Syllabus for Multi-Disciplinary Minor (MDM)
In
Machine Learning and Artificial Intelligence

(Under the New 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. The emergence of these technologies has the potential to 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, 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 will be able to 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 cutting-edge 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 holistic 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 Objectives:

Programme Outcomes (POs) for Machine Learning and Artificial Intelligence (MDM)

PO1	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 being able to apply them in solving complex problems relevant to the society and industry.
PO2	Foundation of Statistics: 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. and being able to apply them in solving real life problems.
PO3	Foundation of Computer Programming: Understand and employ modern computational methods in 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.
PO4	Foundation of Data Centric Study of Engineering Applications: An innovative curriculum that will train engineering students to create data models that represent the underlying system or process. These models can be statistical, mathematical, or machine learning models, depending on the application.
PO5	Project based Teaching Learning: An innovative teaching framework to engage students in both academic and industrial research and open multiple future paths in different verticals.
PO6	Conduct investigations of complex problems: 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 working solutions.

PO7	Problem analysis: Identify, formulate, review research literature, and analyze complex real life problems using mathematics, statistics, and computational methods.
PO8	Societal Applications of AI and ML: Apply reasoning informed by the existing knowledge pool to convert into a quantitative framework, collect relevant information and address various societal issues using modelling and statistical data analytics tools including deep learning and artificial intelligence.
PO9	Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the practice of mathematics, statistics, and data sciences in all verticals of industry and society.
PO10	Individual and teamwork: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.
PO11	Communication: Communicate effectively on complex industrial/natural problems and understand the functional requirements, identify the gaps and being able to provide solutions using modern tools and technologies offering advanced data sciences and machine learning techniques.
PO12	Life-long learning: Recognize the need for and have the preparation and ability to engage in independent and life-long learning, acquire appropriate skills in Mathematics and its application for the benefit of humankind.

C. Intake: To be decided later.

D. Eligibility criteria: To be decided later.

E. Structure of the MDM course:

Subject Code	Semester	Subject	Credits	Hrs/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	0	50	50	100
MAT 1502	V	Mathematical Methods in AI and ML	4	4	0	0	20	30	50	100
MAP 1602	VI	Machine Learning	2	0	0	4	0	50	50	100
MAP 1603	VII	Deep Learning	2	0	0	4	0	50	50	100
MAP 1604	VIII	AI Project	2	0	0	4	0	50	50	100
		Total	14							600

F. Detailed syllabus:

	Course Code: MAT 1501	**Course Title: Statistical Computing**	**Credits = 2**		
			L	**T**	**P**
	Semester: III	**Total contact hours: 60**	**2**	**0**	**0**
List of Prerequisite Courses					
Basic linear algebra and differential calculus, probability, and statistics					
List of Courses where this course will be prerequisite					
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)					
Description of relevance of this course in the MDM in Machine Learning and AI					
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.					
Course Contents (Topics and subtopics)			**Hours**		
1	**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);		12		

	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)	
2	**Statistical estimation and regression techniques:** Concept of population and sample, Sampling distribution, Maximum likelihood estimation, Simple linear regression, polynomial regression, and multiple regression	8
3	**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-Smironov test	10
4	Illustration of various statistical tests and curve fitting exercises will be illustrated using R/Python.	
		30
	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, 2021	
3	Kevin P. Murphy, Machine Learning: A Probabilistic Perspective, MIT 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.	K1, K2, K3
CO2	Understand the method of maximum likelihood and use it to estimate parameters of various probability distributions from the real data.	K2, K3, K4
CO3	Apply the concepts of linear and nonlinear regression and apply them to solve real life predictive modelling problems.	K2, K3, K4
CO4	Apply appropriate testing procedure to solve data analysis problems and interpret the results from the software outputs.	K2, K3, K5
CO5	Apply basic nonparametric tests for analysing data without distributional assumptions	K4
CO6	Understand the principals of various statistical data analysis procedures and interpret the outputs from the statistical software.	K4, K5

Mapping of Course Outcomes (COs) with Programme Outcomes (POs)

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12
CO1	5	5	3	3	3	1	1	0	5	1	0	5
CO2	5	5	3	4	0	1	1	0	5	1	0	5
CO3	5	5	5	4	0	1	1	1	5	1	0	5
CO4	4	5	3	5	4	5	4	1	5	3	4	5
CO5	4	5	3	5	4	5	4	4	5	3	4	5
CO6	5	5	5	5	3	5	5	3	5	4	3	5

<table>
<tr><td rowspan="3"></td><td rowspan="2">**Course Code: MAP 1601**</td><td rowspan="2">**Course Title: Data Analytics with R/Python**</td><td colspan="3">**Credits = 2**</td></tr>
<tr><td>**L**</td><td>**T**</td><td>**P**</td></tr>
<tr><td>**Semester: IV**</td><td>**Total contact hours: 60**</td><td>**0**</td><td>**0**</td><td>**4**</td></tr>
<tr><td colspan="6"></td></tr>
<tr><td colspan="6">**List of Prerequisite Courses**</td></tr>
<tr><td colspan="3">Statistical Computing (MAT 1501)</td><td colspan="3"></td></tr>
<tr><td colspan="6">**List of Courses where this course will be prerequisite**</td></tr>
<tr><td colspan="6">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="6">**Description of relevance of this course in the MDM in Machine Learning and AI**</td></tr>
<tr><td colspan="6">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.</td></tr>
<tr><td colspan="3">**Course Contents (Topics and subtopics)**</td><td colspan="3">**Hours**</td></tr>
<tr><td>1</td><td colspan="2">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.</td><td colspan="3">10</td></tr>
<tr><td>2</td><td colspan="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.</td><td colspan="3">6</td></tr>
<tr><td>3</td><td colspan="2">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</td><td colspan="3">8</td></tr>
<tr><td>4</td><td colspan="2">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</td><td colspan="3">6</td></tr>
<tr><td>5</td><td colspan="2">Multiple linear regression, modelling with interactions, modelling with categorical predictors, interpreting the output and report generation, perform regression diagnostics</td><td colspan="3">6</td></tr>
<tr><td>6</td><td colspan="2">Visualization of time series data and basic forecasting techniques</td><td colspan="3">4</td></tr>
<tr><td>7</td><td colspan="2">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</td><td colspan="3">20</td></tr>
<tr><td></td><td colspan="2"></td><td colspan="3">**60**</td></tr>
<tr><td colspan="6">**List of Textbooks / Reference Books**</td></tr>
<tr><td>1</td><td colspan="2">Jiawei Han, Micheline Kamber, and Jian Pei, Data Mining: Concepts and Techniques, Elsevier Inc. 2012</td><td colspan="3"></td></tr>
<tr><td>2</td><td colspan="2">Viktor Mayer-Schönberger and Kenneth Cukier, Big Data: A Revolution That Will Transform How We Live, Work, and Think, Oxford University Press, 2014</td><td colspan="3"></td></tr>
<tr><td>3</td><td colspan="2">Wes McKinney, Python for Data Analysis: Data Wrangling with pandas, NumPy and Jupyter , 3rd Edition, 2022.</td><td colspan="3"></td></tr>
<tr><td>4</td><td colspan="2">Hadley Wickham and Garrett Grolemund, R for Data Science, 2nd Edition, 2023</td><td colspan="3"></td></tr>
<tr><td>5</td><td colspan="2">Data Science and Big Data Analytics: Discovering, Analyzing, Visualizing, and Presenting Data, EMC Education Services, 2022</td><td colspan="3"></td></tr>
<tr><td>6</td><td colspan="2">John W. Tukey, Exploratory Data Analysis, Addison-Wesley Series in Behavioral Science, 1977</td><td colspan="3"></td></tr>
<tr><td>7</td><td colspan="2">Cole Nussbaumer Knaflic, Storytelling with Data: A Data Visualization Guide for Business Professionals, John Wiley, 2015i</td><td colspan="3"></td></tr>
<tr><td>8</td><td colspan="2">Changquan Huang, Alla Petukhina, Applied Time Series Analysis and Forecasting with Python, Springer, 2022</td><td colspan="3"></td></tr>
<tr><td>9</td><td colspan="2">Marco Peixeiro, Time Series Forecasting in Python, Manning Publications, 2022</td><td colspan="3"></td></tr>
<tr><td colspan="3">**Course Outcomes (students will be able to….)**</td><td colspan="3"></td></tr>
<tr><td>CO1</td><td colspan="2">Understand the fundamentals of data visualization and apply appropriate visualization techniques to perform exploratory data analysis for real data sets</td><td colspan="3">K1, K4, K5</td></tr>
<tr><td>CO2</td><td colspan="2">Understand the data analytics fundamentals, data types and data wrangling</td><td colspan="3">K1, K3, K4</td></tr>
</table>

CO3	Work on real life data analytics project and apply appropriate statistical techniques to analyse the data sets	K1, K3, K5
CO4	Perform feature engineering and select important features using different regularisation techniques	K2, K3, K5
CO5	Understand the basic structure of the time series data and apply basic statistical methods for forecasting	K1, K4
CO6	Generate industry standard reports using different tools for data analytics project	K4, K5, K6

Mapping of Course Outcomes (COs) with Programme Outcomes (POs)												
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12
CO1	2	5	3	3	3	2	5	3	5	2	4	5
CO2	3	5	3	4	1	2	4	3	5	2	4	5
CO3	3	5	5	4	5	5	5	5	5	5	4	5
CO4	4	5	4	5	4	4	4	3	5	3	4	5
CO5	3	5	4	5	2	4	4	2	5	3	4	5
CO6	1	5	5	5	5	5	5	4	5	5	3	5

	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 AI					
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 on their mathematical foundations. These concepts will be uses in the Machine Learning and Deep Learning courses.					
Course Contents (Topics and subtopics)			**Hours**		
1	Review of vectors and matrices, $\mathbb{R}^n$ 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 Subgradient 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.	K2, K3, K4, K5
CO2	Understand the classical optimization techniques and use them to solve engineering problems.	K1, K2, K3
CO3	Understand the various gradient based optimization techniques and their use in AI-ML	K2, K3, K4, K5
CO4	Understand the standard nature inspired optimization technique and their uses to solve engineering problems	K1, K3, K4
CO5	Applying classical and numerical optimization techniques to solve real life problems	K3, K4, K5
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	K1, K3, K4

Mapping of Course Outcomes (COs) with Programme Outcomes (POs)

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12
CO1	5	4	3	3	1	1	1	1	5	1	1	5
CO2	5	3	3	4	1	1	1	1	5	1	1	5
CO3	5	3	5	4	1	1	1	1	5	1	1	5
CO4	5	2	3	5	1	5	4	1	5	3	4	5
CO5	5	4	3	5	4	5	4	4	5	3	4	5
CO6	5	5	5	5	1	5	5	3	5	4	3	5

	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 AI	
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.	K1
CO2	apply appropriate machine learning techniques to solve regression problems involving real data	K2, K4, K5
CO3	apply appropriate machine learning techniques to solve classification problems involving real data.	K2, K4, K5
CO4	apply dimension reduction methods to solve problems involving real data.	K3, K5
CO5	use software to build machine learning models and interpret the results and generate industry standard reports	K3, K4
CO6	apply machine learning techniques to perform model selection and perform decision making from different domains	K3, K4, K5

Mapping of Course Outcomes (COs) with Programme Outcomes (POs)

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12
CO1	2	5	5	3	3	2	5	2	5	2	4	5
CO2	3	5	5	4	1	4	4	4	5	2	4	5
CO3	3	5	4	4	5	4	5	4	5	5	4	5
CO4	4	5	3	5	4	4	4	4	5	3	4	5

CO5	3	5	5	5	2	3	4	3	5	3	4	5
CO6	3	5	5	5	5	5	5	4	5	5	3	5

	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 AI		
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, 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.	K1, K2
CO2	utilize GPU acceleration and deep learning libraries, such as TensorFlow and PyTorch, to speed up model training	K4, K5
CO3	understand statistics and optimization principles in deep neural networks.	K2, K3, K4
CO4	apply deep learning algorithms in solving real life problems such as text classification, sentiment analysis etc.	K4, K5
CO5	interpret the outputs from deep learning algorithms and communicate the findings to the peers in respective domains	K2, K3, K4

Mapping of Course Outcomes (COs) with Programme Outcomes (POs)												
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12
CO1	2	5	5	3	3	2	5	2	5	2	4	5
CO2	3	5	5	4	1	4	4	4	5	2	4	5
CO3	3	5	4	4	5	4	5	4	5	5	4	5
CO4	4	5	3	5	4	4	4	4	5	3	4	5
CO5	3	5	5	5	2	3	4	3	5	3	4	5

	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 AI	
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	K2, K3, K4
CO3	Undertake the identification of complex real-life problems from various domains which requires data driven solutions using AI and ML techniques	K3, K4, 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	K5, K6
CO6	Develop the knowledge, skills and attitude of a professional data scientist equipped with scientific understanding of AI and ML	K3, K6

Mapping of Course Outcomes (COs) with Programme Outcomes (POs)												
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12
CO1	1	5	5	3	3	2	5	2	5	2	4	5
CO2	3	5	5	4	1	4	4	4	5	2	4	5
CO3	3	5	4	4	5	4	5	4	5	5	4	5
CO4	4	5	3	5	4	4	4	4	5	3	4	5
CO5	2	5	5	5	2	3	4	3	5	3	4	5
CO6	3	5	5	4	1	4	4	4	5	2	4	5

Assignment of Course Coded Minor Courses in Mathematics

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