	2	0	0	4	0	50	50	100
		Total	14							600

H. Evaluation:

a. **Theory Courses (MAT1501, MAT1502)**

Continuous Assessment Test (CAT): Three CAT will be conducted each of which will carry 10% weightages. Best two will be considered (total 20% weightage). At least one continuous assessment will be based on the use of statistical data analysis tools in computer lab.

Mid semester: Total 30 Marks (theory paper)

End semester: Total 50 Marks (theory paper)

b. **Practical Courses (MAP1601, MAP1602, MAP1603)**

Midsemester: 30 Marks (Theory + Lab)

Group Project: 20 Marks (Presentation and report)

End Semester: 50 Marks (Computer Lab based Practical Examination followed by viva-voce examination)

c. **AI Project (MAP1604)**

i. In the AI project, students will be guided by faculty members of the Department of Mathematics. Depending on the project topics, students may also be assigned an external mentor (along with department mentor) from other departments of ICT or industry or other academic institutions.

ii. Students will have to submit (i) a written report of the work carried out, and (ii) Evaluation of the student from the Industry Mentor. Students will be presenting their work to a committee of two faculty members of the Institute. The presentation would be evaluated by the committee and students will be given a grade based on the following parameters.

iii. Format for Evaluation by Faculty Members of the Institute and assigning grade:

Name of the Student	
Roll Number of the Student	
Name of the course	
Semester and Academic Year	
Name and designation of the department mentor	
Email	
Phone number	

	Item	Marks (out of 100)
Report	Understanding of overall background of the project	05
	Technical work on 1. Problem Definition and Literature review 2. Materials and Methods 3. Data Collection and Processing 4. Model building and model deployment (if within the scope) 5. Results, Analysis, and Interpretation	30
	Conclusion	10
	Writing skills including formatting as per the given instructions	05
Presentation	1. Presentation based on the work performed and its analysis. 2. Presentation skill	20
External Mentor	If the assigned project does not have an external mentor, then the marks will be assigned by the primary mentor from the department of mathematics.	30
Total		

Total points earned (out of 100): __________

Any other remarks:

Signature of the Mentor:
Date:

iv. Format of the evaluation by the external mentor is given below: If there is no external mentor, the following will be filled by the project mentor from the department of mathematics.

Name of the Student	

Roll Number of the Student	
Name of the course	
Semester and Academic Year	
Name and designation of the external mentor	
Name and address of the organization of external mentor	
Email	
Phone number	

Parameters	Insufficient opportunity to observe (1 points)	Needs improvement (2 points)	Satisfactory (3 points)	Good (4 points)	Excellent (5 points)
General behavior: Ethics and attendance					
Oral and written communication skills					
Interpersonal skills					
Technical knowledge					
Professional skills: Initiative and motivation					
Managerial skill: Time and Resource					

Total points earned (out of 30): __________

Any other remarks:

Signature of the Mentor:
Date:

- The candidates who obtain 40% and more marks of the total marks of a subject head shall be deemed to have passed the respective subject head.
- The candidates who obtain marks less than 40% of the total marks of a subject head shall be deemed to have failed in the respective subject head (Grade FF).

I. Instructors (Tentative):

a. Statistical Computing (ARB/VA/ASR)
b. Data Analytics with R/Python (AK/ARB/IE)
c. Mathematical Methods for AI and ML (AK/ARB/GB/ASR)
d. Machine Learning (ARB/AK/IE)
e. Deep Learning (IE/ARB/AK)
f. AI Project (IE + Institute Faculty)

List of Faculty members who will be engaged in teaching MDM course:

a. Dr. Ajit Kumar (AK)
b. Dr. Amiya Ranjan Bhowmick (ARB)
c. Dr. Vikram Aithal (VA)
d. Dr. Akshay Sakharam Rane (ASR)
e. Dr. Gunvant Birajdar (GB)
f. Industry Expert (IE)

J. Detailed syllabus:

<table>
<tr><td rowspan="2"></td><td>Course Code: MAT 1501</td><td colspan="2">Course Title: Statistical Computing</td><td colspan="3">Credits = 2</td></tr>
<tr><td></td><td colspan="2"></td><td>L</td><td>T</td><td>P</td></tr>
<tr><td></td><td>Semester: III</td><td colspan="2">Total contact hours: 30</td><td>2</td><td>0</td><td>0</td></tr>
<tr><td colspan="7"></td></tr>
<tr><td colspan="7">List of Prerequisite Courses</td></tr>
<tr><td colspan="3">Basic linear algebra and differential calculus, probability, and statistics</td><td colspan="4"></td></tr>
<tr><td colspan="7">List of Courses where this course will be prerequisite</td></tr>
<tr><td colspan="7">Data Analytics with R/Python (MAP 1601), Mathematical Methods for AI and ML (MAT 1502), Machine Learning (MAP 1602), Deep Learning (MAP 1603), AI Project (MAP 1604)</td></tr>
<tr><td colspan="7">Description of relevance of this course in the MDM in Machine Learning and Artificial Intelligence</td></tr>
<tr><td colspan="7">This course is a foundation course covering major concepts from Probability and statistical estimation theory. Introduced concepts which will be used in all Machine Learning and Deep Learning courses.</td></tr>
<tr><td colspan="3">Course Contents (Topics and subtopics)</td><td colspan="4">Hours</td></tr>
<tr><td>1</td><td colspan="2">Probability distributions: Review of probability, Random variables and cumulative distribution function; probability mass function and probability density function; Some common univariate distributions: Binomial, Poisson, Geometric, Uniform, exponential, Normal, Gamma, beta etc.; Expectation and Moments (central and raw moments); Generating functions: moment generating function and characteristic function; Multiple random variables and Joint distribution; marginal distributions, independence, Random variables and their distributions, Distribution of Functions of random variables (emphasis on transformation formula)</td><td colspan="4">12</td></tr>
<tr><td>2</td><td colspan="2">Statistical estimation and regression techniques: Concept of population and sample, Sampling distribution, Maximum likelihood estimation, Simple linear regression, polynomial regression, and multiple regression</td><td colspan="4">8</td></tr>
<tr><td>3</td><td colspan="2">Testing of hypothesis and tests related to normal distribution: Sampling from normal distribution and tests for mean and variance, tests on several means and several variances with practical problems and applications.
Basic nonparametric tests: Sign test, Mann-Whitney U test, Kruskal-Wallis one way ANOVA, Kolmogorov-Smirnov test</td><td colspan="4">10</td></tr>
<tr><td>4</td><td colspan="2">Illustration of various statistical tests and curve fitting exercises will be illustrated using R/Python.</td><td colspan="4"></td></tr>
<tr><td></td><td colspan="2"></td><td colspan="4">30</td></tr>
<tr><td colspan="7">List of Textbooks / Reference Books</td></tr>
<tr><td>1</td><td colspan="3">Gareth James, Daniela Witten, Trevor Hastie, and Robert Tibsherany, An Introduction to Statistical Learning: with Applications in R, Springer, 2011</td><td colspan="3"></td></tr>
</table>

2	Gareth James, Daniela Witten, Trevor Hastie, and Robert Tibsherany, An Introduction to Statistical Learning: with Applications in Python, Springer, 2021	
3	Kevin P. Murphy, Machine Learning: A Probabilistic Perspective, MIT (Massachusetts Institute of Technology) Press, 2012	
4	Richard L. Scheaffer, Madhuri S. Mulekar, and James T. McClave, Probability and Statistics for Engineering Applications, Cengage Learning, 2011	
5	Jay L. Devore, Probability and Statistics for Engineering and the Sciences, Cengage Learning, 2016	
6	William Navidi, Statistics for Engineers and Scientists, McGraw-Hill Education, 2010	
7	John A. Rice, Mathematical Statistics and Data Analysis, Duxbury Press, 1995	
8	Alexander M. Mood, Duane C. Boes, and Franklin A. Graybill, Introduction to the Theory of Statistics, McGraw-Hill Education, 1973	
Course Outcomes (students will be able to….)		
CO1	Compute the distributions of the functions of random variables using different techniques and apply approximation methods to compute their expectation and variances.	K2
CO2	Understand the method of maximum likelihood and use it to estimate parameters of various probability distributions from the real data.	K2
CO3	Apply the concepts of linear and nonlinear regression and appmorly them to solve real life predictive modelling problems.	K3
CO4	Apply appropriate testing procedures to solve data analysis problems and interpret the results from the software outputs.	K3
CO5	Apply basic nonparametric tests for analyzing data without distributional assumptions	K3
CO6	Apply the principals of various statistical data analysis procedures and interpret the outputs from the statistical software.	K3

Mapping of Course Outcomes (COs) with Programme Specific Outcomes (PSOs)						
	PSO1	PSO2	PSO3	PSO4	PSO5	PSO6
CO1	3	3	2	1	1	1
CO2	3	3	2	2	0	1
CO3	3	3	3	3	0	1
CO4	3	3	2	3	2	1
CO5	2	3	2	3	1	1
CO6	2	3	3	3	2	3

3, Strong Contribution; 2, Moderate Contribution; 1, Low Contribution; 0– No Contribution

K, knowledge level from cognitive domain

	Course Code: MAP 1601	**Course Title: Data Analytics with R/Python**	**Credits = 2**		
			L	**T**	**P**
	Semester: IV	**Total contact hours: 60**	**0**	**0**	**4**
List of Prerequisite Courses					

Statistical Computing (MAT 1501)		
List of Courses where this course will be prerequisite		
Mathematical Methods for AI and ML (MAT 1502), Machine Learning (MAP 1602), Deep Learning (MAP 1603), AI Project (MAP 1604)		
Description of relevance of this course in the MDM in Machine Learning and Artificial Intelligence		
This course is designed to give students exposure to various statistics and data visualization techniques. This course will train students to handle large data sets using software and address various research questions using data analytics techniques.		
Course Contents (Topics and subtopics)		**Hours**
1	Introduction to R/Python (Variables, data types, and basic operations Input and output statements), Conditional statements (if, else) Looping structures (for and while), writing functions, basic plotting.	10
2	Overview of Exploratory Data Analysis and understanding key steps, computation, and interpretation of measures of central tendency (mean, median, mode) Calculation and interpretation of measures of dispersion (variance, standard deviation, mean absolute deviation), skewness, kurtosis, and other distributional characteristics, use of software to check distributional assumptions.	6
3	Understanding various sources of data from different domains, Data cleansing and handling missing values, understand various techniques for data imputation, outlier detection and treating the outliers, Data transformation, feature engineering, dealing with continuous and categorical features, detecting multicollinearity, feature extraction for different data types of data	8
4	Data visualization: bar charts, boxplot, histograms, violin plots, various plots with respect to groups and interpretations, scatter plots and correlation analysis, heatmaps, Covariance and scatter matrix plots, Contingency table, and chi-square tests	6
5	Multiple linear regression, modelling with interactions, modelling with categorical predictors, interpreting the output and report generation, perform regression diagnostics	6
6	Visualization of time series data and basic forecasting techniques	4
7	Project: Case studies and report generation, exploring real-world case studies of data visualization in engineering and interdisciplinary domains, Applying data visualization techniques to an engineering project	20
		60
List of Textbooks / Reference Books		
1	Jiawei Han, Micheline Kamber, and Jian Pei, Data Mining: Concepts and Techniques, Elsevier Inc. 2012	
2	Viktor Mayer-Schönberger and Kenneth Cukier, Big Data: A Revolution That Will Transform How We Live, Work, and Think, Oxford University Press, 2014	
3	Wes McKinney, Python for Data Analysis: Data Wrangling with pandas, NumPy and Jupyter , 3rd Edition, 2022.	
4	Hadley Wickham and Garrett Grolemund, R for Data Science, 2nd Edition, 2023	
5	Data Science and Big Data Analytics: Discovering, Analyzing, Visualizing, and Presenting Data, EMC Education Services, 2022	
6	John W. Tukey, Exploratory Data Analysis, Addison-Wesley Series in Behavioral Science, 1977	

7	Cole Nussbaumer Knaflic, Storytelling with Data: A Data Visualization Guide for Business Professionals, John Wiley, 2015i	
8	Changquan Huang, Alla Petukhina, Applied Time Series Analysis and Forecasting with Python, Springer, 2022	
9	Marco Peixeiro, Time Series Forecasting in Python, Manning Publications, 2022	
Course Outcomes (students will be able to….)		
CO1	Understand the fundamentals of data visualization and apply appropriate visualization techniques to perform exploratory data analysis for real data sets	K2
CO2	Understand the data analytics fundamentals, data types and data wrangling	K2
CO3	Work on real life data analytics project and apply appropriate statistical techniques to analyze the data sets	K3
CO4	Perform feature engineering and select key features using different regularization techniques	K3
CO5	Understand the basic structure of the time series data and apply basic statistical methods for forecasting	K3
CO6	Generate industry standard reports using different tools for data analytics project	K4

Mapping of Course Outcomes (COs) with Programme Specific Outcomes (PSOs)						
	PSO1	PSO2	PSO3	PSO4	PSO5	PSO6
CO1	1	3	2	1	1	1
CO2	1	3	2	2	0	1
CO3	1	2	3	2	3	3
CO4	2	3	1	3	2	2
CO5	1	3	1	3	0	2
CO6	0	3	3	3	3	2

3, Strong Contribution; 2, Moderate Contribution; 1, Low Contribution; 0– No Contribution
K, knowledge level from cognitive domain

	Course Code: MAT 1502	**Course Title: Mathematical Methods for AI and ML**	**Credits = 4**		
			L	**T**	**P**
	Semester: V	**Total contact hours: 60**	**4**	**0**	**0**
List of Prerequisite Courses					
Statistical Computing (MAT 1501)					
List of Courses where this course will be prerequisite					
Machine Learning (MAP 1602), Deep Learning (MAP 1603), AI Project (MAP 1604)					
Description of relevance of this course in the MDM in Machine Learning and Artificial Intelligence					
This is a foundation course for Machine Learning and AI. This will give students a deeper understanding of different AI and ML methods by emphasizing their mathematical foundations. These concepts will be used in the Machine Learning and Deep Learning courses.					
Course Contents (Topics and subtopics)			**Hours**		

1	Review of vectors and matrices, ￼ as a vector space, subspaces, linear span, linear dependence, linear independence, basis and dimension of vector subspaces, Applications of Eigenvalues and eigenvectors, Inner product spaces, Orthogonality, and applications to least square problems. Matrix Factorizations and its applications, Matrix Derivatives	12
2	Introduction and formulation of Optimization Problems, Convexity, Review of Local Maxima, and local minima along with first and second order conditions. One dimensional optimization technique, Direct search optimization methods such as Powell's and Nelder-Mead methods, Gradient Descent methods, Newton and quasi-newton methods, Projected Gradient Descent Methods, Proximal and Sub gradient Descent Method, Accelerated gradient method, Constrained Optimization methods: Lagrange Multiplier and Karush-Kuhn Tucker (KKT) methods with applications. Introduction to convex optimization, Popular Nature inspired optimization techniques.	24
3	Statistical foundations for AI and ML: Parameter learning via maximum likelihood, Marginal and conditional likelihood, Score function and Fisher Information, Cramer - Rao Inequality, Expectation-maximization algorithm, Gaussian mixture models, large sample properties of maximum likelihood estimates, Weighted least squares method, likelihood ratio tests	12
4	Exploration of concepts learned in modules 1, 2 and 3 using R/Python.	12
		60
List of Textbooks / Reference Books		
1.	David C Lay, Linear Algebra and its Applications, Addition-Wesley, 4th Edition, 2018	
2.	G. C. Cullen, Linear Algebra with Applications, Addison Wesley, 1997	
3.	Gilbert Strang, Linear Algebra and Its Applications, Cengage publications, 2005	
4.	Lars Eldén, Matrix Methods in Data Mining and Pattern Recognition, SIAM, 2019	
5.	Edvin K. P. Chong & S. H. Zak, An Introduction to Optimization, Wiley Publication, 2013	
6	Charu C. Aggarwal, Linear Algebra and Optimization for Machine Learning, Springer, 2020	
7	Suvrit Sra, Sebastian Nowozin, and Stephen J. Wright, Mathematical Optimization for Machine Learning, PHI, 2012	
8	Jorge Nocedal and Stephen J. Wright, Numerical Optimization, Springer, 2006	
9	Stephen Boyd, Lieven Vandenberghe, Convex Optimization, Cambridge Univ. Press, 2004	
10	Suvrit Sra, Sebastian Nowozin, and Stephen J. Wright, Convex Optimization Methods in Machine Learning, MIT Press, 2012	
11	Marc Peter Deisenroth, A. Aldo Faisal, Cheng Soon Ong, Mathematics for Machine Learning, Cambridge University Press, 2021	
12	A Vasuki, Nature-Inspired Optimization Algorithms, CRC Press, 2020	
13	Yudi Pawitan, In All Likelihood: Statistical Modelling and Inference Using Likelihood, Oxford University Press, 2001	
14	Alan Agresti, Maria Kateri, Foundations of Statistics for Data Scientists: With R and Python, Chapman & Hall/CRC Texts in Statistical Science, 2021	
15	Jianqing Fan, Runze Li, Cun-Hui Zhang, Hui Zou, Statistical Foundations of Data Science, CRC Data Science Series, 2020	

Course Outcomes (students will be able to….)		
CO1	Understand the concepts in linear algebra and apply them to solve problems in AI and ML.	K3
CO2	Understand the classical optimization techniques and use them to solve engineering problems.	K3
CO3	Understand the various gradient based optimization techniques and their use in AI-ML	K3
CO4	Understand the standard nature inspired optimization technique and their uses to solve engineering problems	K3
CO5	Applying classical and numerical optimization techniques to solve real life problems	K3
CO6	Construct the likelihood function based on the data and apply appropriate optimization method to compute the parameter estimates and compute standard error of the estimates	K4

Mapping of Course Outcomes (COs) with Programme Specific Outcomes (PSOs)						
	PSO1	PSO2	PSO3	PSO4	PSO5	PSO6
CO1	3	2	1	1	0	0
CO2	3	1	1	2	0	0
CO3	3	1	3	2	0	0
CO4	3	1	1	3	0	1
CO5	3	2	1	3	2	2
CO6	3	3	3	3	0	2

3, Strong Contribution; 2, Moderate Contribution; 1, Low Contribution; 0– No Contribution

K, knowledge level from cognitive domain

	Course Code: MAP 1602	Course Title: Machine Learning	Credits = 2		
			L	T	P
	Semester: VI	Total contact hours: 60	0	0	4

List of Prerequisite Courses	
Statistical Computing (MAT 1501), Data Analytics with R/Python (MAP 1601), Mathematical Methods for AI and ML (MAT 1502)	
List of Courses where this course will be prerequisite	
Deep Learning (MAP 1603), AI Project (MAP 1604)	
Description of relevance of this course in the MDM in Machine Learning and Artificial Intelligence	
Machine learning is a critical and foundation component of several AI applications. This course gives the students exposure to various machine learning concepts and their applications in real life problems.	

	Course Contents (Topics and subtopics)	Hours
1	Overview of machine learning concepts and applications, Supervised, unsupervised, and reinforcement learning, Elements of a machine learning system	4

2	**Supervised learning:** Regression problem, K-nearest neighbour regression, Linear model selection and regularization, Validation set approach, Leave-One-Out-Cross Validation, K-fold cross validation, Best subset selection, Forward Selection, Backward selection, Hybrid selection, shrinkage methods: Ridge regression, Lasso, Least angle regression, Elastic Net, resampling techniques and bootstrap based inference, Comparison between different supervised learning methods, Application using Real life case studies, Hands-on implementation will be done using R/Python.	10
3	**Supervised learning:** Classification problems, logistic regression, Decision tree and random forests, Naïve Bayes algorithm, Anomaly detection, evaluation metrics for classification, Hands-on implementation and analysis of regression models, Bagging and Boosting using R/Python	10
4	**Unsupervised learning:** Introduction to clustering, K-means clustering, Hierarchical clustering, Evaluation metrics for clustering, DBSCAN algorithm, Hands-on implementation and analysis of clustering models using R/Python	10
5	**Dimensionality reduction techniques:** Principal component analysis, multidimensional scaling, Hands-on implementation of dimensionality reduction techniques using R/Python	6
6	**Generative models:** Introduction to generative models and its implementation using R/Python	6
7	Machine learning group projects	14
		60
List of Textbooks / Reference Books		
1	Gareth James, Daniela Witten, Trevor Hastie, and Robert Tibshirani, An Introduction to Statistical Learning: with Applications in R, Springer, 2011.	
2	Gareth James, Daniela Witten, Trevor Hastie, and Robert Tibshirani, An Introduction to Statistical Learning: with Applications in Python, Springer, 2023	
3	Kevin P. Murphy, Machine Learning: A Probabilistic Perspective, MIT Press, 2012.	
4	Andreas C. Müller and Sarah Guido, Introduction to Machine Learning with Python: David Barber A Guide for Data Scientists, O'Reilly Media, 2016.	
5	Hands on Machine Learning with R by Bradley Boehmke and Brandon Greenwell, CRC Press, 2020.	
6	Ethem Alpaydin, Introduction to Machine Learning, The MIT Press, Cambridge, 2004.	
7	Ian H. Witten, Eibe Frank, Mark A. Hall, Data Mining: Practical Machine Learning Tools and Techniques, Elsevier, 2011.	
8	Venkata Reddy Konasani, Shailendra Kadre, Machine Learning and Deep Learning Using Python and TensorFlow, Mc Graw Hill, 2021.	
Course Outcomes (students will be able to….)		
CO1	understand standard machine learning algorithms.	K2
CO2	apply appropriate machine learning techniques to solve regression problems involving real data	K3
CO3	apply appropriate machine learning techniques to solve classification problems involving real data.	K3
CO4	apply dimension reduction methods to solve problems involving real data.	K3
CO5	use software to build machine learning models and interpret the results and generate industry standard reports	K4

CO6	apply machine learning techniques to perform model selection and perform decision making related to the problems from different domains	K4

Mapping of Course Outcomes (COs) with Programme Specific Outcomes (PSOs)						
	PSO1	PSO2	PSO3	PSO4	PSO5	PSO6
CO1	1	3	3	1	1	1
CO2	1	3	3	2	0	2
CO3	1	3	2	2	3	2
CO4	2	3	1	3	2	2
CO5	1	3	3	3	1	1
CO6	1	3	3	3	3	3

3, Strong Contribution; 2, Moderate Contribution; 1, Low Contribution; 0– No Contribution
K, knowledge level from cognitive domain

	Course Code: MAP 1603	**Course Title: Deep Learning**	**Credits = 2**		
			L	**T**	**P**
	Semester: VII	**Total contact hours: 60**	**0**	**0**	**4**
List of Prerequisite Courses					
Statistical Computing (MAT 1501), Data Analytics with R/Python (MAP 1601), Mathematical Methods for AI and ML (MAT 1502), Machine Learning (MAP 1602)					
List of Courses where this course will be prerequisite					
AI Project (MAP 1604)					
Description of relevance of this course in the MDM in Machine Learning and Artificial Intelligence					
Deep learning is a critical and foundation component of several AI applications. This course gives the students exposure to various deep learning concepts and their applications in real life problems.					
Course Contents (Topics and subtopics)			**Hours**		
1	Introduction to popular deep learning frameworks (e.g., TensorFlow, PyTorch), Setting up the development environment, Building models in TensorFlow and Keras.		8		
2	Neural Networks and its basic architecture, Activation functions, relationship with regression framework, Multilayer neural networks, backpropagation algorithm, Training neural networks and optimization		8		
3	Deep neural networks, Architecture of Convolutional neural network (CNN) and its applications, Case studies for CNN: AlexNet, VGG, GoogLeNet, etc., Applications to Natural language and sequence learning, Image processing and feature extraction using CNNs (Convolutional Neural Network), Applications of CNNs in chemical engineering (e.g., image analysis, particle tracking etc.)		10		
4	Architecture of Recurrent neural networks (RNN): Long-Short-Term-Memory (LSTM), Bidirectional LSTM, Gated Recurrent Units (GRU) and their applications;		6		

5	Introduction to generative models (e.g., GANs - Generative Adversarial Networks) and its implementation in R/Python	6
6	Introduction to Reinforcement Learning and its applications (e.g., application in process optimization)	6
7	Deep Learning Projects (group projects)	16
		60
	List of Textbooks / Reference Books	
1	Charu C. Aggarwal, Neural Networks and Deep Learning, Springer, 2018	
2	Ian Goodfellow and Yoshua Bengio and Aaron Courville, Deep Learning, MIT Press, 2016	
3	The Elements of Statistical Learning by Jerome H. Friedman, Robert Tibshirani, and Trevor Hastie, Springer, 2003	
4	Josh Patterson, Adam Gibson, Deep Learning: A Practitioner's Approach, O'Reilly, 2017	
5	Ovidiu Calin, Deep Learning Architectures: A Mathematical Approach, Springer, 2020	
6	John Paul Mueller, Luca Massaron, Deep Learning for Dummies, 2019	
7	Venkata Reddy Konasani, Shailendra Kadre, Machine Learning and Deep Learning Using Python and TensorFlow, Mc Graw Hill, 2021	
	Course Outcomes (students will be able to….)	
CO1	understand basic principles of Deep Learning and artificial Intelligence.	K2
CO2	utilize GPU acceleration and deep learning libraries, such as TensorFlow and PyTorch, to speed up model training	K3
CO3	understand statistics and optimization principles in deep neural networks.	K2
CO4	apply deep learning algorithms in solving real life problems such as text classification, sentiment analysis etc.	K3
CO5	interpret the outputs from deep learning algorithms and communicate the findings to the peers in respective domains	K4

Mapping of Course Outcomes (COs) with Programme Specific Outcomes (PSOs)

	PSO1	PSO2	PSO3	PSO4	PSO5	PSO6
CO1	1	3	3	1	1	0
CO2	2	3	3	2	0	2
CO3	2	3	2	2	3	2
CO4	2	3	1	3	2	2
CO5	1	3	3	3	0	1

3, Strong Contribution; 2, Moderate Contribution; 1, Low Contribution; 0– No Contribution
K, knowledge level from cognitive domain

	Course Code: MAP 1604	**Course Title: AI Project**	**Credits = 2**		
			L	**T**	**P**
	Semester: VIII	**Total contact hours: 60**	**0**	**0**	**4**
List of Prerequisite Courses					

	Statistical Computing (MAT 1501), Data Analytics with R/Python (MAP 1601), Mathematical Methods for AI and ML (MAT 1502), Machine Learning (MAP 1602), Deep Learning (MAP 1603)	
	List of Courses where this course will be prerequisite	
	NIL	
	Description of relevance of this course in the MDM in Machine Learning and Artificial Intelligence	
	This is a project-based course which will provide students with hands on experience of using Artificial Intelligence techniques for solving real life problems from a wide variety of research domains including but not limited to healthcare, chemical engineering, climate science, financial analytics, computer vision, Reinforcement learning, etc. The students will also be exposed to the development of various AI applications and in this course, they expected to create their own applications.	
	Course Contents (Topics and subtopics)	**Hours**
1	Overview on AI, Ethical considerations in AI development and deployment, Understand and address biases in AI models, Understand the lifecycle of AI model.	8
2	Introduction to Transformer and ChatGPT, Transformer building blocks (Self-Attention, Feed-Forward Layers), Multi-head attention, Positional encoding for sequence information. Transformer examples: BERT (Bidirectional Encoder Representations from Transformers), GPT (Generative Pre-trained Transformer), T5 (Text-to-Text Transfer Transformer), Transformer-XL and XLNet	12
2	**Capstone Project**: It may be domain specific project which will require ML and AI concepts learned in different courses, such as a) **AI for Healthcare:** Medical image analysis: Analysing images like X-rays or MRIs to detect anomalies or disease; Drug Discovery: Use AI to analyse molecular structures and predict potential drug candidates. b) **Reinforcement learning:** Building AI agents that can play games. c) **Natural Language Processing (NLP):** Sentiment Analysis, Text summarization, Chatbot development d) **Computer Vision:** Object detection and recognition, e) AI in Process optimization and simulations in Chemical reactors f) Design AI-driven chemical engineering process control g) AI-based climate prediction models and climate change impact assessment h) AI-based carbon emission tracking and reduction i) ChatGPT development stack j) AI application in Stock market research k) Transformers for Speech Recognition (ASR) and Speech Synthesis (TTS)	40
		60
	List of Textbooks / Reference Books	
1	Thomas E. Quantrille, Erik B. Conklin, and Jonathan S. Kalb, Artificial Intelligence in Chemical Engineering, 2012	
2	Jingzheng Ren, Lichun Dong, Weifeng Shen, Yi Man, Applications of Artificial Intelligence in Process Systems Engineering, 2021	
3	Amit Sehgal, Prabhu Jyot Singh, R. M. Mehra, Rashmi Priyadarshini, Artificial Intelligence, Applications and Innovations, CRC Press.	
5	Jolanta Burke, Majella Dempsey, Undertaking Capstone Projects in Education: A Practical Guide for Students, Taylor, and Francis, 2021	
6	Ankit Jain, Armando Fandango, Amita Kapoor, TensorFlow Machine Learning	

	Projects, Packt Publishing Limited, 2018	
7	Santanu Pattanayak, Intelligent Projects Using Python, Packt Publishing Limited, 2019	
8	Giuseppe Ciaburro, Keras Reinforcement Learning Projects, Packt Publishing Limited, 2018	
Course Outcomes (students will be able to….)		
CO1	Understand various ethical aspects related to the applications of AI in addressing different problems in society and industry	K1, K2
CO2	Demonstrate sound technical knowledge on the implementation aspects of various ML and AI models	K3
CO3	Undertake the identification of complex real-life problems from various domains which requires data driven solutions using AI and ML techniques	K5, K6
CO4	Design AI and ML based solutions for complex real-life problems	K5, K6
CO5	Communicate the outcomes of ML and AI based solutions to the problems to the stakeholders in written and oral forms	K4, K5
CO6	Develop the knowledge, skills and attitude of a professional data scientist equipped with scientific understanding of AI and ML	K6

Mapping of Course Outcomes (COs) with Programme Specific Outcomes (PSOs)

	PSO1	PSO2	PSO3	PSO4	PSO5	PSO6
CO1	0	3	3	1	1	1
CO2	1	3	3	2	0	2
CO3	1	3	2	2	3	2
CO4	2	3	1	3	2	2
CO5	1	3	3	3	0	1
CO6	1	3	3	1	1	2

3, Strong Contribution; 2, Moderate Contribution; 1, Low Contribution; 0– No Contribution
K, knowledge level from cognitive domain

Assignment of Course Codes: Minor Courses in Mathematics

- Theory Course Codes: Starts from MAT 1501 to MAT 1509
- Lab Course Codes: Starts from MAP 1601 to MAP 1609