Department of Mathematics
Minor in Data Science

1. Introduction

Data Science is the art of generating insight, knowledge and predictions by processing of data gathered about a system or a process. It emerges as a multi-disciplinary field that generally highlight the use of statistics, predictive modelling and machine learning without changing its application, irrespective of the domain. Today, data science has far reaching implications in many fields, both academic and applied research domains like governance, finance, security, transportation, healthcare, energy management, agriculture, population studies, weather prediction, economics, social sciences, predictive maintenance, structural health monitoring, smart manufacturing and computational structural biology. The growing importance of data science has in turn led to the need of inculcating it in the educational ecosystem to come up with the future workforce.

2. Objectives of the minor

The main objective of specialization in Data Science is to equip students with the fundamental concepts, approaches, and methods in data science. On the completion of the minor, students will develop critical and logical thinking to solve problems in data science and further will be able to use appropriate technology that aids their problem-solving and data analysis.

3. Minor Compulsory courses (8 Credits)

S. No.	Course Name	Course Level (400/600/700)	L-T-P structure
1	Introduction to Data Science	700	1-0-0
2	Statistical Inference and Simulation Techniques	400	3-0-0
3	Advanced Machine Learning	700	3-0-0
4	Applied ML Lab	700	0-0-2

4. Minor Electives courses (12 Credits)

S. No.	Course Name	Course Level (400/600/700)	L-T-P structure
1	Introduction to Financial Engineering	400	3-0-0
2	Stochastic Calculus for Finance	400	3-0-0
3	Time Series Analysis	400	3-0-0
4	Reliability Engineering and Life Testing	400	3-0-0
5	Introduction to Game Theory	400	3-0-0
6	Optimization	400	3-0-0
7	Non-linear dynamics and chaos	400	3-0-0
8	Maths for Big Data	400	2-1-0
9	Discrete Mathematical Structures and Applications	600	3-0-0
10	Mathematical Biology	700	3-0-2
11	Statistical Models and Regression	700	3-0-0
12	Topological Data Analysis	700	3-0-0
13	Group Theory for Machine Learning	700	3-0-0

14	Visual Analytics	700	3-0-0
15	Image and Video Analytics	700	3-0-0
16	Text Mining	700	3-0-0
17	Artificial Intelligence	400	3-0-0
18	Advanced Artificial Intelligence	700	3-0-0
19	Information Retrieval	-	3-0-0
20	Graph Theoretic Algorithms	700	3-0-0
21	Image and Video Forensics	700	3-0-0
22	Social Networks	400	3-0-0
23	Introduction to AR and VR	700	3-0-0
24	Coding Theory	700	3-0-0
25	Project	-	0-0-12

Notes: The permission of Senate is requested for the following:

(1) To include the 700 level courses (highlighted in Yellow colour) in the Elective list of MTech (Data and Computational Sciences).

(2) To include the courses with S.No. 9, 10 and 11 in the Elective list of MSc (Mathematics).

5. Offered for: All BTech students except BTech CSE, BTech AI&DE and BTech EE

6. Detailed Course Content of Compulsory Courses

Title	**Applied ML Lab**	Number	MAP7xxx
Department		L-T-P [C]	0-0-2 [1]
Offered for	Minor in Data Science	Type	
Prerequisite			

Objectives

The Instructor will introduce students to the importance of Machine Learning techniques and their applicability to the problems involved in their domain.

Learning Outcomes

The students are expected to have the ability to design and implement Machine Learning techniques for the problems of the domain.

Contents

The lab course is a mini project laboratory where the students will select a problem(s) from their domain and will solve the selected problem on the basis of machine learning algorithms. This unique lab will provide an opportunity to the students to undertake ML based research in their own domain.

Textbook

1. Research literature

Reference Books

2. Research literature

Online Course Material

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7. Detailed Course Content of Elective Courses

Title	**Discrete Mathematical Structures and Applications**	Number	MAL6xxx
Department	Mathematics	L-T-P [C]	3-0-0 [3]
Offered for	Minor in Data Science	Type	
Prerequisite			

Objectives

The Instructor will:

1. Introduce the methods of analytical, abstract and critical thinking.
2. Provide logical and mathematical tools for problem solving skills.
3. Provide formal definitions in combinatorics and graph theory with their applications.

Learning Outcomes

The students are expected to have the ability to:

1. Understand the notion of mathematical thinking, mathematical proofs, and algorithmic thinking, and be able to apply them in problem solving.
2. Understand some basic properties of graphs and related discrete structures, and be able to relate these to practical examples.

Contents

Mathematical Logic [7 Lectures]: Propositional Logic, First Order Logic, Proof techniques, Mathematical Induction, application to verify the algorithms and processes.

Set Theory and Algebra [9 Lectures]: Sets, Paradoxes in Set Theory, Inductive Definitions of Sets and Proof by Induction, Relations, Functions, Partial Orders, Lattice, Boolean Algebra, Groups and Rings: Examples and Basic Properties, Error-correcting codes [6 Lectures], Secret sharing, Applications in Cryptography specifically in RSA cryptography, (k,n)-threshold scheme and visual cryptography [3 Lectures].

Combinatorics [12 Lectures]: Recurrence relations, common techniques for solving recursions, Permutations, Combinations, Counting, Polya Counting, Stirling numbers, Bell numbers, Combinatorial Sums [8 Lectures]; Applications of combinatorics in Machine Learning and Number Theory [4 Lectures].

Graph Theory [14 Lectures]: Connectivity, Trees and its properties, Cut vertices & edges, Covering, Matching, Independent sets [7 Lectures]; Coloring, Planarity, Isomorphism, Applications of Graphs in Supply Chain, Networks and Marketing Analytics [7 Lectures].

Text Books

1. Rosen, K. H., (1999), Discrete Mathematics and Its Applications, McGraw-Hill.
2. Epp, S.S., (2004) Discrete Mathematics with Applications, Thomson-Brooks/Cole.

Reference Books

1. K. A. Ross and C. R. B. Wright, (2003) Discrete Mathematics (Fifth Edition), Prentice Hall.
2. Van Lint, J. H. and Wilson, R. M., (2009), A Course in Combinatorics, Cambridge University Press
3. Matousek, J. and Nesetril, J., (2008), Invitation to Discrete Mathematics, Oxford University Press.

Online Course Material

1. Dr. Kamala Krithivasan, Discrete Mathematical Structures, NPTEL Course Materials, Department of Computer Science and Engineering, IIT Madras. https://nptel.ac.in/courses/106/106/106106094/#

Title	**Statistical Models and Regression**	Number	MAL7XX0
Department	Mathematics	L-T-P [C]	3–0–2 [4]
Offered for	Minor in Data Science	Type	Core
Prerequisite	Probability, Statistics and Random Processes		

Objectives

The Instructor will discuss the following aspects

1. Statistical Modelling
2. Linear and Non-linear Regression
3. ANOVA and Analysis of Categorical Data

Learning Outcomes

The students are expected to have the ability to:

1. Understand applications of regression and assumptions
2. Formation of Contingency Tables and Its Analysis
3. Use of R for Analysis of Real Data

Contents

Introduction to Statistical Modeling [6 Lectures]: Model Diagnostics, Transformations, Multicollinearity, Influence, Model Building, Variable Selection.

Linear regression [8 Lectures]: Bi-variate Gaussian Distribution, Assumptions for linear regression, Estimation of Parameters by Least Square Approximation, Hypothesis Test and Confidence Intervals for Model Parameters, Multiple Linear Regression with data examples, Residual Analysis

Regression Cont [14 Lectures]: Introduction to Logistic Regression and Poisson Regression Within the More General Regression Approach, Exponential Family of Distributions, Generalized Linear Model With Data Examples. Introduction to Multiple Approaches to Variable Selection Illustrated with an Extensive Data Analysis Example

Analysis of Variance [6 Lectures]: One way and Two way ANOVA with applications

Analysis of Categorical Data [8 Lectures] – Contingency Table, Log-linear Modeling, Measures of Association, Testing of Hypotheses of associations for 2-way and 3-way tables

Lab R Programing: Reading in Data, Tables, Linear regression and basic plotting, One way ANOVA and QQ-norm plots, Two way ANOVA and Box Plots, Logistic and Poisson regression, Analysis of contingency table, demonstration of the tools for some data.

Textbooks:

1. Montgomery D. C., Peck, E. A. and Vining, G. G. (2013) Introduction to Linear Regression Analysis, Wiley
2. Althem, P. M. E. (2015) Introduction to Statistical Modelling in R, Cambridge University Press

Reference Books:

1. Draper, N.R. and Smith, H. (2011). Applied Regression Analysis, Wiley Series.
2. Rohatgi, V.K. and Saleh, A.K.M.E. (2008). An Introduction to Probability and Statistics, Wiley.

Self-Learning Material:

Salabh, Linear Regression Analysis and Forecasting**,** NPTEL Course Material, Department of Mathematics and Statistics, IIT Kanpur, https://nptel.ac.in/courses/111/104/111104098/

Title	**Topological Data Analysis**	Number	MAL7xxx
Department		L-T-P [C]	3-0-0 [3]
Offered for	Minor in Data Science	Type	
Prerequisite			

Objectives

The Instructor will:

1. Provide the introduction to the topological data analysis.
2. Provide new methods lying at the interface between pure mathematics, applied mathematics, and computer science.

Learning Outcomes

The students are expected to have the ability to:

3. Be familiar with basics in topology that are useful for data analysis.
4. Develop a comprehensive understanding of extracting topological information from data.
5. Appreciate the connection of Pure and Applied mathematics with computer science.

Contents

Introduction (4 lectures): Motivation for topological data analysis, Basic concepts (graphs, connected components, topological space, manifold, point clouds), Combinatorial structures on point cloud data, topology based dimension reduction, topology-based data partition and classification.

Topological Homology (5 lectures): Homotopy, homeomorphism, Classification of surfaces up to homeomorphism, Simplicial complexes, topological realization, Triangulability, Simplicial Approximation, Simplicial homology, Chains spaces, Boundary operators, Homology group, Morphisms.

Topological Persistence (5 lectures): Topological filtrations, Incremental algorithm for filtrations, persistent homology groups, Persistence diagrams, persistence decomposition, persistence matrix reduction, stability of matrix reduction, transpositions, switches, types of switching, Bottleneck distance, Stability of filtrations and persistence.

Topological Inference (8 lectures): Topological distance functions, medial axis and reach, topology from data, homotopy equivalence, Cech and Rips filtrations, nerves filtration, persistent nerves, sparsified filtrations and their usage in inference.

Topological Learning (10 lectures): Learning with Persistence Diagrams, kernal Hilbert space, Kernels for persistence diagrams, Explicit Feature Map in R^d, Wasserstein Gaussian kernel, Frechet means in diagrams space, Hilbert space embedding, Deviation inequality, Confidence regions, landscapes, Subsampling with landscapes.

Manifold Learning (10 lectures): Motivation for manifold learning, Multi-dimensional Scaling (MDS), metric MDS, isomaps, isomap interpolation, Local Linear Embedding, Maximum Variance Unfolding, Laplacian Eigenmap, Manifold Geometry and its application to clustering.

Textbook

1. H. Edelsbrunner, J. Harer, (2009) Computational Topology: An Introduction. AMS Press.
2. S. Oudot, (2015) Persistence Theory: From Quiver Representations to Data Analysis. AMS Surveys and Monographs, Vol. 209.
3. James R. Munkres, (1984) Elements of Algebraic Topology, Perseus.
4. Trevor Hastie, Robert Tibshirani and Jerome Friedman, (2009) The Elements of Statistical Learning (2nd edition). Springer-Verlag.

Reference Books

Research literature

Online Course Material

1. http://www.enseignement.polytechnique.fr/informatique/INF556/

Title	**Group Theory for Machine Learning**	Number	MAL7xxx
Department		L-T-P [C]	3-0-0 [3]
Offered for	Minor in Data Science	Type	
Prerequisite			

Objectives

The Instructor will:

1. Provide the introduction of group theoretic aspect for Machine Learning
2. Give sufficient knowledge of the subject which can be used by students for further applications in their respective domains of interest.

Learning Outcomes

The students are expected to have the ability to:

1. Develop a comprehensive understanding of harmonic analysis of group theory.
2. Appreciate the connection of group theory and machine learning.

Contents

Introduction to groups for Machine Learning (4 lecture): Groups as systems of transformations, Group axioms, Classes of groups: finite, countable, and Lie groups.

Group representations (6 lecture): Group equivalence and reducibility, isomorphism, homomorphism, normal subgroups, direct product and semi-direct product of groups, classification of groups, group action, groups in the real world (quantum mechanics, robotics and permutations).

Harmonic analysis on the symmetric group (8 lecture): Permutation cycle notation and cycle type, Partial rankings, commutative and non-commutative harmonic analysis, convolution theorem and Plancherel's theorem, Decomposition of the group into isotypal components, Young diagrams, Young tableaux and Young's orthogonal representation.

Application of group theory (8 lecture): Spectral analysis of ranking data, Fast Fourier transforms, the Cooley-Tukey algorithm and its interpretation in terms of subgroups, Clausen's FFT for permutation and multi-object tracking.

Lie groups and invariance (10 lecture): Definition of Lie groups, Generators, the exponential map and Lie algebra, the rotation groups: parametrization and representations, connection to spherical harmonics Homogeneous spaces, the Euclidean motion groups, the classical spectrum and bispectrum and their generalization to non-commutative groups, Kakarala's completeness results, application to fast pattern matching, rotation and translation invariant features in image processing.

Group theory in Deep learning (6 lecture)

Textbook

1. H. Edelsbrunner, J. Harer, (2009) Computational Topology: An Introduction. AMS Press.
2. Chirikjian, G. S., Kyatkin, A. B., (2001) Engineering applications of noncommutative harmonic analysis. CRC Press.
3. Diaconis, P., (1988) Group Representation in Probability and Statistics. Volume 11 of IMS Lecture Series, Institute of Mathematical Statistics.
4. Kanatani, K., (1990) Group theoretical methods in image understanding, Springer-Verlag.

Reference Books

Research literature

Online Course Material

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Title	**Visual Analytics**	Number	MAL7xxx
Department		L-T-P [C]	3-0-0 [3]
Offered for	Minor in Data Science	Type	
Prerequisite			

Objectives

The Instructor will:

1. Provide the introduction to the science and technology of visual analytics.
2. Provide exposure on both theoretical foundations and application methodologies.
3. Practical experience building and evaluating visualization systems.

Learning Outcomes

The students are expected to have the ability to:

1. Understand the purpose of visualization in general and visual analytics in particular.
2. Develop a comprehensive understanding of this emerging, multidisciplinary field.
3. Apply that understanding toward a focused research problem in a real-world application.

Contents

Introduction (2 lectures): Motivation, Historical Perspective on Visual Analytics and overview.

Data Visualization and Visualization Models (5 lectures): Exploring the digital age, visualization as a tool, defining data visualization, visualization design objectives and process, classification of data visualization, Reference model, Data state reference model, Visual analytics model, Sense making Loop, Visual Analytics Process.

Data Mining and Interaction (8 lectures): Data representation, Extracting salient features from data, encoded representation of data, Data aggregation and sampling, data reduction and projection, data integration, data attributes, visualization attributes, Interaction operators, operands and space, Interaction with data and problem space, Interaction with visual interfaces, data structure space, animating transformation and interaction control.

Visualizing Techniques (14 lectures): Visualization of spatial data (one-, two- and three-dimensional data) (3 lectures), visualization of Geospatial data (point, line and area data) (3 lectures), visualization of time oriented data, visualization of multivariate data (5 lectures), visualization of trees, graphs and networks (3 lectures).

Analytic Provenance and Evaluation Methods (7 lectures): Data provenance, Information provenance, Human-Visualization Interactions, Epistemic Action, Nested Model of VIS Design, Matching methods and metrics, Insight-based evaluation.

Advanced Visualization Analytics (6 lectures): Interactive graphics (Mosaic plots, parallel coordinate plots and Trellis Displays), infographics, types of infographics, visualization of high dimensional data.

Textbook

1. Tamara Munzner, 1st edition (2014), Visualization Analysis and Design (AK Peters Visualization Series), A K Peters/CRC Press.
2. Daniel Keim, Jörn Kohlhammer, Geoffrey Ellis, and Florian Mansmann, (2010). Mastering the Information Age Solving Problems with Visual Analytics, Published by the Eurographics Association.
3. Matthew Ward, Georges Grinstein, and Daniel Keim, (2010), Interactive Data Visualization: Foundations, Techniques, and Applications, A K Peters Ltd.

Reference Books

1. Claus O. Wilke, 1st edition (2019), Fundamentals of Data Visualization, O'Reilly Media
2. Koponen, J. and Hildén, J., (2019), Data Visualization Handbook, CRC Press.
3. Jason Lankow, J., Ritchie, J., and Crooks, R., (2012), Infographics: The Power of Visual Storytelling, John Wiley & Sons.

Online Course Material

http://www.cs.smith.edu/~jcrouser/SDS235/

Title	**Image and Video Analytics**	Number	MAL7xxx
Department		L-T-P [C]	3-0-0 [3]
Offered for	Minor in Data Science	Type	
Prerequisite			

Objectives

The Instructor will:

1. Provide the key techniques and theory used in image and video analytics.
2. To develop the understanding of different types of analytics processes.
3. Provide exposure to a number of common image and video analytics application domains.

Learning Outcomes

The students are expected to have the ability to:

1. Identify and apply appropriate principles for image and video analytics.
2. Appreciate the implementation described in the image and video analytics applications.

Contents

Introduction and Image basics [2 Lectures]: Image formation, Digital Image, Image sampling and quantization, Definition, Digital Image Characteristics, Representation and visualization.

Feature extraction [4 Lectures]: Global image measurement, feature specific measurement, characterizing shapes, Hough Transform.

Representation and Description [7 Lectures]: Region Identification, Contour Based and Region Based Shape Representation and Description– Shape Classes, active contours, active shape and active appearance, Syntactic and Hybrid Texture Description Methods.

Image Understanding [5 Lectures]: Control Strategies, Point Distribution Models, RANSAC, Scene Labeling and Constraint Propagation.

Introduction to Video Analytics [3 Lectures]: Fundamentals of video, Advantages of employing video analytics (security and non-security), Distinguish between edge and server based analytics, Distinguish between computing and graphical processing power requirements in video analytics.

Object Detection and Tracking [3 Lectures]: Background modeling, shadow detection, eigen faces, texture modeling, Object Tracking using Active Contours.

Tracking & Video Analysis [7 Lectures]: Tracking and Motion Understanding, Kalman filters, condensation, particle, Bayesian filters, hidden Markov models, Motion estimation and Compensation-Block Matching Method, Hierarchical Block Matching, Overlapped Block Motion and compensation, Motion Estimation, Mesh Based Method, Optical Flow Method.

ML-driven Video Analytics Systems [10 Lectures]: ML based object detection and recognition, machine learning optimizations for modern video analytics without violating latency and query accuracy expectations. Case studies in Face Detection and Recognition, Natural Scene Videos, Crowd Analysis, Video Surveillance, Traffic Monitoring, Intelligent Transport System.

Textbook

1. M. Sonka, V. Hlavac and R. Boyle, (2007) Image Processing, Analysis and Machine Vision, Third Edition, Cengage Learning.
2. D. Zhang, (2019) Fundamentals of Image Data Mining: Analysis, Features, Classification and Retrieval, Springer.
3. A Murat Tekalp, (1995) Digital Video Processing, Pearson.
4. F. Camastra and A. Vinciarelli, (2015) Machine Learning for Audio, Image and Video Analysis Theory and Applications, Springer.

Reference Books

Research literature

Online Course Material

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Title	**Text mining**	Number	MAL7xxx
Department		L-T-P [C]	3-0-0 [3]
Offered for	Minor for Data Science	Type	
Prerequisite			

Objectives

The Instructor will:

1. Introduce a variety of basic principles, techniques for text mining.
2. Use these tools for text categorization, text clustering and topic modelling.
3. Explore various text mining applications.

Learning Outcomes

The students are expected to have the ability to:

1. Understand principles and various techniques for text mining
2. Apply the tools for text categorization, text clustering and topic modelling
3. Carry of sentiment analysis, Document summarization, develop recommendation system, carry out text visualization

Contents

Introduction (2 Lectures): Definition of text mining, motivation for Text mining, challenges with text data and its applications.

Document representation (7 lectures): Representation of unstructured text, document models (vector-space models and language models), determining the vocabulary of terms, Bag-of-Words representation, document frequency, Generative view of text documents, perplexity.

Natural language processing (6 lectures): Basic techniques in natural language processing, tokenization, part-of-speech tagging, chunking, syntax parsing and named entity recognition, Public NLP toolkits, Embedding space, Word2Vec, Glove.

Text categorization and clustering (7 lectures): Text categorization algorithms, Identifying the clustering structure of a corpus of text documents, assigning documents to the identified cluster(s), connectivity-based clustering and centroid-based clustering.

Topic modeling (8 lectures)*:* Uncovering the hidden thematic structure in document collections, the general idea of topic modelling, Probabilistic Latent Semantic Indexing (pLSI) and Latent Dirichlet Allocation (LDA), and their variants for different application scenarios, including classification, imagine annotation, collaborative filtering, and hierarchical topical structure modeling.

Text Mining Applications (12 lectures)*:* Sentiment analysis (sentiment polarity prediction, review mining, and aspect identification) (4 lectures), Document summarization and recommendation (Extraction-based summarization methods, the basic concepts of recommendation algorithms, especially the content-based and collaborative filtering based solutions) (4 lectures), Text visualization (visual representations of abstract data to reinforce human cognition, mathematical and programming tools to visualize a large collection of text documents) (4 lectures).

Textbooks

1. Michael W. Berry and Jacob Kogan, (2010), *Text Mining: Applications and Theory*, Wiley.
2. Charu C. Aggarwal and ChengXiang Zhai, (2012), *Mining Text Data*, Springer.

Reference Books

1. Christopher D. Manning, Prabhakar Raghavan, and Hinrich Schuetze, (2007), *Introduction to Information Retrieval*, Cambridge University Press.
2. Dan Jurafsky and James H Martin, (2000), *Speech & Language Processing - An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition* (2nd edition), Pearson Education India.

Online Course Material

http://www.cs.virginia.edu/~hw5x/Course/TextMining-2019Spring/_site/

Title	**Mathematical Biology**	Number	**MAL7XX**
Department	Mathematics	L-T-L-P [C]	3-0-2-0
Offered for	Minor in Data Science	Type	
Prerequisite			

Objectives

The Instructor will:

1. This course is an exploration in applications of mathematical modeling in the analysis of biological systems including population biology, physiology and in the biomedical sciences.
2. To show how mathematics can be used in an integrated way to analyze biological systems.
3. To develop student's skills in algebraic manipulation, and the calculus of ordinary differential equations, introduced in the context of biological systems.

Learning Outcomes

After the completion of this course, students should:

1. have an enhanced knowledge and understanding of mathematical modeling in the analysis of biological systems,
2. interpret biological assumptions in terms of mathematical equations
3. be better able to assess biological inferences that rest on mathematical arguments.

Contents

Discrete Processes in Biology: The Theory of Linear and Nonlinear Difference Equations Applied to Population Biology (6 lectures)

Continuous Processes and Ordinary Differential Equations: Bacterial Growth in a Chemostat, Dimensional Analysis, Steady-State Solutions, Stability and Linearization, Application to related problems such as Delivery of drugs by continuous infusion, Modeling of Glucose -Insulin Kinetics etc (6 lectures)

Phase Plane Methods and Qualitative Solutions: Systems of two first order ODEs, The Direction Field, Nullclines, Phase Plane Diagrams for Linear Systems, Constructing a Phase Plane Diagram for the Chemostat. (6 lectures)

Epidemiology and the SIRS Model: Analysis of equations, interpreting ɑ, Nullcline analysis, Immunization, Variation STDs (5 lectures)

Application of Continuous Models to Population Dynamics: Malthus Model, Logistic Growth, Predator Prey Systems and The Lotka -Volterra Equations, and Population in Competition. Numerical Methods to solve system of differential equations (6 lectures)

Chemical Kinetics: Chemical Networks, Introduction to Enzymatic Reactions, Quasi-Steady State Approximations and Michaelis-Menten Reactions, Fast and Slow Behavior, Singular Perturbation Analysis, Inhibition, Allosteric Inhibition, Cooperativity. (6 lectures)

Numerical Methods to solve ODE: Euler's method, finite difference methods, shooting method, multistep methods, Taylors, Runge–Kutta–Fehlberg methods, ode45, linprog**.** (7 lectures)

Textbooks

1. Leah, Edelstein, Keshet, Mathematical Models in Biology, SIAM publications.
2. J.D. Murray, Mathematical Biology Vol. I, II, 3rd edition, Springer publications.
3. Martin A. Nowak-Evolutionary Dynamics: Exploring the equations of life, The Beklnap Press of Harvard University Press, 2006
4. J.N. Kapur, Mathematical Models in Biology and Medicine, East-West Press Private limited.
5. K. Atkinson, W. Han, D. Stewart, Numerical Solutions of ODE, John Wiley and Sons publications

Reference Books

1. Fred Brauer and Carlos Castillo-Chavez, Mathematical Models in Population Biology and Epidemiology, second edition, Springer publications.
2. Haberman, R, Mathematical Models: an introduction to applied mathematics, SIAM publisher

Online Course Reference Material

1. Dr. Ameeya Kumar Nayak, IIT Roorkee, Mathematical Modeling, Analysis and application: https://nptel.ac.in/courses/111107113/