Academic Program Description Form

University Name: Al- Nahrain University

Faculty/Institute: College of Science

Scientific Department: Computer Science

Academic or Professional Program Name: PhD in Computer Science

Final Certificate Name: PhD in Computer Science

Academic System: Semesters

Description Preparation Date: 2025-2026

File Completion Date: 17/11/2025

Signature: K.H.A.

Head of Department Name:

Assi. Prof. Dr. Khamael Al-Dulaimi

Date:

Signature:

Scientific Associate Name:

Assist. Prof Dr. Manaf Adnan Saleh

Date:

The file is checked by: Dr. Orooba Nadhim Harbi

Department of Quality Assurance and University Performance

Director of the Quality Assurance and University Performance Department:
Dr. Orooba Nadhim Harbi

Date: 17/11/2025

Signature:

جمهورية العراق
وزارة التعليم العالي والبحث العلمي
جامعة النهرين كلية العلوم
مكتب العميد
Dean's office
Republic of Iraq
Ministry of Higher Education and Scientific Research
Al-Nahrain University / College of Science

Approval of the Dean

Prof. Dr. Asmaa Hadi Mohammed

Course Description Form

1. Course Name:
Deep Learning
2. Course Code:
Ph.D.
3. Semester / Year:
First / PhD
4. Description Preparation Date:
20/12/2025
5. Available Attendance Forms:
In the class
6. Number of Credit Hours (Total) / Number of Units (Total)
45 hours / 3 units
7. Course administrator's name (mention all, if more than one name)
Name: Prof. Dr. Ban N. Dhannoon Email: ban.n.dhannoon@nahrainuniv.edu.iq
8. Course Objectives

Course Objectives	• **This course discusses the latest deep learning models that researchers are currently using. Different deep architectures and their components are discussed in detail.** • **It also discusses algorithms used to train deep architectures to improve deep models. These deep architectures are not only capable of learning complex tasks but can even outperform humans in some custom applications.**

9. Teaching and Learning Strategies

Strategy	**Provide lectures in PowerPoint slide show** **Execute selected methods for more understanding**

10. Course Structure

Week	Hours	Required Learning Outcomes	Unit or subject name	Learning method	Evaluation method
1	3	• Shallow Learning • Why to Use Deep Learning • AI categories • According to its capabilities (ANI vs. AGI vs. ASI)		Powerpoint	

		• According to its functions (Reactive, limited memory, theory of mind, and self-awareness) • vs. AGI vs. ASI) • Limitations of AI • Advantages and disadvantages of AI • Key characteristics of machine learning • Types of ML (supervised, unsupervised, semi-supervised, and reinforcement) • Limitations of ML • Key differences between ML and DL • Testing and Validating (types of cross-validation) • Bias and Variance in ML • Overfitting vs underfitting (reasons, techniques to reduce over- and under-fitting) • Regularization Techniques: Dropout, L1, and L2 Regularization • NN Example			
2	3	• Convolutional Neural Network (ConvNet/CNN) • Evolution of CNN Models • AlexNet: (2012) • ZFNet: (2013) • VGGNet: (2014) • GoogLeNet: (2015) • ResNet: (2015) • Inception-ResNet: (2017) • Xception (Extreme Inception) • SqueezeNet • ShuffleNet (2017)			
3	3	• Architecture of CNN. • A typical CNN layers			

		• Example of a convolution operation • Hyperparameters • Activation Function • Pooling Layer • Dropout			
4	3	• Training Convolution Neural Networks • Gradient descent • Forward and backward pass • Loss Functions and Softmax Classifier			
5	3	• Gradient Descent-Based Optimization Techniques • Improving Gradient Descent (AdaGrad, AdaDelta, RMSProp, and Adam)			
6	3	Mid 1			
7	3	• Challenges in Training Deep Networks (problems and solutions) • Weight Initialization Techniques • Transfer learning • Fine-Tuning vs. Transfer Learning			
8	3	• LeNet-5 architecture • AlexNet architecture • ZFNet architecture • VGGNet architecture • GoogleNet architecture • ResNet (residual blocks)			
9	3	• (DenseNet) • Capsule Network • RNN • LSTM • GRU			
10	3	• Restricted Boltzmann Machine (RBM)			
11	3	• Deep Belief Network • Autoencoders • Deep Autoencoders • Generative Adversarial Networks			
12		• Supervised Deep Learning in Face Recognition • VGG vs Modified VGG-Face Architecture			
13		Mid 2			

14	3	• Supervised Deep Learning in Fingerprint Recognition. • Automatic Fingerprint Identification System (AFIS) • Deep Learning Architectures segmentation and classification for Fingerprint Recognition			
15	3	• Unsupervised Deep Learning in Character Recognition • Unsupervised Pretraining • Supervised Fine Tuning			

11. Course Evaluation

Final Exam 70
Mid1 Exam 10
Mid2 Exam 10
Two monthly projects 10

12. Learning and Teaching Resources

Required textbooks (curricular books, if any	• Advances in Deep Learning, 2020
Main references (sources)	• Dive in Deep Learning 2019
Recommended books and references (scientific journals, reports…)	• The Little Book of Deep Learning, François Fleuret, 2023
Electronic References, Websites	• Youtube

Course Description Form

1. Course Name:
Mathematical Methods for Computer Science
2. Course Code:
3. Semester / Year:
First Semester / PhD
4. Description Preparation Date:
1/9/2025
5. Available Attendance Forms:
Attendance Mandatory
6. Number of Credit Hours (Total) / Number of Units (Total)
30 Hours (2 hours theoretical * 15 Weeks) / 2 Units
7. Course administrator's name (mention all, if more than one name)
Name: Assist. Prof. Dr. Zainab Namh Abdula Email: zainab.namhabdula@nahrainuniv.edu.iq
8. Course Objectives

Course Objectives	This course provides PhD students with a mathematical foundation for advanced topics in computer science. It focuses on linear systems, vector spaces, and algebraic structures, enabling students to analyze and solve linear equations using matrix-based methods. The course covers eigenvalues, eigenvectors, and matrix decompositions such as SVD for high-dimensional data analysis, along with approximation techniques including least-squares and orthogonal projections. It also extends linear algebra concepts to infinite-dimensional spaces and Fourier analysis, highlighting their applications in areas such as machine learning, data science and signal processing.

9. Teaching and Learning Strategies	
Strategy	Lectures Seminars Frequent Quizzes HomeWorks

10. Course Structure

Week	Hours	Required Learning Outcomes	Unit or subject name	Learning method	Evaluation method
W1	2	Students will be able to identify sets, relations, and functions, and define Group properties to establish the algebraic foundation for vector spaces	**Foundations and Linear Systems** Mathematical Preliminaries & Algebraic Structures **Sets and Logic:** Numbers, Sets, Relations, and Functions. **Algebraic Structures:** Introduction to Groups. **Abelian Groups:** Definition and properties (contextualizing Vector Spaces). **Introduction to Linear Algebra:** Overview of the field.	Lecture Slides	Oral Questions
W2	2	Students will be able to compute matrix inverses and determinants to classify linear systems as homogeneous or non-homogeneous	**Systems of Linear Equations** Homogeneous vs. Non-Homogeneous Systems. Matrix operations (Addition, Multiplication, Transpose). Matrix Inverses and properties. Determinants**:** Calculation and properties.	Lecture Slides	Oral Questions Homework
W3	2	Students will be able to encode row operations (swapping, scaling, elimination) into elementary matrices for computational manipulation	**Solving System of Linear Equations** Encoding Row Operations Permutation Row Scaling Elimination.	Lecture Slides	Oral Questions
W4	2	Students will be able to apply Gaussian Elimination to convert matrices into RREF and analyze the rank to determine solution existence.	**Gaussian Elimination:** The full algorithmic process. **Echelon Forms:** Row Echelon Form (REF). Reduced Row Echelon Form (RREF). **Rank:** Analyzing solution sets based on pivots.	Lecture Slides	Oral Questions Quiz
W5	2	Students will be able to determine the Linear Independence, Span, Basis, and Dimension of a given Vector Space.	**Vector Spaces** **The Vector Space Definition:** Axioms and examples. **Structure:** Linear Combinations and Span. **Linear Independence:** Concepts and testing.	Lecture Slides	Oral Questions

Week	Hours	Required Learning Outcomes	Unit or subject name	Learning method	Evaluation method
			Basis and Dimension: Determining the basis and rank of a space.		
W6	2	Students will be able to calculate norms, inner products, and angles to determine distance and orthogonality in Euclidean space.	**Analytic Geometry (Euclidean Space)** **Standard Norms:** Vector lengths and distances. **Inner Products:** Dot products in R^n **Geometry:** Angles between vectors. **Orthogonality:** Perpendicular vectors and orthogonal sets.	Lecture Slides	Oral Questions and Homework
W7	2	Mid			
W8	2	Students will be able to construct the characteristic polynomial to compute the Eigenvalues and Eigenvectors of a square matrix.	**Eigenvalues and Eigenvectors** **The Trace:** Definition and properties. **Characteristic Polynomial:** Deriving the polynomial from determinants. **Eigen-theory:** Calculating Eigenvalues and Eigenvectors.	Lecture Slides	Oral Questions
W9	2	Students will be able to diagonalize matrices	**Matrix Decomposition I** **Eigendecomposition:** A = PDP^-1. **Diagonalization:** Conditions for diagonalizability. **Symmetric Matrices:** Spectral Theorem for symmetric matrices.	Lecture Slides and Worked Examples	Quiz
W10	2	Students will be able to compute the Singular Value Decomposition for rectangular matrices and interpret its use in data compression and recommender systems	**Matrix Decomposition II (SVD)** **Singular Value Decomposition (SVD):** Concept and calculation. **Applications of SVD:** Low-rank approximation and data compression. **Relationship to Eigenvalues:** A^TA and AA^T.		
W11	2	Students will be able to formulate the Normal Equations to solve Least Squares problems using Orthogonal	**Projections and Approximations** **Orthogonal Projections:** Projecting vectors onto subspaces. **The Normal Equations:**	Lecture Slides and Worked Examples	Oral Questions

Week	Hours	Required Learning Outcomes	Unit or subject name	Learning method	Evaluation method
		Projections	Structure and derivation (A^TAx = A^Tb). **Least Squares:** Solving unsolvable systems.		
W12	2	Students will be able to evaluate system sensitivity using matrix norms and extend vector concepts to infinite-dimensional Hilbert spaces.	**Sensitivity Analysis** - Matrix & Vector Norms Infinite Dimensional Spaces **Function Spaces:** Inner products of functions. **Hilbert Space:** Introduction to complete inner product spaces. **Orthogonality in Function Spaces:** Orthogonal polynomials.	Lecture Slides and Worked Examples	Oral Questions
W13+14	4	Students will be able to apply Fourier Series and Transforms to convert functions between the time/space domain and the frequency domain.	**The Laplacian Operator:** Definition in R^n (Divergence of Gradient). **Eigenfunctions** **Fourier Analysis** **Fourier Series:** Decomposition of periodic functions. **Fourier Transform:** Transformation from time/space domain to frequency domain.	Lecture Slides and Worked Examples	Oral Questions
W15	2		Seminars		

11.Course Evaluation

Assessment Type	Marks
Homework	5
Attendance	5
Mid Exam	20
Final Exam	70
Total	100

12.Learning and Teaching Resources

Required textbooks (curricular books, if any)	Linear Algebra for Computer Vision, Robotics, and Machine Learning. University of Pennsylvania. Gallier, J., & Quaintance, J. (2025). *Mathematics for Machine Learning*. Cambridge University Press. Deisenroth, M. P., Faisal, A. A., & Ong, C. S. (2020). Numerical Algorithms Methods for Computer Vision, Machine Learning, and Graphics. Justin Solomon. CRC Press Taylor and Francis Group. Solomon, J. (2015). *Mathematical Methods: Lecture Notes*. Department of Computing, Imperial College London. Deisenroth, M., & Cheraghchi, M. (2016).

Main references (sources)	
Recommended books and references (scientific journals, reports...)	
Electronic References, Websites	

Course Description Form

1. Course Name: Optimization Theory and Algorithms
2. Course Code:
3. Semester / Year: First Semester/ Ph.D. Studies
4. Description Preparation Date:2025-2026
5. Available Attendance Forms: Full time
6. Number of Credit Hours (Total) / Number of Units (Total):30 hour\ 2 units
7. Course administrator's name (mention all, if more than one name)
Name: Ass. Prof.Dr.Nadia Fadhil AL-Bakri Email: nadia.f.al-bakri@nahrainuniv.edu.iq
8. Course Objectives

Course Objectives	○ Understand fundamental concepts of optimization theory and different types of optimization problems. ○ Develop the ability to formulate real-world problems as optimization models. ○ Gain knowledge of unconstrained and constrained optimization techniques. ○ Apply linear programming methods, including the simplex algorithm, to solve optimization problems. ○ Analyze and implement nonlinear optimization methods, particularly gradient-based approaches. ○ Explore stochastic and nature-inspired optimization algorithms. ○ Understand and apply multi-objective optimization techniques. ○ Gain practical knowledge of evolutionary programming methods. ○ Apply optimization techniques in various areas such as machine learning, control systems, data mining, logistics, and finance. ○ Develop skills in implementing optimization algorithms using appropriate software tools.

9. Teaching and Learning Strategies

Strategy	○ **Lectures:** Deliver core theoretical concepts and mathematical foundations optimization. ○ **Interactive Discussions:** Encourage critical thinking and problem-solv through class discussions. ○ **Problem-Solving Sessions:** Practice solving optimization problems manu and computationally.

	○ **Case Studies:** Analyze real-world applications in areas like machine learning a logistics. ○ **Hands-on Programming:** Implement optimization algorithms using softw tools and programming languages. ○ **Group Work:** Promote collaborative learning through team-based assignme and projects. ○ **Research-Based Learning:** Assign recent research papers to explore advan optimization techniques. ○ **Presentations:** Students present topics such as evolutionary algorithms multi-objective optimization. ○ **Assignments and Projects:** Apply theoretical knowledge to pract optimization problems. ○ **Self-Directed Learning:** Encourage independent study using textbooks a recent publications.

10. Course Structure

Week	Hours	Required	Unit or subject name	Learning method	Evaluation method
1	2 theory		Introduction to Optimization: Basic concep types of optimization problems and challenges. Derivatives and Gradients	Formal Lectures	Class Activity
2	=		Linear Programming and Application in Lin Programming Graphical method (Geometric Approach). 2- Simplex method. Modelling LP problems Convex sets	Formal Lectures	Class Activity and Quiz
3	=		Stochastic Gradient Descent (SGD) Stochastic and mini-batch gradient descent	Formal Lectures	Class Activity
4	=		Optimization algorithms	Formal Lectures	Class Activity
5	=		Metaheuristics	Formal Lectures	Class Activity
6	Mid1 exam				
7	=		Multi Objective Optimization Concepts	Formal Lectures	Class Activity
8	=		Pareto optimization	Formal Lectures	Class Activity
9			Salp Swarm algorithm Genetic Algorithm for Diamond Extraction Optimization	Formal Lectures	Class Activity and Quiz
10	=		Pelican Optimization Algorithm	Formal Lectures	Class Activity

					and Quiz
11	Mid2				
12,13	=		Honey Badger Algorithm Swift Optimization Algorithm	Formal Lectures	Class Activity
14,15	=		Nature-Inspired Optimization Algorithm Hunger Game Search	Formal Lectures	Class Activity

11. Course Evaluation

Distributing the score out of 100 according to the tasks assigned to the student such as daily preparation, daily oral, monthly, or written exams, reports .... etc

12. Learning and Teaching Resources

Required textbooks (curricular books, if any)	1-Global Optimization Algorithms–Theory and Application 2-OPTIMIZATION Algorithms and Applications. 3-Algorithms for Optimization. 4-Linear Programming. 5-Introduction to the Theory of Nonlinear Optimization. 6-Optimization Theory.
Main references (sources)	
Recommended books and references (scientific journals, reports…)	
Electronic References, Websites	

Course Description Form

1. Course Name:
Pattern Recognition
2. Course Code:
3. Semester / Year:
PhD– First Course– 2025–2026
4. Description Preparation Date:
15/10/2025
5. Available Attendance Forms:
Attendance Mandatory
6. Number of Credit Hours (Total) / Number of Units (Total)
30 Hours (2 Hours Theoretical)*15/ 2 Credit
7. Course administrator's name (mention all, if more than one name)
Name: Assistant Professor Dr. Khamael Al-Dulaimi Email :khamail.abbass@nahrainuniv.edu.iq

8. Course Objectives

Course Objectives	**Understand the fundamental concepts of pattern recognition**, including classification, clustering, and pattern analysis **Analyse data and extract meaningful features** for effective pattern representation. **Differentiate between parametric and non-parametric approaches**, as well as statistical and machine learning-based methods. **Apply common pattern recognition algorithms** such as k-Nearest Neighbours, Bayesian classifiers, and Support Vector Machines to real-world datasets. **Evaluate the performance of pattern recognition systems** using standard metrics such as accuracy, precision, and recall. **Understand the impact of feature selection, high dimensionality, and noise** on recognition performance. **Relate pattern recognition techniques to real-world applications**, including computer vision, image recognition, signal processing, and cybersecurity

9. Teaching and Learning Strategies

Strategy	**Research-Based Learning** Students critically review recent journal and conference papers, focusing on methodology, assumptions, limitations, and research gaps. **Advanced Scholarly Discussions** Seminars and discussions are used to compare and debate pattern recognition models and algorithms, fostering high-level analytical thinking. **Open-Ended Problem Solving** Students are challenged with open research problems that require proposing novel approaches or improving existing techniques rather than applying predefined solutions. **Integration of Theory and Research Practice** Students conduct experimental studies using real-world or benchmark datasets and analyse results in a publication-oriented manner

10. Course Structure

Week(s)	Hours	Intended Learning Outcomes	Module / Topic	Teaching Method	Assessment Method
1	2	Understand the concept of pattern recognition and its various applications	**Module 1: Foundations of Pattern Recognition** • Definitions and Scope • Applications in Computer Vision, NLP, Bioinformatics • Pattern Recognition System Architecture • Supervised vs Unsupervised vs Semi-supervised Learning	Lectures	In-class questions
2–4	2	Mathematical analysis of algorithms	**Module 2: Statistical Pattern Recognition** • Bayes Decision Theory • Maximum Likelihood Estimation (MLE) • Bayesian Estimation • Parametric vs Non-parametric Methods • Gaussian Mixture Models (GMM) • Expectation Maximisation (EM)	Lectures	Problem analysis and application of algorithms on real datasets
5–7	2	Mathematical analysis of algorithms and detailed	**Module 3: Feature Extraction and Selection** • Feature Space &	Lectures + Examples	Problem analysis and application of

		explanation of deriving numerical outputs for single and multivariate cases, and evaluating the quality of linear models	Dimensionality Reduction • PCA, LDA, ICA • Mutual Information & Entropy-Based Selection • Wrapper vs Filter Methods		algorithms on real datasets
8	2	—	**Midterm Exam 1**	—	Written exam
9	2	Understand how to obtain data outputs using classification algorithms	**Module 4: Classifiers and Decision Boundaries** • Linear Classifiers (Perceptron, LDA) • k-NN and Variants	Student Seminar	Method analysis, explanation, and application on data
10	2	Understand how to obtain data outputs using neural-based algorithms	**Module 5: Neural Approaches** • Multi-Layer Perceptron (MLP) • Convolutional Neural Networks (CNNs)	Student Seminar	Method analysis, explanation, and application on data
11	2	Understand how to obtain data outputs using clustering algorithms	**Module 6: Clustering and Unsupervised Learning** • k-Means • DBSCAN • Hierarchical Clustering	Student Seminar	Method analysis, explanation, and application on data
12	4	Understand how to obtain data outputs using ensemble techniques	**Ensemble Methods** • Bagging • Boosting	Student Seminar	Method analysis, explanation, and application on data
13	2	—	**Midterm Exam 2**	—	Written exam
14–15	4	Mathematical analysis of a selected problem, hypothesis formulation, and logical interpretation of results	**Selected Topics**	Discussion of results	Group project

11. Course Evaluation

Assessment Type	Marks
Quizzes	7
Projects	8
Mid Exam	10
Final Exam	50
Total	100

12. Learning and Teaching Resources

Required textbooks (curricular books, if any)	Textbooks and References - Duda, R. O., Hart, P. E., & Stork, D. G. (2001). Pattern Classification. Wiley-Inter science. Theodoridis, S., & Koutroumbas, K. (2009). Pattern Recognition (4th ed.). Academic Press. -
Main references (sources)	Bishop, C. M. (2006). Pattern Recognition and Machine Learning. Springer. -
Recommended books and references (scientific journals, reports…)	Murphy, K. P. (2012). Machine Learni A Probabilistic Perspective. MIT Pres Jain, A. K., Duin, R. P. W., & Mao (2000). Statistical pattern recognition review. IEEE Transactions on Patt Analysis and Machine Intelligence, 22(4-37.
Electronic References, Websites	Research paper+ websites for dataset

Course Description Form

1. Course Name:
Ethical Hacking and Cyber Security
2. Course Code:
3. Semester / Year:
Second semester/ PhD
4. Description Preparation Date:
1−2−2026
5. Available Attendance Forms:
6. Number of Credit Hours (Total) / Number of Units (Total)
45 h/3 units
7. Course administrator's name (mention all, if more than one name)
Name: Asst. Prof. Dr. Dalal N. Hamood Email: dalal.naeem@nahrainuniv.edu.iq
8. Course Objectives

Course Objectives	The main objective of this course is: - to understand the basics of cybersecurity. - identify types of cyberattacks, -discover security vulnerabilities, -protect systems and networks, and -think like an attacker.

9. Teaching and Learning Strategies	
Strategy	Lectures Homework Problem-based learning Case studies

10. Course Structure

Week	Hours	Required Learning Outcomes	Unit or subject name	Learning method	Evaluation method
Week1	3 h		(Networking) 1: TCP/IP .2: Layers in TCP/IP .3: Ports & Sockets	Lecture	Quiz

Week2	3 h		What is Hacking? Types of Hackers Google Dorks as Hacking Tools Footprinting	Lecture	Quiz
Week3	3 h		Phases of Hacking Passive Reconnaissance Ac Reconnaissance	Lecture	Quiz
Week4	3 h		Port Scanning NMAP as Scanning T NMAP Scripting Tool Exploit Searching	Lecture	Quiz
Week5	3 h		Enumeration Types of enumeration Tools of enumeration	Lecture	Quiz
Week6	3 h		Vulnerabilities Assessment Types of vulnerabil Assessment Thread of vulnerabilities	Lecture	Quiz
Week7	3 h		Vulnerabilities assessment Server OS Vulnerabilities assessment Of Embedded System	Lecture	Quiz
Week8	3 h		Exam mid1		
Week9	3 h		Cyber Attacks define Cyber Attacks Types Case study (A Breach-Attack View) System hacking Network hacking	Lecture	Quiz
Week10	3 h		What is Cyber Secur Essential Terminologies, cyber space	Lecture	Quiz
Week11	3 h		Password management Securing your system	Lecture	Quiz
Week12	3 h		Network security Wireless security IDS IPs VPN	Lecture	Quiz
Week13	3 h		Web application security Web server security	Lecture	Quiz
Week14	3 h		Post-Quantum cryptography Lattice based Hash based	Lecture	Quiz
Week15	3 h		Exam mid2		

11. Course Evaluation

Distributing the score out of 100 according to the tasks assigned to the student such as daily preparation, daily oral, monthly, or written exams, seminar.... etc

12. Learning and Teaching Resources

Required textbooks (curricular books, if any)	
Main references (sources)	Ethical Hacking 2021 Cyber security Essential 2022

Recommended books and references (scientific journals, reports…)	
Electronic References, Websites	Computer Lab + Java Language

Course Description Form

1. Course Name:
Intelligent Data Mining
2. Course Code:
3. Semester / Year:
PhD–Second Course– 2025–2026
4. Description Preparation Date:
20/1/2026
5. Available Attendance Forms:
Attendance Mandatory
6. Number of Credit Hours (Total) / Number of Units (Total)
30 Hours (2 Hours Theoretical)*15/ 2 Credit
7. Course administrator's name (mention all, if more than one name)
Name: Assistant Professor Dr. Khamael Al-Dulaimi Email :khamail.abbass@nahrainuniv.edu.iq

8. Course Objectives

Course Objectives	• **Understand the theoretical foundations of data mining** Students will develop a deep understanding of statistical modelling, computational approaches to data mining, and feature extraction, allowing them to critically analyse modern data mining systems data mining. • **Analyse the statistical limits and scalability of mining algorithms** Students will be able to evaluate the limitations of data mining techniques, including issues of dimensionality, sparsity, and statistical reliability, especially in large-scale datasets data mining. • **Design and evaluate large-scale data mining systems** Students will get the ability to design and implement mining algorithms using distributed frameworks such as MapReduce and understand their computational and communication costs

9. Teaching and Learning Strategies

Strategy	**Research-Based Learning** Students critically review recent journal and conference papers, focusing on methodology, assumptions, limitations, and research gaps. **Advanced Scholarly Discussions** Seminars and discussions are used to compare and debate pattern recognition models and algorithms, fostering high-level analytical thinking. **Open-Ended Problem Solving**

	Students are challenged with open research problems that require proposing novel approaches or improving existing techniques rather than applying predefined solutions. **Integration of Theory and Research Practice** Students conduct experimental studies using real-world or benchmark datasets and analyse results in a publication-oriented manner

10. Course Structure

Week(s)	Hours	Intended Learning Outcomes	Module / Topic	Teaching Method	Assessment Method
1	2	Understand the concept of data mining and distinguish between statistical and computational modelling approaches	**Module 1: Introduction to Data Mining** • What is Data Mining • Statistical Modelling • Computational Approaches to Modelling • Feature Extraction	Lectures	In-class questions
2	2	Analyse the theoretical limits of data mining and apply text-based weighting and hashing techniques	**Module 2: Statistical Foundations** • Statistical Limits on Data Mining • Importance of Words in Documents • Hash Functions	Lectures	Problem analysis
3	2	Evaluate distributed data mining algorithms and analyse their computational and communication complexity	**Module 3: MapReduce and Big Data Frameworks** • Algorithms Using MapReduce • Extensions to MapReduce • Communication-Cost Model • Complexity Theory for MapReduce	Seminar	Algorithm analysis and discussion
4	2	Design and analyse similarity detection techniques for large-scale datasets	**Module 4: Finding Similar Items** • Shingling of Documents • Similarity-Preserving Summaries • Distance Measures • Locality-Sensitive Hashing	Seminar	Applied problem solving
5	2	Apply stream mining techniques and evaluate approximation algorithms under memory constraints	**Module 5: Mining Data Streams** • Filtering Streams • Counting Distinct Elements • Estimating Frequency Moments	Seminar	Problem analysis
6	2	Analyse transactional datasets and extract frequent patterns	**Module 6: Frequent Itemset Mining** • Frequent Itemsets • Association Rule Concepts	Seminar	Applied data analysis
7		Mid term exm			

8	2	Compare clustering techniques and evaluate their suitability for complex data spaces	**Module 7: Clustering Techniques •** Clustering Techniques • Hierarchical Clustering • Clustering in Non-Euclidean Spaces	Lectures	Method comparison
9	2	Design and analyse recommendation systems using different filtering strategies	**Module 8: Recommendation Systems •** Content-Based Recommendation • Collaborative Filtering • Dimensionality Reduction	Student Seminar	Seminar presentation & discussion
10	2	Apply dimensionality reduction techniques and analyse their mathematical foundations	**Module 9: Dimensionality Reduction •** Eigenvalues and Eigenvectors • PCA • Singular Value Decomposition (SVD)	Lectures	Problem analysis
11		Mid term exm			
12+13+14+15		projects			

11. Course Evaluation

Assessment Type	Marks
Quizzes	7
Projects	8
Mid Exam	10
Final Exam	50
Total	100

12. Learning and Teaching Resources

Required textbooks (curricular books, if any)	Data Mining: Concepts and Techniques by Jiawei Han, Micheline Kamber, and Jian Pei (3rd edition).
Main references (sources)	
Recommended books and references (scientific journals, reports…)	• **Han, J., & Kamber, (2001/2011).** *Data Mining: Concepts & Techniques.* Morgan Kaufmann. • **Hastie, T., Tibshirani, R., & Friedm J. (2009).** *The Elements of Statisti Learning: Data Mining, Inference, & Prediction.* Springer.

	• **Hand, D. J., Mannila, H., & Smyth (2001).** *Principles of Data Mining.* M Press. • **Aggarwal, C. C. (2015).** *Data Mini The Textbook.* Springer. • **Larose, D. T. (2005).** *Discover Knowledge in Data: An Introduction Data Mining.* Wiley.
Electronic References, Websites	Research paper+ websites for dataset

Course Description Form

1. Course Name:

Research Methodology

2. Course Code:

3. Semester / Year:

Second Semester 2025–2026

4. Description Preparation Date:

1–2–2026

5. Available Attendance Forms:

Traditional Attendance (in-person), Blended Attendance

6. Number of Credit Hours (Total) / Number of Units (Total)

7. Course administrator's name (mention all, if more than one name)

Dr. Suhad A. Yousif Email: suhad.a.yousif@nahrainuniv.edu.iq

8. Course Objectives

Course Objectives	□ Develop a structured understanding of scientific research beyond implementation, emphasizing knowledge generation rather than system development. □ Enable students to distinguish between engineering solutions and scientific contributions. □ Train students to formulate clear research problems and research questions based on knowledge gaps. □ Introduce principles of experimental design, variables, and research validity. □ Equip students with skills in scientific writing, argumentation, and critical evaluation of research work. □ Enhance awareness of ethical research practices and academic integrity.

9. Teaching and Learning Strategies

Strategy	• **Conceptual Lectures:** Focus on understanding scientific reasoning, not only procedures. • **Analytical Discussions:** Evaluate real research papers to identify strengths and weaknesses. • **Hands-On Activities:** Apply research tools (Overleaf, EndNote, Excel) in practical scenarios. • **Problem-Based Learning:** Guide students to define research problems and design solutions. • **Mini Research Tasks:** Encourage students to think critically and justify methodological choice

10. Course Structure

Week	Hours	Required Learning Outcomes	Unit or subject name	Learning method	Evaluation method
1	2	Introduction to Research Methodology	Overview of Research Process	Lectures	Class Participation
2	2	Problem Identification and Objectives	Defining Research Problems	Lectures and Activities	Assignment
3	2	Literature Review Techniques	Finding and Analyzing Sources	Lectures and Labs	Research Article Analysis

4	2	Research Design Basics	Types of Research Designs	Lectures	Quiz
5	2	Data Collection Methods	Surveys, Interviews, and Experiments	Hands-On Lab	Assignment
6	2	Introduction to Overleaf	Writing Research Papers with LaTeX	Lab	Lab Exercise
7	2	LaTeX Basics	Document Formatting in Overleaf	Lab	Lab Exercise
8	2	Advanced LaTeX Features	Tables, Figures, and Citations	Lab	Assignment
9	2	Advanced Office Tools	Excel for Data Analysis, PowerPoint for Presentation Design	Lab	Assignment
10	2	Managing References	Using EndNote	Lab	Assignment
11	2	Qualitative Research Techniques	Content Analysis, Case Studies	Lectures and Labs	Lab Exercise
12	2	Writing the Research Proposal	Proposal Structure and Presentation	Lab	Proposal Submission
13-14	4	Research Project Work Sessions	Developing and Finalizing Projects	Guided Labs	Project Feedback
15	2	Final Presentations	Research Findings and Discussion	Presentations	Grading and Feedback

11. Course Evaluation

- 20% for the formal final written exam
- 20% for practical assignments and lab exercises
- 60% for the final project evaluation

12. Learning and Teaching Resources

Required textbooks (curricular books, if any)	"Research Design: Qualitative, Quantitative, and Mixed Methods Approaches" by John W. Creswell Focus: Comprehensive overview of research designs and methodologies.
Main references (sources)	The Craft of Research" by Wayne C. Booth, Gregory G. Colomb, and Joseph M. Williams Focus: Practical advice on crafting strong research papers.
Recommended books and references (scientific journals, reports…)	• Journal of Research Methodology • Articles on advances in qualitative and quantitative research methods.
Electronic References, Websites	Overleaf (https://www.overleaf.com) Collaborative LaTeX editor for writing and formatting research papers.

Course Description Form

1. Course Name:
Sentiment Analysis: Theory and Applications
2. Course Code:
Ph.D.
3. Semester / Year:
Second / PhD
4. Description Preparation Date:
6/2/2026
5. Available Attendance Forms:
In the class
6. Number of Credit Hours (Total) / Number of Units (Total)
30 hours / 2 units
7. Course administrator's name (mention all, if more than one name)
Name: Prof. Dr. Ban N. Dhannoon Email: ban.n.dhannoon@nahrainuniv.edu.iq
8. Course Objectives

Course Objectives	• **Sentiment analysis is the computational study of people's opinions, sentiments, emotions, moods, and attitudes. This fascinating problem offers numerous research challenges, but promises insights useful to anyone interested in opinion analysis and social media analysis.** • **The course covers core areas of sentiment analysis as well as related topics such as debate analysis, intention mining, and fake-opinion detection.**

9. Teaching and Learning Strategies

Strategy	**Provide lectures in PowerPoint slide show** **Execute selected methods for more understanding**

10. Course Structure

Week	Hours	Required Learning Outcomes	Unit or subject name	Learning method	Evaluation method
1	2	• Sentiment Analysis Applications • Sentiment Analysis Research • Sentiment Analysis As Mini-NLP		Powerpoint	
2	2	• Definition of Opinion • Definition of Opinion Summary			
3	2	• Affect, Emotion, and Mood • Different Types of Opinions			

4	2	• Supervised Sentiment Classification. • Classification Using Traditional Machine Learning Algorithms • Classification Using a Custom Score Function • Classification Using Deep Learning • Classification Based on Lifelong Learning			
5	2	• Unsupervised Sentiment Classification • Sentiment Rating Prediction • Cross-Domain Sentiment Classification • Cross-Language Sentiment Classification • Emotion Classification of Documents			
6	2	Mid 1			
7	2	• Subjectivity • Sentence Subjectivity Classification • Sentence Sentiment Classification • Dealing with Conditional Sentences • Dealing with Sarcastic Sentences • Cross-Language Subjectivity and Sentiment Classification • Using Discourse Information for Sentiment Classification • Emotion Classification of Sentences • Multimodal Sentiment and Emotion Classification			
8	2	• Aspect Sentiment Classification • Aspect Sentiment Classification • Rules of Sentiment Composition • Negation and Sentiment • Modality and Sentiment • Coordinating Conjunction *But* • Sentiment Words in Non-Opinion Contexts • Rule Representation • Word Sense Disambiguation and Coreference Resolution			

9	222	• Aspect and Entity Extraction • Frequency-Based Aspect Extraction • Using Supervised Learning • Mapping Implicit Aspects • Grouping Aspects into Categories • Exploiting Topic Models • Entity Extraction and Resolution • Opinion Holder and Time Extraction			
10	2	Mid 2			
11	2	• Sentiment Lexicon Generation • Dictionary-Based Approach • Corpus-Based Approach • Sentiment Word Embedding • Desirable and Undesirable Facts			
12	2	• Analysis of Comparative Opinions • Identifying Comparative Sentences • Identifying the Preferred Entity Set • Special Types of Comparisons • Entity and Aspect Extraction			
13	2	• Opinion Summarization and Search • Aspect-Based Opinion Summarization • Enhancements to Aspect-Based Summaries • Contrastive View Summarization • Traditional Summarization • Summarization of Comparative Opinions • Opinion Search • Existing Opinion Retrieval Techniques			
14	2	• Analysis of Debates and Comments • Recognizing Stances in Debates • Modeling Debates/Discussions • Modeling Comments			

15	2	• Detecting Fake or Deceptive Opinions • Different Types of Spam • Supervised Fake Review Detection • Supervised Yelp Data Experiment • Automated Discovery of Abnormal Patterns • Model-Based Behavioral Analysis			

11. Course Evaluation

Final Exam 70
Mid1 Exam 10
Mid2 Exam 10
Two monthly projects 10

12. Learning and Teaching Resources

Required textbooks (curricular books, if any	• Sentiment Analysis Unveiled Techniques Applications
Main references (sources)	• Sentiment analysis : mining opinions, sentiments, and emotions, 2020
Recommended books and references (scientific journals, reports…)	•
Electronic References, Websites	• Youtube