भारतीय सूचना प्रौद्योगिकी अभिकल्पना एवं विनिर्माण संस्थान , कर्नूल

INDIAN INSTITUTE OF INFORMATION TECHNOLOGY DESIGN AND MANUFACTURING KURNOOL

Jagannathagattu, Kurnool – 518007, Andhra Pradesh, INDIA

(An Institute of National Importance under the Ministry of Education, Govt. of India)

M. Tech. Programme in
Data Analytics and Decision Sciences (DADS)
(With effective from the A.Y. 2021-22)

Scheme, Syllabi and Regulations

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
INDIAN INSTITUTE OF INFORMATION TECHNOLOGY
DESIGN AND MANUFACTURING KURNOOL
KURNOOL-518007, ANDHRA PRADESH, INDIA.
June, 2021

Institute Vision

To become a leading institute of higher learning in Information Technology enabled design & manufacturing to create technologies and technologists befitting the industries globally.

Institute Mission

To become a center of excellence pioneering in education, research & development, and leaders in design & manufacturing.

Department of Computer Science and Engineering

The department of Computer Science and Engineering offers undergraduate, postgraduate and doctoral programmes. The fast-changing scenario in Information Technology necessitates the department to actively extend its curriculum, research and other development activities. The programmes offered in the department has a comprehensive curriculum on latest emerging areas of Information Technology with major emphasis on learning by doing.

Department Vision

To become a premier provider of innovative, cost-effective and eco-friendly solutions in the cutting-edge areas of computer science and engineering.

Department Mission

To produce world class computer professionals by providing a nurturing environment, hands on experience, collaborative research environment in order to prepare the graduates to deal with industry-oriented products and technologies.

S.No	**Name of the Programme**	**Started in**	**Current sanctioned Intake**
1.	B. Tech in Computer Science & Eng.	2015-16	70
2.	B. Tech in Artificial Intelligence and Data Sciences	2020-21	60
3.	M. Tech in Computer Science & Eng. With Specialization in Data Analytics and Decision Sciences (DADS)	2020-21	15
4.	Ph.D. (Full-time)	2020-21	-

About M.Tech. Programme in Data Analytics and Decision Sciences (DADS)

M. Tech. in Computer Science and Engineering with specialization in Data Analytics and Decision Sciences prepares students to become leaders in knowledge-driven professions by providing a learning environment strongly focused on collaborative and interdisciplinary research. Students learn to reach across traditional academic boundaries, to seek the knowledge and resources needed to solve important technological problems. The course structure is designed to include courses on nascent topics to equip our students with the latest developments in Computer Science and Engineering.

Duration of this programme in Full Time: **2 Years**

Curriculum and Syllabus

Department of Computer Science and Engineering

Scheme for M. Tech. in

Data Analytics and Decision Sciences (DADS)

Sl. No.	Course Code	Course Name	Category Code	I	P	No. of Credits
Semester I						
1	CS501T	Mathematical Foundations for Data Science	PEC	3	0	3
2	CS502T	Advanced Data Structures and Algorithms	PEC	3	0	3
3	CS503T	Principles of Data Analytics	PEC	3	0	3
4	CS504T	Statistical Learning	PEC	3	0	3
5	CS505T	Decision Sciences	PEC	2	2	3
6	CS51XT	Elective-I	PEC	3	0	3
7	CS506P	Decision Sciences Practice	PEC	1	3	3
8	CS601	Seminar	PCD	0	3	2
Total				**18**	**8**	**23**
Semester II						
1	CS507T	Marketing Science and Predictive Analytics	PEC	3	0	3
2	CS508T	Advanced Decision Modelling Techniques	PEC	3	0	3
3	CS509T	Machine Learning	PEC	3	0	3
4	CS510T	Decision Support Systems	PEC	2	2	3
5	CS52XT	Elective-II	PEC	3	0	3
6	CS52XT	Elective-III	PEC	3	0	3
7	CS507P	Predictive Analytics Practice	PEC	0	3	2
8	CS509P	Machine Learning Practice	PEC	0	3	2
9	CS602	Comprehensive Viva-Voce	PCD	0	3	2
Total				**17**	**11**	**24**
Semester III						
1	CS603	Dissertation Work-I	PCD	0	25	10
Semester IV						
1	CS604	Dissertation Work-II	PCD	0	25	10

PEC: Professional Engineering Course

PCD: Professional Career Development

	List of Electives					
Sl. No.	**Code**	**Course Name**	**Category**	**I**	**P**	**Credit**
1	CS511T	Data Mining	PEC	3	0	3
2	CS513T	Advanced Database Systems	PEC	3	0	3
3	CS514T	Artificial Intelligence	PEC	3	0	3
4	CS515T	Social Media and Networks Analytics	PEC	3	0	3
5	CS516T	Time Series Analysis	PEC	3	0	3
6	CS517T	Data Exploration and Visualization	PEC	3	0	3
7	CS518T	Game Theory	PEC	3	0	3
8	CS519T	Randomized and Approximation Algorithms	PEC	3	0	3
9	CS520T	Cloud Computing	PEC	3	0	3
10	CS521T	Big Data Processing	PEC	3	0	3
11	CS522T	Scalable Systems for Data Science	PEC	3	0	3
12	CS523T	Recommender Systems	PEC	3	0	3

PEC: Professional Engineering Course

SEMESTER-I

Course Title	Course Code	Structure (I-P-C)		
Mathematical Foundations for Data Science	CS501T	**3**	**0**	**3**

Prerequisite: Nil

Course outcomes:

CO1	Ability to use the mathematical concepts in the field of data science
CO2	Employ the techniques and methods related to the area of data science in variety of applications
CO3	Apply logical thinking to understand and solve the problem in context.

Syllabus:

Basics of Data Science: Introduction; Typology of problems; Importance of linear algebra, statistics and optimization from a data science perspective; structured thinking for solving data science problems.

Linear Algebra: Matrices and their properties (determinants, traces, rank, nullity, etc.); Eigenvalues and eigenvectors; Matrix factorizations; Inner products; Distance measures; Projections; Notion of hyperplanes; half-planes.

Probability, Statistics and Random Processes: Probability theory and axioms; Random variables; Probability distributions and density functions (univariate and multivariate); Expectations and moments; Covariance and correlation; Statistics and sampling distributions; Hypothesis testing of means, proportions, variances and correlations; Confidence (statistical) intervals; Correlation functions; White-noise process.

Optimization: Unconstrained optimization; Necessary and sufficiency conditions for optima; Gradient descent methods; Constrained optimization, KKT conditions; Introduction to non-gradient techniques; Introduction to least squares optimization; Optimization view of machine learning. Introduction to Data Science Methods: Linear regression as an exemplar function approximation problem; linear classification problems.

References:

<u>Textbooks:</u>

1. G. Strang. Introduction to Linear Algebra, Wellesley-Cambridge Press, Fifth edition, USA, 2016.

2. Bendat, J. S. and A. G. Piersol. Random Data: Analysis and Measurement Procedures. 4th Edition. John Wiley & Sons, Inc., NY, USA, 2010

Reference books:

3. Montgomery, D. C. and G. C. Runger. Applied Statistics and Probability for Engineers. 5th Edition. John Wiley & Sons, Inc., NY, USA, 2011.
4. David G. Luenberger. Optimization by Vector Space Methods, John Wiley & Sons (NY), 1969.
5. Cathy O'Neil and Rachel Schutt. Doing Data Science, O'Reilly Media, 2013.

Course Title	**Course Code**	**Structure (I-P-C)**		
Advanced Data Structures and Algorithms	CS502T	**3**	**0**	**3**

Prerequisite: Nil

Course outcomes:

CO1	Understand the implementation of symbol table using hashing techniques
CO2	Apply advanced abstract data type (ADT) and data structures in solving real world problem
CO3	Effectively combine the fundamental data structures and algorithmic techniques in building a solution to a given problem
CO4	Develop algorithms for text processing applications

Syllabus:

Dictionaries: Definition, Dictionary Abstract Data Type, Implementation of Dictionaries, Hashing: Review of Hashing, Hash Function, Collision Resolution Techniques in Hashing, Separate Chaining, Open Addressing, Linear Probing, Quadratic Probing, Double Hashing, Rehashing, Extendible Hashing.

Skip Lists: Need for Randomizing Data Structures and Algorithms, Search and Update Operations on Skip Lists, Probabilistic Analysis of Skip Lists, Deterministic Skip Lists, Trees: Binary Search Trees (BST), AVL Trees, Red Black Trees: Height of a Red Black Tree, Red Black Trees Bottom-Up Insertion, Top-Down Red Black Trees, Top-Down Deletion in Red Black Trees, Analysis of Operations.

2-3 Trees: Advantage of 2-3 trees over Binary Search Trees, Search and Update Operations on 2-3 Trees, Analysis of Operations, B-Trees: Advantage of B- trees over BSTs, Height of B-Tree, Search and Update Operations on 2-3 Trees, Analysis of Operations, Splay Trees: Splaying, Search and Update Operations on Splay Trees, Amortized Analysis of Splaying.

Text Processing: Sting Operations, Brute-Force Pattern Matching, The Boyer-Moore Algorithm, The Knuth-Morris-Pratt Algorithm, Standard Tries, Compressed Tries, Suffix Tries, The Huffman Coding Algorithm, The Longest Common Subsequence Problem (LCS), Applying Dynamic Programming to the LCS Problem, Computational Geometry: One Dimensional Range Searching, Two Dimensional Range Searching, Constructing a Priority Search Tree, Searching a Priority Search Tree, Priority Range Trees, Quadtrees, k-D Trees.

References:

Textbooks:

1. Mark Allen Weiss, Data Structures and Algorithm Analysis in C++, second Edition, Pearson, 2004.
2. T.H. Cormen, C.E. Leiserson, R.L.Rivest, Introduction to Algorithms, Third Edition Prentice Hall, 2009.

Reference books:

Michael T. Goodrich, Roberto Tamassia, Algorithm Design, First Edition, Wiley, 2006.

Course Title	Course Code	Structure (I-P-C)		
Principles of Data Analytics	CS503T	**3**	**0**	**3**

Prerequisite: Nil

Course outcomes:

CO1	Understand the ideas of statistical approaches to learning
CO2	Work with big data platform and explore the data analysis techniques for business applications
CO3	Design efficient algorithms for mining the data from large volumes
CO4	Perform appropriate statistical tests using R and visualize the outcome
CO5	Understand the significance of exploratory data analysis (EDA) in data science and apply basic tools (plots, graphs, summary statistics) to perform EDA
CO6	Apply basic machine learning algorithms (Linear Regression, k-Nearest Neighbors (k-NN), k-means, Naive Bayes) for predictive modeling. Explore the merits of Naive Bayes technique
CO7	Recognize the characteristics of machine learning techniques that are useful to solve real-world problems
CO8	Identify basic approaches used for feature generation and feature selection algorithms (Filters, Wrappers, Decision Trees, and Random Forests) and to apply the techniques in applications

CO9	Identify and explain fundamental mathematical and algorithm paradigms that constitute a recommendation engine. Build their own recommendation system using existing components

Syllabus:

Introduction: What is Data Science? Big Data and Data Science hype and getting past the hype, Why now?, Datafication, Current landscape of perspectives, Skill sets, Life cycle of Data Science, Different phases.

Exploratory Data Analysis and the Data Science Process: Basic tools (plots, graphs and summary statistics) of EDA, Philosophy of EDA, The Data Science Process, Case Study: RealDirect (online real estate firm), Three Basic Machine Learning Algorithms: Linear Regression, k-Nearest Neighbors (k-NN), k-means.

One More Machine Learning Algorithm and Usage in Applications: Motivating application: Filtering Spam, Why Linear Regression and k-NN are poor choices for Filtering Spam, Naive Bayes and why it works for Filtering Spam, Data Wrangling: APIs and other tools for scrapping the Web, Feature Generation and Feature Selection (Extracting Meaning From Data), Motivating application: user (customer) retention, Feature Generation (brainstorming, role of domain expertise, and place for imagination), Feature Selection algorithms: Filters; Wrappers; Decision Trees; Random Forests, Recommendation Systems: Building a User-Facing Data Product: Algorithmic ingredients of a Recommendation Engine, Dimensionality Reduction, Singular Value Decomposition, Principal Component Analysis, Exercise: build your own recommendation system.

Data Visualization: Basic principles, ideas and tools for data visualization, Case study on industry projects, Exercise: create your own visualization of a complex dataset, Data Science and Ethical Issues: Discussions on privacy, security, ethics, A look back at Data Science, Next-generation data scientists.

References:

Textbooks:

1. Cathy O'Neil and Rachel Schutt. Doing Data Science, Straight Talk from the Frontline. O'Reilly, 2014.
2. Jure Leskovek, Anand Rajaraman and Jerey Ullman. Mining of Massive Datasets, Cambridge University Press, 2014.

Reference books:

3. Kevin P. Murphy. Machine Learning: A Probabilistic Perspective. MIT Press, 2013.
4. Foster Provost and Tom Fawcett. Data Science for Business: What You Need to Know about Data Mining and Data-analytic Thinking. O′Reilly, 2013.
5. Trevor Hastie, Robert Tibshirani and Jerome Friedman. Elements of Statistical Learning, Second Edition. Springer, 2009.

6. Avrim Blum, John Hopcroft and Ravindran Kannan. Foundations of Data Science.2018.
7. Mohammed J. Zaki and Wagner Miera Jr. Data Mining and Analysis: Fundamental Concepts and Algorithms. Cambridge University Press, 2014.
8. Jiawei Han, Micheline Kamber and Jian Pei. Data Mining: Concepts and Techniques, Third Edition. Morgan Kaufmann, 2011.

Course Title	**Course Code**	**Structure (I-P-C)**		
Statistical Learning	CS504T	**3**	**0**	**3**

Prerequisite: Nil

Course outcomes:

CO1	Familiarize with a broad range of approaches and techniques in machine learning
CO2	Choose effective methods to solve various learning problem
CO3	Explore statistical learning methods and their application to modern problems in science, industry, and society
CO4	Build analytics pipelines for regression problems and classification problems
CO5	Build analytics pipelines for recommendation problems

Syllabus:

Probabilistic formulations of prediction problems: Plug-in estimators, empirical risk minimization, Linear threshold functions, perceptron algorithm, Risk bounds, Concentration inequalities, Uniform convergence, Rademacher averages; combinatorial dimensions, Convex surrogate losses for classification, Linear regression**, Regularization and linear** model selection, Feature Selection Methods, Cross Validation methods.

Game-theoretic formulations of prediction problems, High Dimensional methods, Lasso, Ridge Regression, Dimensionality Reduction, Minimax strategies for log loss, linear loss, and quadratic loss, Universal portfolios, Online convex optimization.

Neural networks: Stochastic gradient methods, Combinatorial dimensions and Rademacher averages, Hardness results for learning, efficient learning algorithms.

Kernel methods: Reproducing kernel Hilbert spaces, Mercer's theorem, convex optimization for kernel methods, Represented theorem, Ensemble methods: AdaBoost, AdaBoost as I-projection, Convergence and consistency of AdaBoost.

References:

Textbooks:

1. James, G., Witten, D., Hastie, T., Tibshirani, R. An Introduction to Statistical Learning with Applications in R, Springer, 2013.
2. Hastie, T., Tibshirani, R. and Friedman, J. The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Second Edition, Springer, 2009

Course Title	**Course Code**	**Structure (I-P-C)**		
Decision Sciences	CS505T	**2**	**2**	**3**

Prerequisite: Nil

Course outcomes:

CO1	Familiarize with the usage of Microsoft Excel for business analysis
CO2	Understand the role of quantitative techniques for managerial decision making
CO3	Ability to structure problems and to perform logical analyses
CO4	Explore the functionalities from various models and to use those insights to communicate, persuade and motivate change

Syllabus:

Decision making process, Introduction to spreadsheet modeling and problem solving, Spreadsheet engineering, Spreadsheet analysis, Modeling and Prototyping,

Measures of Central Tendency and Measures of Dispersion, Data analysis, Modeling in Practice, Enterprise Resource Planning, Introduction to Optimization and Solver, Case study.

Creating optimization models, Optimization models and sensitivity analysis, Production planning, Revenue management, Sales force sizing and allocation, Case Study.

Introduction to simulation, Simulation techniques and examples, Simulation modeling and analysis, managing risk with insurance, Optimization in simulation, assessing acquisition value with simulation.

References:

Textbooks:

1. Francis J. Clauss, Applied Management Science and Spreadsheet Modeling, Duxbury.
2. Jeffrey D. Camm and James R. Evans, Management Science: Modeling, Analysis, and Interpretation, South-Western.

Reference books:

3. Cliff Ragsdale, Spreadsheet Modeling and Decision Analysis, South-Western.
4. Wayne L. Winston and S. Christian Albright, Practical Management Science: Spreadsheet Modeling and Applications, Duxbury.
5. Jeffrey Moore et al., Introductory Management Science, Prentice-Hall.

Course Title	**Course Code**	**Structure (I-P-C)**		
Decision Sciences Practice	CS506P	**1**	**3**	**3**

Prerequisite: Nil

Course outcomes:

CO1	Familiarize with various features of R language
CO2	Understand the role of quantitative techniques for managerial decision making
CO3	Ability to perform data analysis with popular datasets
CO4	Explore and familiarize with experiments in linear model selection, cross validation and other statistical learning techniques

Syllabus:

1. Designing a spreadsheet that will allow an analyst to predict the monthly expenses in a company.
2. Importing and exporting spreadsheet data.
3. Regression: linear regression, test of significance, residual analysis, polynomial regression using R tool.
4. Experiments on cross validation, and linear model selection.
5. Experiments on advanced linear regression methods such as lasso and ridge regression.
6. Exploratory data analysis: Charts and Plots, Data Visualization, combining visualization and data transformation that allows to efficiently explore the data.
7. Information Extraction from given Textual data.
8. Apply the techniques of Linear Algebra using R tool on given dataset.
9. Optimization in R: Common R Packages for Linear, Quadratic and Non-linear optimization and sensitivity analysis.
10. Linear Programming in R: lpsolve.

Capstone Project.

References:

<u>Textbooks:</u>

1. Francis J. Clauss, Applied Management Science and Spreadsheet Modeling, Duxbury.
2. Jeffrey D. Camm and James R. Evans, Management Science: Modeling, Analysis, and Interpretation, South-Western.

Reference books:

3. Cliff Ragsdale, Spreadsheet Modeling and Decision Analysis, South-Western.
4. Wayne L. Winston and S. Christian Albright, Practical Management Science: Spreadsheet Modeling and Applications, Duxbury.
5. Jeffrey Moore et al., Introductory Management Science, Prentice-Hall.

SEMESTER-II

Course Title	Course Code	Structure (I-P-C)		
Market Science and Predictive Analysis	CS507T	**3**	**0**	**3**

Prerequisite: Nil
Course outcomes:

CO1	Understand the different strategic tools used for predictive analysis
CO2	Recognize the quantitative methods used to apply in predictive analysis
CO3	Apply various tools and techniques which help in predicting the future decision making. Examine the predictive analysis by investigating through decision trees or unstructured data analytics
CO4	Justify the importance of predictive analysis through forecasting techniques like time series analysis. To measure the ability of students to apply the predictive analytics tools in different business scenarios through example projects

Syllabus:
Introduction to Predictive Analysis: Introduction to Analytics, Analytics in Decision Making, Game changers & Innovators, Experts view on Predictive Analysis. Simple Linear Regression (SLR): Case-let Overview Introduction to Regression, Model Development, Model Validation, Demo using Excel & R Programming

Multiple Linear Regression (MLR): Multiple Linear Regression, Estimation of Regression Parameters, Model Diagnostics, Dummy, Derived & Interaction Variables, Multi-co linearity, Model Deployment, Implementation using R Programming

Decision Trees and Unstructured data analysis: Introduction to Decision Trees, CHI-Square Automatic Interaction Detectors (CHAID), Classification and Regression Tree (CART), Analysis of Unstructured data, Naive Bayes Classification, Implementation using R Programming.

Forecasting and Time series Analysis: Forecasting Time Series Analysis, Additive & Multiplicative models, Exponential smoothing techniques, Forecasting Accuracy, Autoregressive and Moving average models, Implementation using R Programming.

References:
<u>Textbooks:</u>

1. Applied Predictive Modeling by Max Kuhn and Kjell Johnson.
2. Predictive Analytics For Dummies by Anasse Bari, Mohamed Chaouchi and Tommy Jung

Reference books:

3. Modeling Techniques in Predictive Analytics with Python and R: A Guide to Data Science (FT Press Analytics) by Thomas W. Miller
4. Predictive Analytics: The Power to Predict Who Will Click, Buy, Lie, or Die by Eric Siegel

Course Title	Course Code	Structure (I-P-C)		
Advanced Decision Modelling Techniques	CS508T	**3**	**0**	**3**

Prerequisite: Nil

Course outcomes:

CO1	Conduct probabilistic sensitivity analysis, including the identification and appropriate parameterization of parameter distributions, correct use and interpretation of the net-benefit framework using ICER planes, CEACs, and confidence intervals
CO2	Identify and understand when other types of advanced decision models are more appropriate than standard decision analysis techniques, and to be able to design, conduct analysis, and interpret results from these approaches.
CO3	To conduct of probabilistic sensitivity analysis and development of sophisticated decision models

Syllabus:

Introductions and overview/discussion of why and how we model, Infectious disease modeling, Introduction to Agent-based modeling and AnyLogic, More with AnyLogic,

Discrete Event Simulation, Decision Trees and Evaluating the use of Imperfect Information, Advanced Sensitivity/Uncertainty Analysis, Advanced Sensitivity Analysis – Methods from Engineering

Advanced Preparation of Sensitivity and Uncertainty Analysis – ICER Planes, CEACs and the Net Benefit Framework, Model Calibration, Building Confidence in Models

Uncertainty Analysis, Value of Information and Design of Simulation

References:

Textbooks:

1. Advances in Decision Analysis: 4 (Mathematical Modelling: Theory and Applications) by Nadine Meskens, M.R. Roubens
2. Mathematical Modelling: Theory and Application, by X. Liao and P. Yu

Course Title	**Course Code**	**Structure (I-P-C)**		
Machine Learning	CS509T	**3**	**0**	**3**

Prerequisite: Nil
Course outcomes:

CO1	Familiarity with traditional and modern learning paradigms with their applications in the real-world systems
CO2	The learners can adapt human training for development of intelligent machines
CO3	Ability to model any real-world practical problem in a machine learning domain
CO4	Thorough grasp on the artificial neural networks with an understanding of the modern deep learning techniques

Syllabus:
Introduction to machine learning: learning systems, classification, clustering, regression, separability of problems; introduction to learning paradigms: supervised, unsupervised, semi-supervised, active, reinforcement with examples; cross-validation; performance evaluation metrics for classification and clustering; curse of dimensionality, feature selection, reduction and expansion, computation of Eigen co-ordinates and principle component analysis

Recognition systems and design cycle, Non-linearly separable problems: solutions through Cover's theorem with examples, parametric learning mechanisms like Maximum likelihood, expectation maximisation, aposteriori probabilities, Instance-based learning, Lazy learning with K-nearest neighbour, Eager learning with basis functions, non-parametric learning using support vector machines (SVMs)

Artificial neural networks: Analogy of biological neural network with artificial neural network; Perceptron learning; gradient descent algorithm; multi-layer perceptrons; back-propagation algorithm; activation functions, delta rule, learning curves: overfitting and underfitting of models; Hebbian learning, self-organising feature map, radial basis function neural networks

Deep neural networks: Introduction and advent of deep learning paradigm, solutions to vanishing and exploding gradient problems, regularisation, activation functions for deep learning, deep feed forward network, convolutional neural network (CNN), pretrained CNN models, attention network, generative models like auto-encoders and adversarial learning, recurrent neural networks, problem solving through deep learning and open areas of research

References:

Textbooks:

1. T. M. Mitchell, Machine Learning, McGraw-Hill, 1997.

2. S. Haykin, Neural Networks: A Comprehensive Foundation. Prentice-Hall of India, 2007.

Reference books:

3. R. O. Duda, P.E. Hart, D. G. Stork, Pattern Classification, John Wiley, 2001

4. I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning, MIT Press, 2016

Course Title	**Course Code**	**Structure (I-P-C)**		
Decision Support Systems	CS510T	**2**	**2**	**3**

Prerequisite: Nil

Course outcomes:

CO1	To provide students with the basic and necessary knowledge, in order that they could identify when a given domain is really a complex one
CO2	To identify how many and of which nature are the decisions involved in complex domains management
CO3	To know how to analyse, to design, to implement and to validate an Intelligent Decision Support Systems (IDSS), emphasising the integration of Artificial Intelligence models and Statistical/Numerical models, and the knowledge discovery from data

Syllabus:

Introduction, Complexity of real-world systems or domains, The need of decision support tools, Decisions Theory, Modelling of Decision Process

Evolution of Decision Support Systems, Historical perspective of Management Information Systems, Decision Support Systems (DSS), Advanced Decision Support Systems (ADSS), Intelligent Decision Support Systems (IDSS), Intelligent Decision Support Systems (IDSS), IDSS Architecture, IDSS Analysis and Design, Requirements, advantages and drawbacks of IDSS, IDSS Validation, Implementation of an IDSS in a computer

Knowledge Discovery in a IDSS: from Data to Models: Introduction, Data Structure, Data Filtering, Knowledge Models: Descriptive models, Associative models, Discriminant Models, Predictive models, Uncertainty Models, Probabilistic models, Fuzzy models, Post-Processing and Model Validation: Post-processing techniques, Validation, Statistical Methods for Hypotheses Verification

Tools and Applications, Software Tools for IDSS Development, Application of IDSS to real-world problems, Future Trends in IDSS and Conclusions

References:

Textbooks:

1. Intelligent decision support methods: the science of knowledge work - DHAR, Vasant; STEIN, Roger, Prentice Hall, 1997. ISBN: 978-0135199350

2. Decision Support Systems in the Twenty-first Century. - MARAKAS, G.M., Upper Saddle River, NJ: Prentice-Hall, 2003. ISBN: 978-0130922069

Reference books:

3. Decision Support Systems and Intelligent Systems - TURBAN, E.; ARONSON, J.E.; LIANG T-P, Pearson/Prentice Hall, 2005.

4. Decision Support Systems: concepts and resources for managers - POWER, Daniel J., Greenwood Publishing Group, 2002.

Course Title	**Course Code**	**Structure (I-P-C)**		
Predictive Analytics Practice	CS507P	**0**	**0**	**3**

Prerequisite: Nil

Course outcomes:

CO1	Structure a business scenario, devise a framework and implement using Data Science methods and Python
CO2	Practical nuances to manage data, execute various data treatment strategies, implement feature engineering, and model development and evaluation steps
CO3	Hands on experience to develop predictive models for number of real life scenarios

Syllabus:

Data Ingestions in Python, Feature Engineering and Data Management Scenarios, Regression Models using Python, Credit Card Spend Estimation – Modeling in Python

Building a Decision Tree Model for Customer Attrition, Tree based Models for a business scenario and compare performance, Unstructured Data and Modeling in Python

Forecasting Model development in Python, Hands on model development using Exponential smoothing techniques, (ARIMA) Model development for a business scenario

Hands on Image Classification using Python, Hands on Emotion Detection from Images, Text Data Manipulations in Python, Practical Model Development or Emotion Detection from Text, Model Development to Deployment in Python

References:

1. The Elements of Statistical Learning Artificial Intelligence for Marketing: Practical Applications
2. S. Dey. Hands-On Image Processing with Python: Expert techniques for advanced image analysis and effective interpretation of image data. Packt Publishing Ltd, 2018.

Course Title	**Course Code**	**Structure (I-P-C)**		
Machine Learning Practice	CS509P	**0**	**0**	**3**

Prerequisite: Nil

Course outcomes:

CO1	Use python programming in solving machine learning (ML) tasks
CO2	Use cloud platforms like Google colab for implementing the ML algorithms over real-world (large-scale) datasets
CO3	Implementation of shallow and deep learning methods on spatio-temporal datasets
CO4	Introduction to some open areas of research and finding their possible solutions through a mini-project

Syllabus:

1. Developing codes for well-known machine learning algorithms in Python: K-nearest neighbour, K-means
2. Evaluating the confusion matrix programmatically to find out performance measures like accuracy, recall, precision and F1 score
3. Evaluating the dimensionality reduction techniques in Python and k-fold cross-validation
4. Implementation of basic artificial neural networks like SLP, MLP and SOM using tensor flow

5. Implementation of deep learning techniques like deep feed-forward networks, CNN on standard computer vision datasets
6. Application of generative models in computer vision tasks
7. A mini-project on real-world deep learning problems
8. Implementation of Association Rule Mining Algorithms
9. Implementation of Sequential Pattern Mining Algorithms

References:

Textbooks:

1. A. Géron. Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow: Concepts, tools, and techniques to build intelligent systems. O'Reilly Media, 2019.
2. M. Fenner. Machine learning with Python for everyone. Addison-Wesley Professional, 2019.

Reference books:

3. A. C. Müller and S. Guido. Introduction to machine learning with Python: a guide for data scientists. " O'Reilly Media, Inc.", 2016.

Course Title	**Course Code**	**Structure (I-P-C)**		
Data Mining	CS511T	**3**	**0**	**3**

Prerequisite: Basic courses in Programming, Data Structures, Algorithms

Course outcomes:

CO1	Analyze Algorithms for Frequent item sets and frequent patterns
CO2	Design algorithms for various types of sequential patterns
CO3	Extract patterns from time series data
CO4	Develop algorithms for Temporal Patterns
CO5	Extend the Graph mining algorithms to Web Mining
CO6	Comprehend Trajectory Data Mining patterns and techniques

Syllabus:

Introduction to Data Mining, KDD process, Data Mining functionalities, Pre-processing of Data

Association Rules: Market Basket problem, Frequent Itemsets, Interesting measures, Apriori and FP growth algorithm, Algorithms for Closed and Maximal frequent itemsets, Quantitative Association Rules.

Sequential Pattern Mining concepts, primitives, GSP algorithm, scalable methods-Prefix Span, SPADE; Closed Sequential Patterns- BIDE algorithm. Transactional Patterns and other temporal based frequent patterns.

Mining Time series Data, Periodicity Analysis for time related sequence data, Trend analysis, and Similarity search in Time-series analysis

Graph Mining, Mining frequent sub-graphs, gpan algorithm, finding clusters, hub and outliers in large graphs, Web Mining

Trajectory Pattern Mining: Moving together patterns, Sequential Pattern mining from trajectories, Trajectory Clustering.

References:

Textbooks:

1. Jiawei Han, Michelin Kamber and Jian Pei - Data Mining: Concepts and Techniques, Third Edition, Elsevier Publication, 2011.

2. Pang-Ning Tan, Michael Steinbach, Vipin Kumar - Introduction to Data Mining, Pearson 2016.

Course Title	**Course Code**	**Structure (I-P-C)**		
Data Mining	CS511T	**3**	**0**	**3**

Prerequisite: Basic courses in Programming, Data Structures, Algorithms

Course outcomes:

CO1	Analyze Algorithms for Frequent item sets and frequent patterns
CO2	Design algorithms for various types of sequential patterns
CO3	Extract patterns from time series data
CO4	Develop algorithms for Temporal Patterns
CO5	Extend the Graph mining algorithms to Web Mining
CO6	Comprehend Trajectory Data Mining patterns and techniques

Syllabus:

Introduction to Data Mining, KDD process, Data Mining functionalities, Pre-processing of Data

Association Rules: Market Basket problem, Frequent Itemsets, Interesting measures, Apriori and FP growth algorithm, Algorithms for Closed and Maximal frequent itemsets, Quantitative Association Rules.

Sequential Pattern Mining concepts, primitives, GSP algorithm, scalable methods-Prefix Span, SPADE; Closed Sequential Patterns- BIDE algorithm. Transactional Patterns and other temporal based frequent patterns.

Mining Time series Data, Periodicity Analysis for time related sequence data, Trend analysis, and Similarity search in Time-series analysis

Graph Mining, Mining frequent sub-graphs, gpan algorithm, finding clusters, hub and outliers in large graphs, Web Mining

Trajectory Pattern Mining: Moving together patterns, Sequential Pattern mining from trajectories, Trajectory Clustering.

References:

Textbooks:

1. Jiawei Han, Michelin Kamber and Jian Pei - Data Mining: Concepts and Techniques, Third Edition, Elsevier Publication, 2011.

2. Pang-Ning Tan, Michael Steinbach, Vipin Kumar - Introduction to Data Mining, Pearson 2016.

Course Title	**Course Code**	**Structure (I-P-C)**		
Advanced Database Systems	CS513T	**3**	**0**	**3**

Prerequisite:

Course outcomes:

CO1	To evaluate emerging architectures for database management systems.
CO2	To develop an understanding of the manner in which relational systems are implemented and the implications of the techniques of implementation for database performance.
CO3	To assess the impact of emerging database standards on the facilities which future database management systems will provide.
CO4	Interpret and explain the impact of emerging database standards

Syllabus:

Theoretical concepts, Relational model conformity and Integrity, Advanced SQL programming, Query optimization, Concurrency control and Transaction management, Database performance tuning, Distributed relational systems and Data Replication

Object oriented, deductive, spatial, temporal and constraint database management systems, New database applications and architectures: e.g. Data Warehousing; Multimedia; Mobility; NoSQL, Native XML databases (NXD), Document orientated databases

SQL standards development, Standards for interoperability and integration e.g. Web Services

Database security - Data Encryption, redaction and masking techniques, Authentication and Authorization, Database Auditing

References:

Textbooks:

1. Date C. J., An Introduction to Database Systems, Addison Wesley Longman (8th Ed), 2003
2. Silberschatz A., Korth H., and Sudarshan S., Database System Concepts, McGraw-Hill (6th Ed), 2010

Course Title	**Course Code**	**Structure (I-P-C)**		
Artificial Intelligence	CS514T	**3**	**0**	**3**

Pre-requisite, if any:

Course Outcomes: At the end of the course, the students will be able to:

CO1	Solve searching problems using A*, Mini-Max algorithms.
CO2	Create logical agents to do inference using first order logic.
CO3	Understand Bayesian Networks to do probabilistic reasoning..
CO4	Perform Statistical learning using EM algorithm

Syllabus:

Formalized symbolic logic: Propositional logic-first order predicate logic, wff conversion to clausal form, inference rules, the resolution principle, dealing with inconsistencies and uncertainties, fuzzy logic.

Probabilistic Reasoning Structured knowledge, graphs, frames and related structures, Knowledge organization and manipulation.

Matching Techniques, Knowledge organizations, Management.

Natural Language processing, Pattern recognition, expert systems.

References:

Text Book(s):

1. Artificial Intelligence, Dan W Patterson, Prentice Hall of India.

2. Artificial Intelligence, Nils J. Nilsson, Elsevier

References & Web Resources:

1. E. Rich and K. Knight, Artificial Intelligence, TMH.
2. Stuart Russell, Peter Norvig, Artificial Intelligence - A Modern Approach, 3/e, Pearson, 2003.

Course Title	Course Code	Structure (I-P-C)		
Social Media and Network Analysis	CS515T	**3**	**0**	**3**

Prerequisite: Nil

Course outcomes:

CO1	Formalize different types of entities and relationships as nodes and edges and represent this information as relational data
CO2	Plan and execute network analytical computations
CO3	Use advanced network analysis software to generate visualizations and perform empirical investigations of network data
CO4	Interpret and synthesize the meaning of the results with respect to a question, goal, or task
CO5	Collect network data in different ways and from different sources while adhering to legal standards and ethics standards

Syllabus:

Class logistics, Overview on Network Analysis, The Network Analysis Process and Methodology, Network Visualization, Sociometric Analysis, Preliminaries on Network Structures, Models and simulation on Network evolution, Sociological direction.

Subgroups and Cliques, Clustering of graphs, Organization of relational data, Mining Social-network graphs, Direct discovery of communities in graph, Neighborhood properties in graphs, Ego Networks, Structural Holes, Cognitive Social Structures.

Introduction: Integration of Text and Network Analysis, Types of Networks Extracted From Texts Across Disciplines, Local Centrality, Global Centrality, Bank centrality in corporate network.

Introduction: Multi-Agent Models for Representing Networks, Social Network Based Multi-Agent systems, Trends on social networks, Case Studies.

References:

Textbooks:

1. Scott, J. Social network analysis: A handbook, Second Edition, Newbury Park. Sage, 2008
2. Knoke. Social Network Analysis, Second Edition, Sage, 2008.

Reference books:

1. Hanneman, Robert A. and Mark Riddle, Introduction to social network methods, Riverside, CA, 2005.

Course Title	**Course Code**	**Structure (I-P-C)**		
Time Series Analysis	CS516T	**3**	**0**	**3**

Prerequisite:

Course outcomes:

CO1	Learn basic analysis of time series data
CO2	Learn basic concepts in time series regression
CO3	Learn auto-regressive and model averaging models
CO4	Learn basic concepts of spectral analysis and space-time models; utilize R for computation, visualization, and analysis of time series data.

Syllabus:

Characteristics of Time Series Data, Basic Models, Intro to R and Reproducibility, Stationarity, Time Series Regression

Into to Time Series Analysis with R, Detrending and De-seasonalizing, Smoothing, Intro to AR models, ARMA Models, ACF and PACF

Estimation and Forecasting, Basics of ARIMA models, Basics of GARCH models, Intro to Spectral Analysis

The Periodogram, Dynamic Linear Models, Filtering and Smoothing in DLMs, Forecasting in DLMs, MLE for DLMs, Conjugate Bayesian Inference

References:

1. Shumway & Stoffer (2011) Time Series Analysis and its applications, with examples in R, 3rd edition, Springer
2. Brockwell & Davis (2016) Introduction to Time Series and Forecasting, 3rd edition, Springer
3. Ruppert & Matteson (2016) Statistics and Data Analysis for Financial Engineering with R examples, 2nd Edition, Springer.

Course Title	Course Code	Structure (I-P-C)		
Game Theory	CS518T	**3**	**0**	**3**

Prerequisite:

Course outcomes:

CO1	Identify strategic situations and represent them as games
CO2	Solve simple games using various techniques
CO3	Analyze economic situations using game theoretic techniques
CO4	Recommend and prescribe which strategies to implement

Syllabus:

Solution Concepts for Static Games: Complete information: rationalizability, Nash equilibrium, epistemic foundations, Incomplete information: Bayesian Nash equilibrium, interim correlated rationalizability, Solution Concepts for Extensive-form Games: Backwards induction, subgame perfection, iterated conditional dominance, Bargaining with complete information

Equilibrium Concepts for Games with Imperfect Information, Signaling and Forward Induction: Stable equilirium, the intuitive criterion, iterated weak dominance, epistemic foundations

Repeated Games, Reputation Formation: Reputation with short-lived opponents, Screening and reputation in bargaining, Supermodular Games

Global Games, Cooperative Games: Nash bargaining solution, core, Shapley value, Non-cooperative implementations

References:

1. Fudenberg, Drew, and Jean Tirole. *Game Theory*. MIT Press, 1991. ISBN: 9780262061414. Fudenberg, Drew, and Jean Tirole. Game Theory. MIT Press, 1991. ISBN: 9780262061414.
2. Martin Osborne, An Introduction to Game Theory, Oxford University Press, 2003.

Course Title	Course Code	Structure (I-P-C)		
Randomized and Approximation Algorithms	CS519T	**3**	**0**	**3**

Prerequisite:

Course outcomes:

CO1	To be able to design linear programming relaxations

CO2	To use randomized rounding to attempt to solve your own problem.
CO3	To develop an approximation algorithm for a specific problem
CO4	To analyze the approximation ratio of approximation algorithms

Syllabus:

Introduction to probability and randomized algorithms. Examples: quicksort, randomized mincut algorithm, Basic inequalities (Markov, Chebyshev) and random variables, Max-cut and derandomization. Permutation routing in a hypercube. Basic Chernoff bound.

Markov chains and random walks (2-SAT example, random walk on a path example). Cover times. Universal traversal sequences, Generation of combinatorial arrays. Random constructions and derandomized algorithms.

Set cover, Steiner tree and TSP, Knapsack, bin packing, Euclidean TSP, LP duality introduction; set cover randomized rounding, Set cover via primal-dual, k-median on a cycle

Max-Sat, Multiway cut, Steiner forest, Group Steiner trees

References:

1. The Design of Approximation Algorithms by David P. Williamson and David B. Shmoys.
2. Juraj Hromkovič, Design and Analysis of Randomized Algorithms: Introduction to Design Paradigms, Springer-Verlag, 2005, ISBN: 978-3-5402-3949-9

Course Title	Course Code	Structure (I-P-C)		
Cloud Computing	CS520T	**3**	**0**	**3**

Prerequisite: Nil

Course outcomes:

CO1	Articulate the main concepts, key technologies, strengths, and limitations of cloud computing and the possible applications for state-of-the-art cloud computing
CO2	Identify the architecture and infrastructure of cloud computing, including SaaS, PaaS, IaaS, public cloud, private cloud, hybrid cloud, etc.
CO3	Choose a suitable technique to address security, interoperability issues
CO4	Provide the appropriate cloud computing solutions and recommendations according to the applications used

Syllabus:

Introduction to Cloud Computing, Gartner's Hype Cycle for Emerging Technologies, Comparisons: Cluster, Grid and Cloud, Cloud Computing at a Glance, Vision, A Close Look, The NIST Model, Cloud Cube Model, Types: Deployment and Service Models, Public, Private, Hybrid and Community Cloud, IaaS, PaaS, SaaS, Characteristics, Applications, Benefits, Disadvantages, Web 2.0, The Laws of Cloudonomics, Obstacles, Cloud Adoption, Measuring the Costs, Service-Level Agreement, Cloud Architecture, Virtual Appliances, Connecting to the Cloud, IaaS Workloads, Open SaaS and SOA, On Demand vs. On Premises IT, Bird's-Eye View of Cloud Computing Vendors, Virtualization, Characteristics of Virtualized Environments, Taxonomy of Virtualized Techniques, Full Virtualization, Paravirtualization, Partial Virtualization, Pros and Cons of Virtualization, Hypervisor

Cloud issues and challenges - Properties - Characteristics - Service models, Deployment models Virtualization – Virtual Machines, Resource Allocation, Leases: Advance Reservation, Best Effort, Immediate, Deadline Sensitive and Negotiated, Swapping and Backfilling, Resource Allocation Measures, Task Scheduling, Task: Dependent and Independent, Job, Application, Workflow: Montage, Epigenomics, SIPHT, LIGO, CyberShake, Machine: Homogeneous and Heterogeneous, Mode: Immediate, Intermediate and Batch, Expected Time to Compute Matrix, Manager Server, Data Center, Virtual Machine, Server, Makespan, Resource Utilization, Average Execution Time, Uncertainty

Introduction to Energy Efficient Task Consolidation, Energy-Conscious Task Consolidation, MaxUtil, Energy-Aware Task Consolidation, Virtual Cluster, CPU Utilization Threshold, Sleep or Power Saving Mode, High-Throughput Computing: Task Computing and Task-based Application Models, Market-Based Management of Clouds, Green Cloud Computing Architecture, Federated Clouds, Pricing Mechanism, SLA Violation.

Introduction to Cloud Security, Case Studies: Manjrasoft Aneka, Amazon Web Services, Google Cloud Platform, Microsoft Azure, Programming support of Google App Engine, Virtual Machine and its Provisioning, Time and Space-shared Provisioning.

References:

Textbooks:

1. R. Buyya, C. Vecchiola and S. T. Selvi, Mastering Cloud Computing Foundations and Applications Programming, Morgan Kaufmann, Elsevier, 2013.

2. B. Sosinsky, Cloud Computing Bible, Wiley, 2011.

Reference books:

3. D. N. Chorafas, Cloud Computing Strategies, CRC Press, Taylor and Francis Group, 2011.

4. Kai Hwang, Geoffrey C. Fox and Jack J. Dongarra, "Distributed and cloud computing from Parallel Processing to the Internet of Things", Morgan Kaufmann, Elsevier , 2012.

5. D. Janakiram, Grid Computing, Tata McGraw-Hill, 2005.

Course Title	Course Code	Structure (I-P-C)		
Big Data Processing	CS521T	**3**	**0**	**3**

Prerequisite:

Course outcomes:

CO1	Ability to identify the characteristics of datasets and compare the trivial data and big data for various applications.
CO2	Ability to select and implement machine learning techniques and computing environment that are suitable for the applications under consideration.
CO3	Ability to understand and apply scaling up machine learning techniques and associated computing techniques and technologies.
CO4	Ability to recognize and implement various ways of selecting suitable model parameters for different machine learning techniques.

Syllabus:

Basic Statistics and R, Relationships and Representations, Graph Databases, Introduction to Spark 2.0.

Language processing with Spark 2.0, Analysis of Streaming Data with Spark 2.0, Applications of Spark ML Library, Basic Neural Network and Tensor Flow.

Advance Tensor Flow, Assessing Quality of Big Data Analysis, Analysis of Images, OCR Applications, Analysis of Speech Signal.

Question Answer Systems, Page Rank like Search systems, Analysis of Streaming Data with Tensor Flow, VoltDB, Data Flow Engines and other memory databases.

References:

1. Matthew J. Salganik. (2017). Bit by Bit: Social Research in the Digital Age. Princeton University Press.
2. Cathy O'Neil. (2016). Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy. Penguin Books.

Course Title	Course Code	Structure (I-P-C)		
Scalable Systems for Data Science	CS522T	**3**	**0**	**3**

Prerequisite:

Course outcomes:

CO1	Types of Big Data, Design goals of Big Data platforms, and where in the systems landscape these platforms fall.

CO2	Distributed programming models for Big Data, including Map Reduce, Stream processing and Graph processing.
CO3	Runtime Systems for Big Data platforms and their optimizations on commodity clusters and Clouds.
CO4	Scaling data Science algorithms and analytics using Big Data platforms.

Syllabus:

The design of distributed program models and abstractions, such as MapReduce, Dataflow and Vertex-centric models, for processing volume, velocity and linked datasets, and for storing and querying over NoSQL datasets. The approaches and design patterns to translate existing data-intensive algorithms and analytics into these distributed programming abstractions.

Distributed software architectures, runtime and storage strategies used by Big Data platforms such as Apache Hadoop, Spark, Storm, Giraph and Hive to execute applications developed using these models on commodity clusters and Clouds in a scalable manner.

Why Big Data platforms are necessary? How they are designed? What are the programming abstractions (e.g. MapReduce) that are used to compose data science applications? How the programming models are translated to scalable runtime execution on clusters and Clouds (e.g. Hadoop)?

How do you design algorithms for analyzing large datasets? How do you map them to Big Data platforms? And how can these be used to develop Big Data applications in an integrated manner?

References:

1. Data-Intensive Text Processing with MapReduce, Jimmy Lin and Chris Dyer, 1st Edition, Morgan & Claypool Publishers, 2010
2. Mining of Massive Datasets, Jure Leskovec, Anand Rajaraman and Jeff Ullman, 2nd Edition (v2.1), 2014.

Course Title	**Course Code**	**Structure (I-P-C)**		
Recommender Systems	CS523T	**3**	**0**	**3**

Prerequisite:

Course outcomes:

CO1	To develop state-of-the-art recommender systems that automate a variety of choice-making strategies with the goal of providing affordable, personal, and high-quality recommendations.

CO2	To implement algorithms and techniques using relevant tools
CO3	Understand the basic concepts of recommender systems, including personalization algorithms, evaluation tools, and user experiences.

Syllabus:

Introduction: Recommender system functions, Linear Algebra notation: Matrix addition, Multiplication, transposition, and inverses; covariance matrices, Understanding ratings, Applications of recommendation systems, Issues with recommender system. Collaborative Filtering: User-based nearest neighbor recommendation, Item-based nearest neighbor recommendation, Model based and pre-processing based approaches, Attacks on collaborative recommender systems.

Content-based recommendation: High level architecture of content-based systems, Advantages and drawbacks of content based filtering, Item profiles, Discovering features of documents, Obtaining item features from tags, Representing item profiles, Methods for learning user profiles, Similarity based retrieval, Classification algorithms. Knowledge based recommendation: Knowledge representation and reasoning, Constraint based recommenders, Case based recommenders.

Hybrid approaches: Opportunities for hybridization, Monolithic hybridization design: Feature combination, Feature augmentation, Parallelized hybridization design: Weighted, Switching, Mixed, Pipelined hybridization design: Cascade Meta-level, Limitations of hybridization strategies. Evaluating Recommender System: Introduction, General properties of evaluation research, Evaluation designs, Evaluation on historical datasets, Error metrics, Decision-Support metrics, User-Centered metrics.

Recommender Systems and communities: Communities, collaboration and recommender systems in personalized web search, Social tagging recommender systems, Trust and recommendations, Group recommender systems.

References:

1. Jannach D., Zanker M. and FelFering A., Recommender Systems: An Introduction, Cambridge University Press (2011), 1st ed.
2. Ricci F., Rokach L., Shapira D., Kantor B.P., Recommender Systems Handbook, Springer (2011), 1st ed.
3. Manouselis N., Drachsler H., Verbert K., Duval E., Recommender Systems For Learning, Springer (2013), 1st ed.

भारतीय सूचना प्रौद्योगिकी अभिकल्पना एवं विनिर्माण संस्थान , कर्नूल

INDIAN INSTITUTE OF INFORMATION TECHNOLOGY DESIGN AND MANUFACTURING KURNOOL

Jagannathagattu, Kurnool – 518007, Andhra Pradesh, INDIA

(An Institute of National Importance under the Ministry of Education, Govt. of India)

ORDINANCES and REGULATIONS

for

Master of Technology Programme

Effective from the A.Y. 2021-22

(July 2021)

ORDINANCE

O.1 The minimum academic qualification for admission through CCMT to IIITDM Kurnool is 60% or 6.5 CGPA in the appropriate branch of engineering or its equivalent.

a. Candidates who have qualified for the award of the Bachelor's degree in Engineering / Technology from educational Institutions approved by AICTE/UGC/Government and who have a valid GATE (Graduate Aptitude Test in Engineering) score are eligible to apply for admission to the M.Tech programme.
b. Associate Membership holders of the professional bodies for admission into their parent disciplines from the following – (i) The Institution of Engineers (India) (AMIE) (ii) The Indian Institute of Metals (AMIM) (iii) The Institution of Electronics and Tele- communication Engineering (AMIETE) with valid GATE Score can also apply.

O.2 Candidates working and sponsored (with full pay and allowances for 24 months) by industry / government organizations / private and public enterprises recognized by DST and engaged in R & D work/ engineering colleges recognized by AICTE / UGC, possessing at least two years of professional experience as on the last date of receipt of applications at IIITDM, Kurnool, can apply, provided they hold:

1. B.E./ B.Tech. degree from AICTE/UGC recognized Engineering Colleges/university with first class or 60% aggregate marks in all the four years or
2. AMIE and other Associate memberships (listed above) with a valid GATE Score

O.3 Admission to the branch of study shall be as decided during CCMT counselling.

O.4 The exact eligibility criteria for admission to the M.Tech programme shall be as approved by the Senate of the Institute from time to time and announced by the Institute on an annual basis.

O.5 The duration of the M.Tech programme will normally comprise of a total of four semesters, including project work.

O.6 Candidates may be permitted to do their project work in industry and other approved organisations as prescribed in the regulations.

O.7 The award of Half-time Teaching Assistantship (HTTA) to the candidates admitted to the M.Tech programme shall be in accordance with the regulations of the Senate of the Institute.

O.8 The award of the M.Tech degree shall be in accordance with the regulations of the Senate of the Institute

REGULATIONS

R.1.0 ADMISSION

R.1.1 The number of seats in each programme for which admission is to be made in the Institute will be decided by its Senate. Seats are reserved for candidates belonging to the Scheduled Castes, Scheduled Tribes, Other backward classes, Economically weaker sections and physically challenged candidates as per the Government of India orders issued from time to time.

R.1.2 Admission to the M.Tech programme in any year will be based on performance in GATE through a conselling conducted by CCMT.

R.1.3 The students admitted into this programme are required to do a minimum of 8 hours work, such as hanlding theory or laboratory classes, tutorials, Assignments, etc.

R.1.4 Foreign nationals whose applications are received through Indian Council of Cultural Relations, Government of India, are also eligible. Foreign Nationals are also eligible under self-financing scheme for which applications are invited through their embassy.

R.1.5 The eligibility criteria for admission including the minimum GATE score required for admission as full time students with HTTA, will be decided by the Senate.

R.1.6 **T**he conditions for admission to M Tech programmes in IIITDM Kurnool wil be given in the CCMT and Institute websites. However, if at any time the Dean(Academic)/Faculty in-charge(Academic)/ Director finds any of the requirements not fulfilled by the candidate, the Dean(Aacdemic)/ Faculty in-charge(Academic)/ Director may revoke his/her admission to the programme.

R.2.0 STRUCTURE OF THE M.TECH PROGRAMME

R.2.1 The programme of instruction for each stream of specialization will consist of

i. core courses (compulsory)
ii. elective courses
iii. project work

The student may be required to give one or more seminars and undergo industrial / practical training during the programme.

R.2.2 The complete programme will be of 4 semester duration. The academic programmes in each semester may consist of course work and/or project work as specified by the Senate for each specialisation. The total contact hours is normally about 32 hours per week.

R.2.3. Every stream of specialisation in the programme will have a curriculum and syllabi for the courses approved by the Senate. The curriculum is so framed such that the minimum number of credits for successful completion of the M.Tech programme of any stream is not less than 67 and not more than 70.

R.2.4 Credits will be assigned to the courses based on the following general pattern:

i. One credit for each lecture period
ii. Two credits for each laboratory or practical session of three periods
iii. Credits for the seminar, project work and industrial / practical training will be as specified in the curriculum.

R.2.5 A student will have to register for all the core courses listed in the curriculum of his/her selected area of specialisation and successfully complete all of them.

However, the Departmental Post Graduate Committee may grant permission to a student not to register for some of the core courses and substitute them by some other courses depending on the courses successfully completed by the student in the undergraduate programme. This has to be intimated to and approved by the Dean (Academic)/Faculty In-charge(Aacdemic) / Director.

R.2.6 Electives will have to be taken from the courses offered by the Department in that particular semester from among the list of approved courses. However, most of the departments permit selection of electives other than those listed against the Department provided they have relevance to the area of specialisation and subject to the approval of the Faculty Adviser.

R.2.7 In some specialisations students may be permitted to register for a maximum of two B.Tech courses. The concerned departments will identify such courses and get prior approval of the Senate.

R.2.8 The medium of instruction, examination, seminar and project reports will be in English.

R.3.0 Faculty Adviser

R.3.1 To help the students in planning their courses of study and for getting general advice on academic programme, the concerned Department will assign a faculty advisor for each M.Tech programme offered in the department in the beginning of every semester.

R.4.0 Class Committee

R.4.1 Every class of the M.Tech programme will have a Class Committee (CC) consisting of Faculty and students.

R.4.2 The constitution of the Class Committee will be as follows:

i) One professor/Head of the department not associated with teaching the class to be nominated by Director to act as the Chairman of the Class Committee.
ii) All faculty teaching the theory /laboratory courses for that class.

iii) Two students from the respective class; and
iv) Faculty Adviser of the respective class.

R.4.3 The basic responsibilities of the class committee are :

a) to review periodically the progress of the classes and discuss issues faced by students.
b) The type of assessment for the course will be decided by the teacher in consultation with the class committee and will be announced to the students at the beginning of the semester.
c) Each class committee will communicate its recommendations to the Head of the Department and the Dean (Academic)/Faculty In-charge(Academic).
d) The class committee without the student members will also be responsible for the finalisation of the semester results.

R. 4.4 The class committee shall meet at least twice in a semster, once at the beginning of the semester and once before commencment of minor II.

R.5.0 Change of Branch

Change of Programme is not permitted once a student is given admission to M.Tech programme.

R.6.0 Registration Requirement

R.6.1 Except for the First semester, registrarion for the semester will be done during a specified week before starting of that semester. Late registration/enrollment will be permitted with a fine as decided by from time to time up to 2 weeks from the last date specified for regsitration.

R.6.2 The M.Tech students are eligible to take extra courses apart from the courses prescribed in the curriculum, namely, one course in 3rd semester and not more than two courses in 4th semester, subject to a maximum of 9 credits, provided a student has no backlog and should have earned CGPA of 7.0 & above by the end of the previous semester. Students taking extra courses should obtain the prior approval of Dean (Academic)/Faculty In-charge(Academic).

R.6.3 During the final project semester, students are not normally permitted to register for courses. However, students who are short of a few credits required for the degree may be allowed by the Dean (Aacdemic)/Faculty In-charge(Academic) to register for one or two courses along with the project under the specific recommendation from the Head of the department.

In such cases the project duration may have to be extended beyond the normal period suitably. However, the M.Tech HTTA will be paid for a maximum period of 24 months only, as per the existing Government of India rules.

R.6.4 Withdrawal from a course registered is permitted upto two weeks from the date of commencement of the semester. Substitution by another course is not permitted. Courses withdrawn will have to be taken when they are offered next, if they belong to the list of core courses (Compulsory courses).

R.6.5 In extraordinary circumstances like medical grounds, a student may be permitted by the Dean (Academic)/Faculty Incharge(Academic) to withdraw from a semester completely. Normally a student will be permitted to withdraw from the programme only for a maximum continuous period of two semesters.

R.7.0 MINIMUM REQUIREMENT TO CONTINUE THE PROGRAMME

R.7.1 A student should have earned not less than 10 credits in the first semester, 26 credits by the end of second semester and 36 credits by the end of third semester.

The student will be asked to leave the programme failing to satisfy this requirement.

R.7.2 In addition to the above, to be eligible to continue in the programme the student should have a minimum CGPA of 5.0, calculated according to the formula in R.23.2. However, in calculating the CGPA for eligibility to continue the programme, only courses the student has successfully completed upto the point under consideration will be taken into account. If the CGPA of any student so calculated falls below 5.0, the student will be issued a warning and if he/she does not make good and get a CGPA less than 5.0 in the following semester also then he/she will be asked to leave the programme.

R.8.0 MAXIMUM DURATION OF THE PROGRAMME

R.8.1 A student is ordinarily expected to complete the M.Tech programme in four semesters. However students who do not complete their project work in third/four semesters, are permitted to submit the report in the fifth semester with the prior approval.

Students should complete the course work in not more than 5 semesters and the entire programme in 8 semesters including the project work from the date of admission to the programme.

R.9.0 DISCONTINUATION FROM THE PROGRAMME

R.9.1 Students may be permitted to discontinue the programme and take up a job provided they have completed all the course work. The project work can be done during a later period either in the organisation where they work if it has R and D facility, or in the Institute. Such students should complete the project within six semesters from the date of admission to the programme.

Students desirous of discontinuing their programme at any stage with the intention of completing the project work at a later date should seek and obtain the permission of the Dean(Aacdemic)/Faculty In-charge(Academic)/Director before doing so.

R.10.0 DISCIPLINE

R.10.1 Every student is required to observe discipline and decorous behaviour both inside and outside the campus and should not indulge in any activity which brings down the prestige of the Institute.

R.10.2 Any act of indiscipline of a student reported to the Dean will be referred to Discipline and Welfare Committee constituted by the Senate from time to time. The Committee will enquire into the charges and recommend suitable punishment if the charges are substantiated. The appropriate committee will consider the recommendation of the Discipline and Welfare Committee and authorize the Dean(Aacdemic)/Faculty in-charge(Academic) to take appropriate action.

R.10.3. **Appeal:** The student may appeal to the Chairman, Senate, whose decision will be final. The Dean(Academic)/Faculty Incharge(Academic) will report the action taken at the next meeting of the Senate.

R. 10.4 Ragging of any form is a criminal and non-bailable offence in our country and current State and Central legislations provide for stringent punishment including imprisonment. Once the involvement of a student in ragging is established, the concerned student will be dismissed from the Institution and will not be admitted into any other Institution. Avenues also exist for collective punishment, if individuals cannot be identified in this inhuman act. Every senior student of the Institute along with the parent shall give an undertaking every year in this regard and this should be submitted at the time of enrolment.

R.11.0 ATTENDANCE

R.11.1 Students are expected to have 100% attendance in a course. However, students with minimum 85% in each course, either theory/practice, will only be allowed to appear in the end semester examinations. Students failing to meet the minimum attendance percentage will have to repeat the course when it is offered next.

R.11.2 Details of attendance shortage of students for each course/practice should be sent to the Dean (Academic) / Faculty in-charge (Aacdemic) through the concerned Head of the Department.

R.12.0 LEAVE RULES

R.12.1 All M.Tech students should apply to the Head of the Department for leave, stating the reasons whenever they are not in a position to attend classes/project work. They will not be eligible for HTTA for the period of absence, if it is unauthorised leave even if they have not fully utilised the eligible leave.

R.12.2 Students are eligible for leave of 30 days in a year which will be regularised @15 days per semester with a provision of carryover from first to second semester and from the third to fourth semester (i.e unutilized leave from the first year cannot be carried over to second year).

The intervening holidays will be treated as part of leave with provision of suffixing and prefixing holidays.

R.13.0 ASSESSMENT PROCEDURE: TESTS AND EXAMINATIONS

R.13.1 For Lecture or / Lecture and Tutorial based subjects, a minimum of two sessional assessments will be made during the semester. The sessional assessment may be in the form of periodical tests, assignments or a combination of both, whichever suits the subject best. The assessment details as decided at the Class Committee will be announced to the students right at the beginning of the semester by the teacher.

R.14.0 END SEMESTER EXAMINATION

R.14.1 There will be one end semester examination of 3 hours duration in each lecture based subject. In case of practice based subjects, a final examination may or may not be conducted. In the case of project, a viva-voce examination will be conducted on the completion of the project work.

R.15.0 PROJECT EVALUATION

R.15.1 Evaluation of Project work will be taken up only after the student completes all the core as well as elective course requirements satisfactorily.

R.16.0 WEIGHTAGE

R.16.1 The following will be the weightages for different subjects.

a. Lecture or lecture and tutorial based subjects:
   Sessional assessment: Minimum of 40%.
   End semester examination: Minimum of 40%

b. Practice based subjects:
   Sessional work: 75 to 100%.
   Final examination: if held: 25%

R.16.2 The markings for all tests/ tutorial/ assignments (if any), practice work and examinations will be on an absolute basis. The final percentages of marks are calculated in each subject as per the stipulated weightages.

R.17.0 Make-up Examination

R.17.1 Students who have missed sessional assessments on valid reasons should apply to the Academic section indicating the reasons for the absence and the Faculty Advisor shall consider these requests suitably.

R.17.2 Students who have missed the end semester examinations on valid reasons, should make an application to the Dean (Academic) /Faculty In-charge(Academic) within ten days from the date of the examination missed. Permission to sit for a make-up examination in the subject(s) is given under exceptional circumstances like hospitalisation or accident to the student. A student who misses this make-up examination will not be normally given another make-up examination.

However, in exceptional cases of illness resulting in the students missing a make-up examination, the Dean (Academic) / Faculty In-charge(Academic) in consultation with the Chairman of the Senate may permit the student to appear for a second make-up examination.

R.17.3 For application on medical grounds, students residing in the hostels should produce a Medical Certificate issued by an Institute Medical Officer only.

Students staying outside the campus permanently/temporarily should produce a medical certificates from registered medical practitioners and the same should be forwarded by the parents/guardian for the purpose of make-up examinations.

The Dean (Academic)/ Faculty in-charge(academic) can use his discretion in giving permission to a student to take a make-up examination, recording the reasons for his/her decision.

R.18.0 Subject wise Grading of Students into Categories

R.18.1 Letter Grades

Each student is awarded a final letter grade at the end of the semester in each subject based on his/her semester performance at the end of the semester. The letter grades and the corresponding grade points are as follows.

Grade	Points	
S	10	Grade points
A	9	
B	8	
C	7	
D	6	
E	4	
U	0	Unqualified/Failure
W	0	Failure due to insufficient attendance
I	0	Incomplete (Subsequently to be changed into pass (E to S) or U garde in the same semester)

R.18.2 A student is considered to have completed a subject successfully and earned the credit if he/she secures an overall letter grade other than U or W or I in that subject.

A letter grade U or W in any subject implies failure in that subject. A subject successfully completed cannot be repeated.

R.18.3 Grades are awarded on relative basis.

R.19.0 Method of Awarding Letter Grades

R.19.1 A final meeting of the Class Committee without the student members will be convened within seven days after the last day of the end semester examination.

The letter grades to be awarded to the students for different subjects will be finalised at this meeting.

R.19.2 Two copies of the result sheets for each subject containing the final grade and two copies along with absolute marks and final grade should be submitted by the teacher to the concerned Faculty Advisor for further processing.

After finalisation of the grades at the Class Committee Meeting, one copy with absolute marks and one without the absolute marks but having only the grades will be forwarded by the Class Committee Chairman to the Dean (Academic)/Faculty In-charge(Academic).

One copy with absolute marks, the final grade will be sent to the Head of the Department in which the course is offered.

R.20.0 DECLARATION OF RESULTS

R.20.1 The letter grades awarded to the students in each subject will be anounced in the Institute web site soon after the final Class Committee meeting.

R.20.2 **The W grade once awarded stays in the record of the student and is deleted when he/she completes that subject successfully later.** The grade acquired by him/her will be indicated in the grade card of the appropriate semester with an indication of number of attempts made in that course.

R.20.3 **'U' grade obtained by the student will be deleted in the grade card when he/she completes that subject successfully later. Further, the number of attempts made by the student in that course, will be indicated in the grade card.**

R.21.0 RE-EXAMINATION OF ANSWER PAPERS

R 21.1 As a process of learning by students and also to ensure transparency, the answer scripts after correction of class tests, minor (s), assignments etc., will be shown to the students within two weeks from the date of test/examination. The performance of the students in minors will be discussed in the Class Review Committee.

R.21.2 In order to ensure transparency in the evaluation of scripts of end-semester examination, those answer scripts also shall be shown to the students up to one day before the finalization of grades. Once the Grades are finalized, the student will no longer have any right to verify his/her answer scripts.

R.21.3 The student can appeal to DAAC for any arbitration within 20 days from the date of official publication of results in the Institute Website.

R. 21.4 Disposal of Answer Scripts

Answer scripts related to a course shall be preserved by the faculty for a period of 6 months from the date of anouncement of results. After this period, the same shall be disposed of as scrap by the institute.

R.22.0 COURSE REPETITION

R.22.1 A student securing 'U' or 'W' grade in any core subject has to repeat it compulsorily when offered next.

R.22.2 A student securing 'U' or 'W' grade in any elective subject has to repeat the course when offered next or he/she can register another equivalent elective course in order to get a sucessful grade.

R.23.0 GRADE CARD

R.23.1 The grade card issued at the end of the semester to each student will contain the following:

a. the credits for each course registered for that semester.
b. the letter grade obtained in each course
d. the total number of credits earned by the student upto the end of that semester.
e. the semester grade point average (SGPA) of all the courses taken in that semester.
f. the Cumulative Grade Point Average (CGPA) of all the courses taken form the first semester till the current semester is shown in the final semester grade card.

R.23.2 The Grade Point Average (GPA) will be calculated by the formula.

$$GPA = \frac{\sum_i C_i \times GP}{\sum_i C_i}$$

Where C_i = credit for the course, GP = the grade point obtained for the course and Σ C_i is sum of credits of the courses that are successfully completed in that semester.

For the cumulative Grade Point Average (CGPA), a similar formula is used except that the ΣiCi is the sum of credits in all the courses taken in all the semesters completed upto the point of time, including those in which the student has secured U or W grades.

R. 23.3. No class/division/rank will be awarded to the students at the end of the M.Tech programme.

The formula for conversion of CGPA to percentage is **CGPA×10**.

R.24.0 PROJECT WORK IN INDUSTRY OR OTHER ORGANISATION

R.24.1 Students who desire to do their project work in industries/R&D organizations, may be permitted to carry out their project work in such organisations during the third/final semester.

R.24.2 A departmental committee shall examine the requests from such students, and fix:

i. An internal guide (a faculty member of the institute) along with an area of project work and

ii. External guide (Scientists or Engineer in the Industry).

R.24.3 The above details should be submitted to the Dean (Academic)/ Faculty In-charge (Academic) through the Head of the Department for further processing.

R.24.4 The students who are permitted to do the project work in an industry will have to pay the tuition and other fees to the Institute for the third and fourth semester as well.

R.24.5 Students who do their project work in Industry/R&D Organizations, are permitted to draw stipend only from one source.

R.25.0 HALF-TIME TEACHING ASSISTANTSHIP

R.25.1 Students who are qualified for M.Tech admission through valid GATE score and are admitted as full time students of the Institute, will be eligible for the award of the HTTA notified by the Institute from time to time.

R.25.2 Self-financing foreign nationals are not eligible for HTTA.

R.26.0 ELIGIBILITY FOR THE AWARD OF M.TECH DEGREE

R.26.1 A student shall be declared to be eligible for the award of M.Tech degree if he/she has

(1) Registered and successfully completed all the core courses and the project.

(2) Successfully acquired the minimum number of credits prescribed in the curriculum of the given stream within the stipulated time.

(3) No dues to the Institute, Library and Hostels and

(4) No disciplinary action pending against him/her.

(5) For students visiting Universities abroad under Exchange programme the following will be followed for credit transfer:

The credits / grades obtained from the university where the student has done courses will be indicated in the grade card.

Institute transcripts should only indicate the courses, credits and grades completed at IIITDM and the courses and credits (without grades) done in other Universities in a particular semester.

The CGPA calculation based on credits done at Institute alone is to be considered for award of prizes.

The credits earned at Universities abroad will be considered for calculation of minimum required credits for award of degree

R.26.0 The final award of the Degree must be recommended by the Senate and approved by the Board of Governors of the Institute.

R.27.0 POWER TO MODIFY

Notwithstanding all that has been stated above, the Senate has the right to modify any of the regulations from time to time.