SEMESTER I

AI6101: APPLIED STATISTICS AND PROBABILITY [3 1 0 4]

Basics of Statistics: The Role of Statistics in Engineering, Basic Principles, Retrospective Study, Observational study, Designed Experiments, Observing Processes Over Time, Mechanistic and Empirical Models, Probability and Probability Models **Measure of central tendency:** mean, median and mode, Measures of dispersion- Range, Quartile Deviation, Mean Deviation, Standard Deviation, Coefficient of variance, Skewness, Kurtosis. **Probability Distribution:** Sample Spaces and Events, Interpretations and Axioms of Probability, Addition Rules, Conditional Probability, Multiplication and Total, Probability Rules, Bayes' Theorem, Random Variables, Concept of Random Variable, Bernoulli Distribution, Binomial Distribution, Poisson Distribution, Normal Distribution. **Correlation and Regression:** Concept and types, Karl Pearson Method, Rank Spearman Method, Least Square Method, Discrete Random Variables and Probability Distributions. Continuous Random Variables and Probability Distributions. Joint Probability **Distributions. Testing of Hypothesis:** Testing of Hypothesis, Null and alternative hypothesis, level of significance, one-tailed and two-tailed tests, tests for large samples (tests for single mean, difference of means, single proportion, difference of proportions), t-test, F- test, Chi-Square Test.

References:

1. Douglas C. Montgomery and George C. Runger, *Applied Statistics and Probability for Engineers*, John Wiley & Sons.
2. Blake I., *An Introduction to Applied Probability*, John Wiley & Sons.
3. Yagolam A. M. and Yagolam I. M., *Probability and Information*, Hindustan Publishing Corporation, Delhi, 1983.

AI6102: ADVANCED DATA STRUCTURES AND ALGORITHMS [3 1 0 4]

Introduction: Overview of data structures and their importance in algorithm design, Performance analysis- time complexity and space complexity, Asymptotic notation (Big O, Omega, Theta) and analyzing algorithm complexity, Divide and conquer algorithms, Greedy algorithms, Dynamic programming, Randomized algorithms**. Trees and Tree-based algorithm:** Balanced BSTs like AVL trees and Red-Black trees, B-trees and their variants, such as B+ trees, Splay trees. **Heaps:** Binary heaps, Binomial Heaps, Fibonacci Heaps. **Advanced Sorting and Searching:** Quicksort and variants, Heapsort, Radix sort, External sorting, Interpolation search, String searching algorithms (Knuth-Morris-Pratt, Boyer-Moore). **Advanced Topics: Dynamic programming:** Principles, overlapping subproblems, memorization, tabulation. **Approximation algorithms:** Greedy algorithms, local search algorithms. **String algorithms:** String matching, suffix trees, pattern matching algorithms. **Maximum Flow:** Flow Networks and Flow, Network Flow, Ford-Fulkerson Algorithm, Maximum Bipartite Matching, **Advanced graph algorithms**: Topological sorting, strongly connected components, graph coloring, maximum matching. **NP-completeness:** Introduction to computational complexity theory, P vs. NP problem, NP-hardness, approximation algorithms. **Advanced Hashing Techniques:** Hash tables and their collision resolution techniques (chaining, open addressing), Perfect hashing and cuckoo hashing.

References:

1. Thomas H Cormen, Charles E. Leiserson, Ronald L. Rivest, Clifford Stein, *Introduction to Algorithms*, (3e), The MIT Press, 2009.
2. Ellis Horowitz, SatrajSahani and Rajasekharam, *Fundamentals of Computer Algorithms*, (2e), University Press Pvt. Ltd, 2009.

AI6103: APPLIED MACHINE LEARNING [3 1 0 4]

Introduction to Applied Machine Learning: Overview of machine learning concepts and applications, Different types of machine learning algorithms, Introduction to popular machine learning libraries and frameworks, Data Preprocessing, Feature scaling and normalization, Handling categorical variables and feature encoding, Model Selection and Evaluation, Train-test split and cross-validation, Evaluation metrics for classification and regression tasks, Hyperparameter tuning and model selection techniques, Model performance comparison and interpretation, **Feature Engineering**: Feature selection and dimensionality reduction, Handling outliers and noisy data, Creating new features and feature transformations, Feature scaling techniques for different algorithms, **Supervised Learning Algorithms**' Linear regression and logistic regression, Decision trees and ensemble methods (e.g., random forests, gradient boosting), Support vector machines (SVM), Neural networks and deep learning, **Unsupervised Learning Algorithms:** Clustering algorithms (e.g., k-means, hierarchical clustering), Dimensionality reduction techniques (e.g., PCA, t-SNE), Model serialization and persistence, **Advanced Topics in Applied Machine Learning**: Natural Language Processing (NLP) and text classification, Time series analysis and forecasting, Reinforcement learning, Overview of Federated and Distributed Machine Learning, Real-Life Applications for Machine Learning Experiments.

References:

1. Jeff Prosise, Applied Machine Learning and AI for Engineers, O'Reilly, 2022.
2. Aurélien Géron, Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow (2e), O'Reilly, 2019.
3. Christopher M. Bishop, Pattern Recognition and Machine Learning (Information Science and Statistics), (2e), Springer, 2007.

AI6130: ADVANCED DATA STRUCTURES AND ALGORITHMS LAB USING PYTHON [0 0 4 2]

Implementation of Basic Data Structures: linked lists, stacks, queues. **Implementation of Advanced Data Structure**: balanced binary search trees (e.g., AVL trees, Red-Black trees), B-trees and their variants (e.g., B+ trees), **Advanced Algorithms:** Divide and conquer algorithms, Dynamic programming, Greedy algorithms, Backtracking, Network flow algorithms. **Algorithm Analysis and Evaluation:** Time and space complexity analysis, Asymptotic notation (Big O, Omega, Theta), Worst-case, average-case, and best-case analysis, Experimental analysis, and benchmarking. **Design and Analysis Techniques:** Divide and conquer, Recursion, Memorization, Iterative algorithms. **Advanced Topics:** Advanced graph algorithms (e.g., shortest paths, minimum spanning trees), String algorithms (e.g., pattern matching, string compression), Geometric algorithms, Approximation algorithms

References:

1. Thomas H Cormen, Charles E. Leiserson, Ronald L. Rivest, Clifford Stein, *Introduction to Algorithms*, (3e), The MIT Press, 2009.
2. Ellis Horowitz, Satraj Sahani and Rajasekharam, *Fundamentals of Computer Algorithms*, (2e), University Press Pvt. Ltd, 2009.

AI6131:DATA VISUALIZATION LAB **[0 0 2 1]**

In th is course, various experiments will be performed, covering various Data Visualization techniques. **Basic Plotting:** matplotlib, plotting with pandas and seaborn, other python visualization tools, Data aggregation, General split-apply-combine, Pivot tables, **Getting started with Tableau Desktop:** Creating the first charts, Filtering and sorting data, Exploratory Data Analysis and Visual Exploration, Understanding the association between two continuous or quantitative factors – Scatterplots, Correlation, Regression diagnostics - Residual Plots, Outliers and Influence Points.

References:

1. Tamara Munzner, *Visualization Analysis & Design*, CRC Press, 2014.
2. Scott Murray, *Interactive Data Visualization for the Web, (2e*), O'Reilly, 2017.
3. Wingston Chang, *R graphics cookbook*, O'Reilly. (2013).
4. Andy Field, Jeremy Miles and Zoe Field, *Discovering Statistics Using R*, SAGE Publications Ltd. 2012.

Semester II

AI6201: NATURAL LANGUAGE UNDERSTANDING [3 1 0 4]

Traditional NLU: Introduction to NLU, Motivation, Morphology, Parts-of-Speech, Language Models, Word Sense Disambiguation, Anaphora Resolution, Basics of Supervised and Semi-supervised Learning for NLU, Hidden Markov Models for language modeling, EM Algorithm, Structured Prediction, Dependency Parsing, Topic Models, Semantic Parsing, Sentiment analysis. **Deep Learning for NLU**: Intro to Neural NLU, Word Vector representations, Neural Networks and backpropagation -- for named entity recognition, Practical tips: gradient checks, overfitting, regularization, activation functions, Recurrent neural networks -- for language modeling and other tasks, GRUs and LSTMs -- for machine translation, Recursive neural networks -- for parsing, Convolutional neural networks -- for sentence classification, Question answering and dialogue system, Graph Neural Network for NLU, Natural Language Generation, Analysis and Interpretability of Neural NLU. **Knowledge Graphs:** Knowledge graph embedding techniques, Inference on knowledge graphs.

References:

1. C. Manning, H. SchüTze, *Foundations of Statistical Natural Language Processing*, MIT Press, 1999.
2. D. Jurafsky, J.H. Martin, *Speech and Language Processing: An Introduction to Natural Language Processing,* Computational Linguistics and Speech Recognition (3rd Edition Draft), 2019.
3. E. Bender, *Linguistic Fundamentals for NLP*, Morgan Claypool Publishers, 2013.

AI6202: DEEP LEARNING **[3 1 0 4]**

Introduction to Deep Learning and its Applications. Introduction to Statistical Learning: Multi-Layer Perceptron, Back Propagation, Linear Regression, etc. **Convolutional Neural Networks:** Convolution, pooling, Activation Functions, Back propagation of CNN, Weights as templates, Translation invariance, Training with shared parameters. CNN Architecture Design and Discussion: Alex Net, VGG, Google Net, Res Net, Capsule Net, etc. Gradient descent and the back propagation algorithm, Unit saturation, the vanishing gradient problem, and ways to mitigate it. RELU Heuristics for avoiding bad local minima, Heuristics for faster training, Nestors accelerated gradient descent, Regularization, Dropout. **Loss Functions and Optimization:** Optimization, stochastic gradient descent, dropout, batch normalization, etc. **Sequential Modelling:** Recurrent and Recursive Nets, RNN, LSTM, GRU, Image captioning, visual question answering, etc. **Visualization and Understanding:** Visualizing intermediate features and outputs, Saliency maps, Visualizing neurons, Cam-Grad, etc. Generative Models: Variational Autoencoders, pix2pix, Deep Convolutional GAN. Neural Attention Models, Attention is all you need, BERT (Bidirectional Transformers), the Illustrated transformer (Vision, and Swin), **Deep Reinforcement Learning:** Reinforcement Learning (RL) Background, Policy gradients, hard attention Q-Learning; **Deep Learning Applications:** Object Detection, RCNN, Fast RCNN, Faster RCNN, YOLO, Retina Net, SSD. Application of deep learning in different real time applications.

References:

1. Ian Goodfellow and YoshuaBengio and Aaron Courville, *Deep Learning*, MIT Press, 2016.
2. Michael A.Nielsen, *Neural Networks and Deep Learning*, Determination Press, 2015.

AI6203: MLOps **[3 1 0 4]**

Introduction to MLOps: Overview of MLOps and its importance in modern AI applications, Understanding the ML pipeline and its components, Challenges, and considerations for MLOps. **Basics of Machine Learning and Data Science:** Overview of machine learning and deep learning model, different frameworks for model development, Design coding environments. Hyperparameter tuning and optimization. **Infrastructure for MLOps:** Overview of cloud computing platforms, Setting up virtual machines and containers. **ML API Development and Deployment:** Flask, FastApi, TensorFlow serving, TensorFlow lite for optimization latency. **Software Development for Machine Learning Apps:** Software Development Paradigms i.e., OOP, YAML language, software testing, code refactoring. **Containerizing ML application:** concepts of the orchestration of developed containers, Kubernetes, and its architecture, running a pod inside Kubernetes, and load balancing and scalability. **Microservices and REST API for ML Deployment:** rest API, an endpoint to access the model. **Container Orchestration and environment concept**: Kubernetes, Docker image, Orchestration environment, the basic commands of Kubernetes and some new CLI tools i.e., kubectl etc. **Continuous Delivery:** CI/CD Pipelines: core components of the various CI/CD pipelines i.e. Jenkins, ArgoCD and Github Action, Data Pipelines & Automated ML Pipelines and Quantization. **Case Studies and Projects:** Real-world MLOps applications and case studies.

References:

1. Mark Treveil, Nicolas Omont, Clément Stenac, Kenji Lefevre, Du Phan, Joachim Zentici, Adrien Lavoillotte, Makoto Miyazaki, Lynn Heidmann. *Introducing MLOps,* O'Reilly Media,2021.
2. Hannes Hapke and Catherine Nelson, *Building Machine Learning Pipelines: Automating Model Life Cycles with TensorFlow,* O'Reilly Media,2021
3. Kostis Kapelonis. *Kubernetes for Machine Learning: Implement Machine Learning workflows on Kubernetes, 2022.*
4. Noah Gift, Alfredo Deza *Practical MLOps,* O'Reilly Media,2021.

AI6230: DEEP LEARNING LAB **[0 0 4 2]**

In this course, various experiments will be performed, covering different deep Learning techniques. **Introduction to Computer Vision Tools:** OpenCV with Python. Building a simple neural network and convolutional neural network. Experiments covering **pre-processing of data**, different classifiers such as Alex Net, VGG, Google Net, Res Net, Capsule Net, etc and data sets will be described in the laboratory manual. Learn and build **Generative Adversarial Networks (GANs),** from their simplest form to state-of-the-art models. Implement, debug, and train GANs as part of a novel and substantial course project. Gaining familiarity with the latest cutting-edge literature on GANs. Deep Convolutional GAN (DCGAN), Wasserstein (WGAN), INFOGAN, Cycle GAN, Super Resolution GAN (SRGAN), and Conditional Gan (CGAN) etc. **Neural Attention Models**, BERT (Bidirectional Transformers), the Illustrated transformer (Vision, and Swin). Reward risk-taking and creative exploration. **Application of deep learning methods** in Object Recognition, Face Detection, and Agricultural applications.

References:

1. Francois Chollet, *Deep Learning with Python*, Manning Publications, 2017.
2. Michael A.Nielsen, *Neural Networks and Deep Learning*, Determination Press, 2015.
3. Ian Pointer, *Programming PyTorch for Deep Learning Creating and Deploying Deep Learning Applications*, O'Reilly Media, 2019.

AI6170 and AI6270: PROJECT (I and II) [0 0 4 2]

The aim of this course is to deepen the understanding of the principles, techniques, and algorithms related to artificial intelligence and machine learning. It provides an opportunity to apply theoretical knowledge gained during coursework to a real-world problem. The project work will involve conducting research and problem solving in AI&ML. Students will undertake a project in the domains pertaining to relevant specialization under the guidance of a supervisor.

OR

AI6171 and AI6271: RESEARCH PRACTICE (I and II) [0 0 4 2]

The aim of the course is to give training and opportunities to the post-graduate students in gaining skills and competence in research methodologies and drafting research reports/ proposals. The course must be completed by the student under the guidance of a supervisor. The supervisor would assign to student an appropriate research-oriented problem to work which is related to his own domain of expertise.

Programme Electives

Programme Electives-I

AI6140: HEALTH INFORMATICS **[3 0 0 3]**

Introduction: Overview, health data, information, and knowledge, electronic health records, system architecture for EHRs, ambulatory EHR functions and interoperability, personal health records and decision aids. **Health Care Information Systems:** Healthcare data standards - Overview, methods, protocols, terminologies, and specifications for the collection, exchange, storage, and retrieval of information associated with healthcare applications. **Data Collection and Quality Assurance:** Data collection, cleaning data, managing change, Using Data for Care Delivery, Coordination, and Quality Improvement, Quality assurance, Security, Privacy. **Clinical Data:** Introduction, medical digital data formats and exchange, medical image formats such as DICOM in the context of health informatics. **Informatics:** Information retrieval, bioinformatics - usage of informatics in genomics and other aspects of molecular biology, patient case history analytics, applications in public health, ethical issue in health informatics. **Medical Diagnostic Decision Support:** probabilistic approaches, clinical scores, logical approaches – expert system, inference engines, case studies. **Digital healthcare:** Telemedicine, mobile for health, public health.

References:

1. Hoyt, R. E., & Yoshihashi, A. K. *Health Informatics: Practical Guide for Healthcare and Information Technology Professionals*, (7e), Lulu.com, 2018
2. Hersh, W. R., & Hoyt, R. E., *Health Informatics: Practical Guide*, (7e), Lulu.com, 2018

AI6141: BIG DATA AND ANALYTICS **[3 0 0 3]**

Foundations of Big Data and Analytics: Evolution and Definition of big data, Challenges of big data; Characteristics of big data analytics, Challenges to big data analytics, Importance of big data analytics, Hadoop Ecosystem, **HDFS(Hadoop Distributed File System):** The Design of HDFS, HDFS Concepts, Command Line Interface, Hadoop file system interfaces, Data flow, Data Ingest with Flume and Scoop and Hadoop archives, **Map Reduce:** Anatomy of a Map Reduce Job, Job Scheduling, Shuffle and Sort, Task Execution, Map Reduce Types and Formats, Map Reduce Features. **NoSQL:** Introduction to NoSQL, NoSQL Business Drivers, NoSQL Data Architecture Patterns, Data Pre-processing: Data cleaning, transformation, and normalization, **Data Analysis:** Data visualization and exploration, Descriptive and inferential statistics, Machine learning algorithms for Big Data Analytics, **Real-time Analytics:** Stream processing and real-time data processing, Real-time analytics with Apache Storm and Apache Spark, **Advanced Analytics:** Data visualization and exploration, Machine learning algorithms for Big Data Analytics, **Research Trends & Case Studies**: Emerging research trends in Big Data Analytics, Current research directions in Big Data Analytics.

References:

1. EMC Education Services, Data Science and Big Data Analytics: Discovering, Analyzing, Visualizing and Presenting Data, (1e), John Wiley & Sons, 2015.
2. Boris lublinsky, Kevin t. Smith, Alexey Yakubovich, *Professional Hadoop Solutions*, (1e), Wrox, 2013.
3. Chris Eaton, Dirk Deroos,*Understanding Big data*, Indian Edition, McGraw Hill, 2015.
4. Byron Ellis - Real-Time Analytics, Techniques to Analyze and Visualize Streaming Data, Wiley, 2-14
5. Jake VanderPlas - Python Data Science Handbook, O Reilly, 2022
6. Seema Acharya, Subhashini Chellappan, *Big Data Analytics*, (1e), Wiley, 2015.

AI6142: CYBER ANALYTICS [3 0 0 3]

Introduction to Cyber Analytics: Overview of the cyber threat landscape, Understanding the importance of analytics in cybersecurity. **Fundamentals of Data Analysis:** Introduction to data analysis techniques and tools. **Introduction to Cyber Analytics:** Definition and scope of cyber analytics, Types of data sources in cybersecurity, Challenges and opportunities in cyber analytics. **Cybersecurity Data Collection and Storage**: Data collection methods and techniques, Privacy data collection. **Data Mining and Machine Learning for Cybersecurity:** Introduction to data mining techniques, Feature selection and extraction in cybersecurity data, Intrusion Detection and Prevention, Log Analysis and Event Correlation, Security information and event management (SIEM) systems. **Incident Response and Forensics:** Incident response processes and frameworks, Digital forensics principles and techniques, Analyzing and interpreting forensic data. **Emerging Trends in Cyber Analytics:** Latest developments and trends in cyber analytics Artificial intelligence and machine learning advancements, Ethical and legal implications of cyber analytics Thread Modelling and Thread identification. Risk analytics and assessment.

References:

1. Jay Jacobs and Bob Rudis, *Data-Driven Security: Analysis, Visualization and Dashboards, (1e)*, 2014
2. Rakesh M. Verma, David J. Marchette, Cybersecurity Analytics, (1e), Chapman & Hall/CRC Data Science Series, 2022

Programme Electives-II

AI6143: COMPUTER VISION **[3 0 0 3]**

Digital Image Processing: Image Formation, Image Filtering, Edge Detection, Principal Component Analysis, Corner Detection, SIFT, **Applications: Large Scale Image Search Single and multi-view geometry:** Camera geometry, multi-view geometry and stereovision, **Image registration:** feature-point based registration for affine transformations/homography; optical flow (nonrigid registration); robust registration, Segmentation and region growing, Knowledge representation and inference, **Machine Learning for Computer Vision:** Object recognition, detection, tracking, Texture classification and recognition, Pyramid paradigms, Shape from Shading and Photometric Stereo, Structure from Motion, Activity recognition, Computational Photography, and super-resolution.

References:

1. David A. Forsyth and Jean Ponce, *Computer Vision: A Modern Approach, Forsyth and Ponce*, (2e), Pearson Education, 2015.
2. Gary Bradski, Adrian Kaehler, *Learning OpenCV: Computer Vision with the Open CV Library*, (1e), O`Reilly Media, 2008.
3. Gonzalez and Woods, *Digital Image Processing*, (3e), Pearson Education, 2008.
4. Hartley & Zisserman, *Multiple View Geometry*, Cambridge Press, 2004

AI6144: COGNITIVE COMPUTING **[3 0 0 3]**

Introduction To Cognitive Computing, Meaning cognitive processes, Development of cognitive psychology: Structuralism, Functionalism, Behaviourism, Memory Research, Gestalt Psychology, Emergence of cognitive psychology, Information Processing, Connectionism, Alternate approaches to cognitive psychology, Research Methods in Cognitive Psychology. **Perceptual Processes,** Object Recognition- theories of object recognition, Bottom-Up and Top-Down Processing, Face Perception, Change Blindness. Attention: Divided attention, Selective Attentkon, Visual attention and Auditory attention. Consciousness: Varieties, Subliminal Perception. Visual Perception ¨Perceptual Organizational Processes, Multisensory interaction and Integration –Synesthesia, Comparing the senses, Perception and Action. **Memory,** Working Memory: Research on Working Memory, Factors affecting the capacity of working Memory, Baddeley's Working Memory Approach. Long Term Memory: Encoding and Retrieval in Long Term Memory, Autobiographical Memory. Memory Strategies: Practice, Mnemonics using Imagery, Mnemonics using organization, The Multimodal Approach, Improving Prospective Memory. Metacognition: Metamemory, TOT, Meta comprehension, **Computing Through Reasoning and Decision Making,** Problem Solving – Types of problem, Understanding Problem Solving Approaches, Factors that influence Problem Solving creativity. Reasoning – Inductive and Deductive Reasoning Decision Making – Heuristics in decision making – representativeness, availability and anchoring and adjustment. The framing effect, Overconfidence in decisions, The Hindsight Bias. Critical thinking, Adaptive thinking, Cognitive Load Management, Design thinking, Virtual Collaboration and Cultural Sensitivity.

References:

1. Robert A. Wilson, Frank C. Keil, *The MIT Encyclopedia of the Cognitive Sciences*, The MIT Press, 1999.
2. Pradeep Kumar Mallick, Prasant Kumar Pattnaik, Amiya Ranjan Panda, Valentina Emilia Bala,*Cognitive Computing in Human Cognition: Perspectives and Applications*, (1e), Springer, 2020.
3. Esther F. Kutter and Martin V. Butz,*How the Mind Comes Into Being: Introducing Cognitive Science from a Functional and Computational Perspective*,(1e), OUP Oxford, 2017.
4. Vijay V Raghavan, Venkat N. Gudivada, Venu Govindaraju, C.R. Rao,*Cognitive Computing: Theory and Applications*, (1e), North Holland, 2016.

AI6145: SPEECH RECOGNITION **[[3 0 0 3]**

Introduction: Basic Concepts, Speech Fundamentals, Acoustic Theory of Speech Production, Acoustic Phonetics, Speech Sounds, Review of Digital Signal Processing concepts; Signal Representation, Short-Time Fourier Transform, Filter-Bank and LPC Methods. **Speech Analysis:** Features, Feature Extraction and Pattern Comparison Techniques: Speech distortion measures – mathematical and perceptual – Log Spectral Distance, Cepstral Distances, Weighted Cepstral Distances and Filtering, Likelihood Distortions, Spectral Distortion using a Warped Frequency Scale, LPC, PLP and MFCC Coefficients, Time Alignment and Normalization – Dynamic Time Warping, Multiple Time – Alignment Paths. **Speech Modeling and Recognition**: Hidden Markov Models- (HMMs) and WFSTs, **HMMs:** Markov Processes, HMMs for Acoustic Modeling, WFSTs for speech recognition, Introduction to Neural network-based acoustic modeling, Language modelling, (R)NN-based language models, **Advanced ASR:** End-to-end deep learning approaches for speech recognition, Search and Decoding, Multilingual and low-resource ASR, Robust ASR Adaptation.

References:

1. Daniel Jurafsky and James H. Martin, *Speech and Language Processing*, (2e), Pearson, 2019.
2. Mark Gales and Steve Young*, The application of hidden Markov models in speech recognition, Foundations and Trends in Signal Processing*, (1e), Now Publishers, 2008.
3. Geoffrey Hinton, Li Deng, Dong Yu, George E. Dahl, Abdel-rahman Mohamed, Navdeep Jaitly, Andrew Senior, Vincent Vanhoucke, Patrick Nguyen, Tara N. Sainath, and Brian Kingsbury, *Deep Neural Networks for Acoustic Modeling in Speech Recognition*, IEEE Signal Processing Magazine, 2012.

Programme Elective -III

AI6240: EXPLAINABLE AI **[3 0 0 3]**

Introduction to Explainable AI: The need for explainability in AI systems, Challenges and trade-offs in AI interpretability, Historical context and evolution of XAI, **XAI Techniques:** Rule-based and symbolic approaches, Model-agnostic methods (e.g., feature importance, partial dependence plots), Local interpretability methods (e.g., LIME, SHAP), Post-hoc explanation techniques (e.g., surrogate models, rule extraction), Interpretable model architectures (e.g., decision trees, linear models), **Evaluating Interpretability:** Quantitative and qualitative evaluation metrics for interpretability, Comparing and assessing different XAI methods, Human factors in evaluating interpretability, **Transparency in Black-Box Models:** Techniques for understanding and explaining black-box models, Probing and sensitivity analysis, Counterfactual explanations, Attribution methods (e.g., Integrated Gradients, Layer-wise Relevance Propagation), **Ethical and Societal Considerations:** Bias, fairness, and accountability in XAI, Legal and regulatory aspects of XAI, Human-AI collaboration and trust, **Case Studies and Real-World Applications:** XAI in healthcare and medical diagnosis, XAI in finance and credit scoring, XAI in autonomous systems and robotics, XAI in natural language processing and image recognition, **Hands-on Projects:** Implementing XAI techniques in Python using popular libraries, Interpreting AI models on real-world datasets, Designing and evaluating XAI interfaces

References:

1. Mayuri Mehta, Vasile Palade, Indranath Chatterjee*, Explainable AI: Foundations, Methodologies and Applications*, (1e), Springer, 2023.
2. Michael Munn, David Pitman, *Explainable AI for Practitioners*, (1e), O'Reilly, 2022.

AI6241: BEHAVIOURAL DATA ANALYSIS **[3 0 0 3]**

Foundations of Behavioural Data Analysis: Introduction to behavioural data analysis, Research methodologies in behavioural sciences, Data collection techniques and experimental design. **Statistical Analysis:** Descriptive statistics and data visualization, Inferential statistics and hypothesis testing, Regression analysis and correlation, Multivariate analysis techniques. **Advanced Analytical Methods**: Time series analysis and forecasting, Natural language processing for behavioural data, Social network analysis, Bayesian statistics and probabilistic modelling. **Data Mining and Big Data Analytics:** Introduction to data mining techniques, Data pre-processing and feature selection, Association rule mining, Handling large-scale behavioural data. **Ethical and Privacy Issues in Behavioural Data Analysis:** Ethical considerations in data collection and analysis, Privacy protection and anonymization techniques, Legal and regulatory frameworks for data analysis.

References:

1. Research Design: Qualitative, Quantitative, and Mixed Methods Approaches by John W. Creswell and J. David Creswell
2. Statistical Methods for Psychology by David C. Howell
3. Ethics of Big Data: Balancing Risk and Innovation by Kord Davis and Doug Patterson

AI6242: Machine Learning for Cybersecurity **[3 0 0 3]**

Introduction and Basics: Data processing, cleaning, visualization, and exploratory analysis, Data set collection and feature extraction, Point estimation, MLE, bias-variance trade-offs, Basic Probability theory and Distributions Estimation Theory, Hypothesis testing , Linear Regression (uni- and multi-variate) and Logistic Regression , clustering, feature selection, Basic Classification Techniques, Unsupervised Learning, Supervised Learning , Spectral Embedding, Manifold detection and Anomaly Detection, Decision Trees, Ensemble learning, Random Forest. **Cyber Security problems that can be solved using Machine learning**, Malware Analysis, Intrusion Detection, Spam detection, Phishing detection, Financial Fraud detection, Denial of Service Detection. **Application**: Spam Filtering. **Security Vulnerability**: Adversarial Attacks on spam filters. **Foundations**: Deep learning basics, Face recognition, Ethical concerns. **Security Vulnerability**: Training data-poisoning attacks on deep learning. **Security Vulnerability:** Adversarial input attacks on Deep Learning. **Privacy**: Training data and model reconstruction attacks; differential privacy. **Application:** Deep fakes and fake news detection. **Societal Implications**: Model accountability and interpretability. **Societal Implications:** Investigating bias and fairness concerns.

References

1. Halder, Soma, and Sinan Ozdemir, *Hands-On Machine Learning for Cybersecurity: Safeguard your system by making your machines intelligent using the Python ecosystem,* Packt Publishing Ltd, 2018.
2. Gupta, Brij B., and Quan Z. Sheng, eds., *Machine learning for computer and cyber security: principle, algorithms, and practices*, CRC Press, 2019.
3. Ganapathi, Padmavathi, and D. Shanmugapriya, eds., *Handbook of Research on Machine and Deep Learning Applications for Cyber Security*, IGI Global, 2019.

Programme Elective-IV

AI6243: QUANTUM ARTIFICIAL INTELLIGENCE [3 0 0 3]

Introduction to Quantum Computing: Quantum Computing Fundamentals, quantum mechanics and quantum computation, Quantum gates, qubits, and quantum circuits. Quantum algorithms (e.g., Grover's algorithm, Shor's algorithm). Quantum feature mapping and feature extraction, Quantum data encoding and decoding, **Quantum AI Ethics and Implications** : Ethical considerations in quantum AI, Bias and fairness in quantum machine learning, Quantum AI and social implications, Quantum Algorithms for Machine Learning: Quantum versions of classical machine learning algorithms, Quantum support vector machines, Quantum clustering algorithms, Quantum principal component analysis, **Introduction to quantum neural networks (QNNs):**Quantum gates and circuits in QNNs, Quantum versions of deep learning architectures (e.g., Quantum Convolutional Neural Networks, Quantum Recurrent Neural Networks), Quantum data augmentation and regularization , Quantum reinforcement learning algorithms, Quantum-inspired exploration-exploitation strategies, Applications of quantum reinforcement learning, **Quantum Optimization:** Quantum-inspired optimization algorithms, Quantum annealing for combinatorial optimization problems, Quantum-inspired gradient-free optimization techniques. **Quantum AI Applications:** Quantum cryptography and secure communication, Quantum AI for Social Networks and Recommendation Systems, Natural Language Processing and Text Analysis

References

1. Nielsen, M. A., & Chuang, I. L., *Quantum Computation and Quantum Information,* Cambridge University Press, 2010.
2. Schuld, M., Sinayskiy, I., &Petruccione, F., *Quantum Machine Learning: Introduction to Quantum Algorithms for Supervised and Unsupervised Learning*, Springer, 2019.
3. Kerenidis, I., & Prakash, A., *Quantum Machine Learning for Data Scientists*, O'Reilly Media, 2019.

AI6244: COMPUTATIONAL GAME THEORY [3 0 0 3]

Introduction: games theory vs decisions theory, games strategies, costs and payoff, basic solution concepts, finding equilibria and learning in games, issues with equilibrium analysis. **Zero-sum games:** secure strategy, Maximin, Maximax, and Minimax Regret Solvability, value of a game. **Normal form games:** dominance, iterated dominance, Nash equilibrium, Computing Nash Equilibria for Matrix Games, N-player games, mixed strategy. **Notions of Equilibrium:** Overview, Graphical Models for Multiplayer Game Theory, Computing Nash Equilibria in Graphical Games. Computing Nash equilibria in Tree Graphical Games, Graphical Games and correlated Equilibria. Extensive form games: subgame perfection, sequential equilibrium, Stackelberg Model of Duopoly, Buying Votes, Committee Decision-Making,Games with State, Connections to Reinforcement Learning, **Bargaining:** Rubinstein bargaining, Nash bargaining. **Repeated games:** Folk theorem and repeated prisoner's dilemma. Tacit collusion. **Incomplete information games:** statis and dynamic games, Bayesian equilibrium, higher order beliefs. **Auctions and mechanism design:** Basic auctions, voting, Vickrey-Clarke-Groves Auction

References:

1. M. J. Osborne and A. Rubinstein, *A Course in Game Theory* (1e), MIT Press,2012.
2. T. Ichiishi, A. Neyman and Y. Tauman, *Game Theory and Applications* (1e), Elsevier,2014.
3. D. Bauso, *Game Theory with Engineering Applications*, SIAM, Philadelphia, 2016.
4. T. Roughgarden, *Twenty Lectures on Algorithmic Game Theory*, Cambridge University Press, 2016.

AI6245: ARTIFICIAL INTELLIGENCE FOR MALWARE DETECTION [3 0 0 3]

Introduction to Artificial Intelligence, Mathematics of Artificial Intelligence, Physics of Artificial Intelligence, Introduction to malware, types of malwares, overview of malware detection (why it is important), overview of malware detection tools, anti-virus, anti-malware, static analysis of malware, dynamic analysis of malware, malware analysis workflow, malware analysis specific tools- demonstration, static and dynamic analysis, file and file formats, identity file formats, capture the malicious domains, machine learning vs deep learning for malware analysis, **applicability of machine learning techniques** (support vector machine, RNN, GNN, LSTM, LDA, PCA, reinforcement learning, KNN, random forest, perceptron, radiant descent, activation functions, K-means, clustering, AdaBoost) for malware detection, reinforcement learning techniques for malware detection, Overview **of deep learning techniques for malware detection and analysis** (ALEXNET, GOOGLENET, INCEPTIONNET, RESNET, SQUEEZENET, Transformer networks (vision transformer, swin transformer), transfer learning), **Applicability of deep learning models** for malware detection and analysis, research paper presentation on malware analysis, current state-of-art-research paper demonstration for malware analysis.

References:

1. M. Stamp, M. Alazab, A. Shalaginov, *Malware Analysis Using Artificial Intelligence and Deep Learning*, Springer, 2021.
2. Z. Yousef, *Malware (The Fallen Age Saga)*, Amazon, 2021.

AI6246: REINFORCEMENT LEARNING **[3 0 0 3]**

Introduction to Reinforcement Learning, Basics of RL, RL Framework and Markov Decision Process (MDP), Policies, Value Functions, and Bellman Equations, **Tabular Methods and Q-Networks,** Planning with Dynamic Programming and Monte Carlo Methods, Temporal-Difference Learning (TD(0), SARSA, Q-Learning), Deep Q-Networks (DQN, DDQN, Dueling DQN, Prioritized Experience Replay), **Model-Based RL and Planning,** Model-Based RL Approach, Dyna Architecture, **Function Approximation in RL,** Introduction to RL with Function Approximation, Prediction with Function Approximation, On-Policy Control with Function Approximation: Sarsa, More on On-Policy Learning with Function Approximation: Average-Reward Case & Eligibility Traces, Off-Policy Learning with Function Approximation, More on RL with Function Approximation: Actor-Critic Methods, **Policy Optimization,** Introduction to Policy-Based Methods, Vanilla Policy Gradient, REINFORCE Algorithm and Stochastic Policy Search, Actor-Critic Methods (A2C, A3C), Advanced Policy Gradient: PPO, TRPO, DDPG, **Bandit Algorithms,** UCB and PAC Bandit Algorithms, Median Elimination and Policy Gradient Bandit Algorithms, **Monte Carlo Methods,** On-Policy Monte Carlo Methods, Off-Policy Monte Carlo Methods, **Recent Advances and Applications,** Hierarchical Reinforcement Learning, Partially Observable Markov Decision Process (POMDP), Meta-Learning, Multi-Agent Reinforcement Learning, Ethics in RL, Applying RL for Real-World Problems, Exploration in RL, Temporal Abstraction, Inverse Reinforcement Learning, Towards Constructing a Mind Using Reinforcement Learning

References:

1. Richard S. Sutton and Andrew G. Barto, *Reinforcement learning: An introduction*, (2e), MIT Press, 2019.
2. Wiering, Marco, and Martijn Van Otterlo. *Reinforcement learning State of Art*, Springer, 2012
3. Russell, Stuart J., and Peter Norvig. *Artificial intelligence: a modern approach*, Pearson Education Limited, 2016.

Programme Elective-V

AI6247: RECOMMENDER SYSTEM [3 0 0 3]

Introduction: Introduction and basic taxonomy of recommender systems (RSs), Traditional and non-personalized RSs, Overview of data mining methods for recommender systems (similarity measures, classification, Bayes classifiers, ensembles of classifiers, clustering, SVMs, dimensionality reduction, Overview of convex and linear optimization principles, **Content-based recommendation**: The long-tail principle. Domain-specific challenges in recommender systems, Content-based recommender systems, Advantages and drawbacks, Basic components of content-based RSs, Feature selection, Item representation Methods for learning user profiles. **Collaborative Filtering:** User-based nearest neighbour recommendation, Item based nearest neighbour recommendation, Model based and pre-processing based approaches, Attacks on collaborative recommender systems. **Advanced CF methods:** Matrix factorization models and dimensionality reduction, Matrix Decomposition, Latent factor models, Solution via alternative projections method, **Examples:** The Netflix data challenge, Constraint-based RSs, Introduction to tensors and their applications. **Evaluating Recommender System**: Introduction, General properties of evaluation research, Evaluation designs, Evaluation on historical datasets, Error metrics, Decision-Support metrics, User-Centred metrics.

References:

1. C.C. Aggarwal, Recommender Systems: The Textbook, Springer, 2016
2. F. Ricci, L Rokach, B. Shapira and P.B. Kantor, Recommender systems handbook, Springer 2010.
3. Jannach D., Zanker M. and FelFering A., Recommender Systems: An Introduction, Cambridge University Press 2011.
4. Manouselis N., Drachsler H., Verbert K., Duval E., Recommender Systems for Learning, Springer 2013.

AI6248: BIOMEDICAL IMAGING **[3 0 0 3]**

Introduction to Biomedical Imaging: Definition and significance of biomedical imaging, Overview of imaging modalities, Imaging in clinical practice and research, X-ray. **Imaging and Computed Tomography (CT):** Principles of X-ray imaging, Radiographic techniques and image acquisition, CT scanner technology and image reconstruction, Clinical applications and limitations of X-ray and CT imaging, **Magnetic Resonance Imaging (MRI):** Principles of MRI, MRI scanner components and operation, Image acquisition, reconstruction, and contrast agents, Clinical applications, and emerging trends in MRI, **Ultrasound Imaging and Nuclear Medicine Imaging:** Principles of ultrasound imaging, Ultrasound transducers and image formation, Doppler imaging and applications, Clinical uses and limitations of ultrasound, Principles of nuclear medicine imaging, Gamma cameras and SPECT imaging, PET imaging and radiotracers, Clinical applications, and advances in nuclear medicine imaging, Optical Imaging, Image Analysis, and **Future Directions:** Principles of optical imaging, Endoscopy and microscopy techniques, Fluorescence imaging and molecular probes, Clinical applications and challenges of optical imaging, Image enhancement and filtering techniques, Segmentation and feature extraction, Image registration and fusion

References:
1. Reiner Salzer, *Biomedical Imaging: Principles and Applications,* (1e), Wiley*, 2012.*
2. Anke Meyer-Bäse and Volker J. Schmid, *Handbook of Biomedical Imaging: Methodologies and Clinical Research,* (1e), Academic Press, 2003.
3. Andrew G. Webb, *Introduction to Biomedical Imaging*, (2e), Wiley, 2022

AI6249: Graph Neural Network **[3 0 0 3]**

Introduction: Introduction to graph learning, Traditional Graph Embedding, Modern Graph Embedding: Structure-Property Preserving Graph Representation Learning, Graph Representation Learning with Side Information. Graph Neural Networks: requirement, and features of Graphs neural network, Applications. **Graph Theory for Graph Neural Networks:** Introduction, Graph Representations, Properties and Measures, Spectral Graph Theory, Graph Fourier Transform, Complex Graphs, Computational Tasks on Graphs. Graph Statistics and Kernel Methods, Neighborhood Overlap Detection, Graph Laplacians, and Spectral Methods. **Node Embeddings:** Neighborhood Reconstruction Methods, Multi-Relational Data and Knowledge Graphs, **Graph Neural Networks:** Introduction, The General GNN Frameworks, Graph Filters, Graph Pooling, Parameter Learning for Graph Neural Networks, **Graph Neural Network Model:** Neural Message Passing, Generalized Neighborhood Aggregation, and Generalized Update Methods. **Generative Graph Models:** Traditional Graph Generation Approaches, Deep Generative Models. **Applications of Graph Neural Networks:** Graph Neural Networks in Natural Language Processing: Semantic Role Labeling, Neural Machine Translation, Relation Extraction, Question Answering, Graph to Sequence Learning, Graph Neural Networks on Knowledge Graphs. **Graph Neural Networks in Computer Vision:** Images as Graphs, Visual Question Answering, Skeleton-based Action Recognition, Image Classification using Graphs, Point Cloud Learning. **A General Perspective on GNNs:** Design Space of Graph Neural Networks, Inductive Representation Learning on Large Graphs, Graph Attention Networks, GNNs for Recommender Systems.

References:

1. Lingfei Wu, Peng Cui, Jian Pei, Liang Zhao, *Graph Neural Networks Foundations, Frontiers, and Applications*, Springer, 2022.
2. William L. Hamilton, *Graph Representation Learning*, Morgan & Claypool, 2020.
3. Zhiyuan Liu, Jie Zhou, *Introduction to Graph Neural Networks*, Morgan & Claypool, 2020.