Mathematics is the backbone of Artificial Intelligence (AI), and to build a strong foundation, you need to cover topics from linear algebra, calculus, probability, statistics, optimization, and discrete mathematics. Below is a **detailed syllabus** to cover for AI:

**1. Linear Algebra (Essential for Machine Learning & Deep Learning)**

* **Vectors and Spaces**
  + Scalars, Vectors, and Matrices
  + Vector Spaces and Subspaces
  + Linear Dependence and Independence
  + Basis and Dimension
* **Matrix Operations**
  + Matrix Addition and Multiplication
  + Transpose and Inverse
  + Determinants and Rank
  + Trace of a Matrix
* **Systems of Linear Equations**
  + Gaussian Elimination
  + Row Echelon Form
  + Homogeneous and Non-Homogeneous Systems
* **Eigenvalues and Eigenvectors**
  + Characteristic Equation
  + Diagonalization
  + Singular Value Decomposition (SVD)
  + Principal Component Analysis (PCA)
* **Vector Norms and Orthogonality**
  + L1, L2, and L∞ Norms
  + Inner Product and Orthogonality
  + Gram-Schmidt Process

**2. Calculus (Essential for Gradient Descent & Neural Networks)**

* **Differential Calculus**
  + Limits and Continuity
  + Differentiation Rules (Product, Quotient, Chain Rule)
  + Partial Derivatives
  + Gradients and Directional Derivatives
  + Taylor Series Approximation
* **Integral Calculus**
  + Definite and Indefinite Integrals
  + Fundamental Theorem of Calculus
  + Multiple Integrals
* **Vector Calculus**
  + Gradient, Divergence, and Curl
  + Jacobian and Hessian Matrices
  + Line and Surface Integrals
* **Optimization Techniques**
  + Gradient Descent and its Variants
  + Lagrange Multipliers
  + Convex and Non-Convex Functions

**3. Probability & Statistics (Essential for Probabilistic Models & AI Decision Making)**

* **Basic Probability Concepts**
  + Random Variables and Probability Distributions
  + Bayes’ Theorem and Conditional Probability
  + Joint, Marginal, and Conditional Probabilities
* **Discrete and Continuous Distributions**
  + Bernoulli, Binomial, Poisson Distributions
  + Gaussian (Normal) Distribution
  + Exponential and Log-Normal Distributions
* **Statistical Inference**
  + Maximum Likelihood Estimation (MLE)
  + Bayesian Inference
  + Confidence Intervals and Hypothesis Testing
* **Markov Chains and Stochastic Processes**
  + Markov Property and Transition Matrices
  + Hidden Markov Models (HMM)
  + Monte Carlo Methods

**4. Optimization (Essential for Machine Learning Models)**

* **Convex Optimization**
  + Convex Sets and Convex Functions
  + Gradient Descent and Stochastic Gradient Descent (SGD)
* **Constrained Optimization**
  + Lagrangian and KKT Conditions
  + Duality in Optimization
* **Optimization Algorithms in AI**
  + Adam, RMSprop, Momentum-Based Methods
  + Simulated Annealing and Genetic Algorithms

**5. Discrete Mathematics (Essential for Graphs, Logic & Algorithms)**

* **Graph Theory**
  + Trees, Graphs, and Networks
  + Shortest Path Algorithms (Dijkstra, A\*)
  + PageRank Algorithm (Google Search)
* **Boolean Algebra & Logic**
  + Propositional and Predicate Logic
  + Truth Tables and Logical Operators
  + Fuzzy Logic in AI
* **Combinatorics & Set Theory**
  + Permutations and Combinations
  + Inclusion-Exclusion Principle
  + Pigeonhole Principle

**6. Information Theory (Essential for Deep Learning & NLP)**

* **Entropy and Information Gain**
* **Shannon’s Theorem**
* **KL Divergence & Cross-Entropy Loss**

**7. Transform Methods (Essential for Signal Processing & Neural Networks)**

* **Fourier Transform**
* **Laplace Transform**
* **Wavelets and Signal Processing**

**How to Study?**

✅ **Prerequisites:** Basic understanding of algebra and calculus  
✅ **Resources:**

* **Linear Algebra** – "Linear Algebra and Its Applications" by Gilbert Strang
* **Calculus** – "Calculus" by James Stewart
* **Probability & Statistics** – "Probability and Statistics for Machine Learning" by Kevin Murphy
* **Optimization** – "Convex Optimization" by Stephen Boyd
* **Graph Theory** – "Introduction to Graph Theory" by Douglas B. West