UNIT – 1

❖ Introduction to Artificial Intelligence (AI)

Artificial Intelligence (AI) is a branch of computer science that focuses on creating machines and software capable of performing tasks that normally require human intelligence. It is the science and engineering of making intelligent systems—especially intelligent computer programs—that can think, reason, learn, understand, and act autonomously or semi-autonomously. AI combines elements of computer science, mathematics, psychology, neuroscience, linguistics, philosophy, and engineering to simulate cognitive functions such as problem-solving, decision-making, learning, perception, and language understanding.

AI can be broadly defined as the ability of a machine or a computer system to acquire knowledge from experience, adapt to new inputs, and carry out tasks in a way that demonstrates human-like intelligence. Unlike traditional software, which follows only predefined rules, AI systems use algorithms and models to process large amounts of data, recognize patterns, and improve their performance over time through techniques like Machine Learning (ML) and Deep Learning (DL).

In essence, AI aims to replicate human intellectual abilities in machines. This involves tasks such as:

- Understanding natural language (e.g., speech recognition and translation).
- Recognizing objects and images (computer vision).
- Making decisions based on data and reasoning (expert systems).
- Learning from past experiences (machine learning).
- Interacting with humans naturally (chatbots, virtual assistants).

❖ Domains of Artificial Intelligence

"The domains of Artificial Intelligence are the major branches or subfields of AI which focus on specific problem-solving capabilities such as learning from data, understanding natural languages, recognizing visual patterns, making decisions, reasoning like humans, and interacting with the real world through robots and intelligent agents. These domains collectively aim to simulate human intelligence in different dimensions, enabling machines to perform tasks autonomously, adapt to changing environments, and continuously improve over time."

Main Domains of AI with Explanation

1. Machine Learning (ML)

- Machines learn patterns from historical data.
- Goal: Improve automatically without explicit programming.
- Applications: Fraud detection, recommendation engines, weather forecasting.

---

2. Natural Language Processing (NLP)

- Machines understand, interpret, and generate human languages.
- Goal: Smooth human-computer communication.
- Applications: Chatbots, translation tools, voice assistants.

---

3. Computer Vision

- Enables machines to see and interpret images/videos.
- Goal: Give visual perception to machines.
- Applications: Face recognition, autonomous vehicles, medical imaging.

---

4. Expert Systems

- Mimic human experts using a knowledge base + inference engine.
- Goal: Provide expert-level solutions in specific domains.
- Applications: Disease diagnosis, troubleshooting in engineering.

---

5. Robotics

- AI-powered robots interact with the physical environment.
- Goal: Perform tasks autonomously or semi-autonomously.

- Applications: Industrial automation, drones, humanoid robots.

---

6. Speech Recognition

- Converts spoken words into text or actions.
- Goal: Enable voice-based interaction.
- Applications: Virtual assistants, dictation software, call-center bots.

---

7. Planning & Decision Making

- AI agents set goals, plan strategies, and make rational decisions.
- Goal: Achieve optimum results with logical reasoning.
- Applications: GPS route planning, business forecasting, game-playing AI.

---

8. Reinforcement Learning

- Agents learn by interacting with the environment and receiving feedback (reward/penalty).
- Goal: Develop self-learning and self-improving systems.
- Applications: Game AI (AlphaGo), self-driving cars, robotic training.

❖ Foundation of Artificial Intelligence (AI)

“The foundation of Artificial Intelligence (AI) refers to the interdisciplinary base of principles, theories, and methods derived from multiple scientific and philosophical fields, which collectively enable the creation of intelligent machines. These foundations include mathematics, which provides the language of logic, probability, and optimization; computer science, which offers algorithms, data structures, and computational models; philosophy, which contributes reasoning, knowledge representation, and ethics; psychology, which explains human behaviours, cognition, and learning patterns; neuroscience, which models the structure and functioning of the human brain for neural networks; linguistics, which focuses on understanding and processing natural languages; and engineering, which provides the tools and hardware to implement intelligent systems. Together, these foundations give AI the ability to simulate human-like intelligence, such as reasoning, problem-solving, learning, decision-making, and perception, thereby enabling machines to act autonomously, adapt to changing environments, and continuously improve their performance over time."

AI Foundations

1. Mathematics

- Provides the theoretical base of AI.
- Important areas:
  - Logic → for reasoning
  - Probability & Statistics → for uncertainty handling
  - Linear Algebra & Calculus → for machine learning and neural networks
- Example: Predicting weather, probability-based spam detection.

---

2. Computer Science

- Gives computational power and algorithms to implement AI.
- Includes:
  - Search algorithms (DFS, BFS, A*)
  - Data structures (trees, graphs)
  - Programming languages (Python, C++, Java)
- Example: Path finding in Google Maps, optimization problems.

---

3. Philosophy

- Oldest foundation of AI.
- Asks: *Can machines think? What is reasoning?*
- Provides concepts of:
  - Knowledge representation
  - Logical reasoning
  - Ethics in AI (safe and fair use)

---

4. Psychology

- Studies human mind and behaviours.
- Helps in understanding:
  - How humans learn (basis of machine learning)
  - How we recognize patterns, emotions, and problem-solve
- Example: Cognitive psychology → AI models for learning.

---

5. Neuroscience

- Explains how the human brain works.
- Inspired Artificial Neural Networks (ANNs).
- Studies neurons, connections, memory, and learning process.
- Example: Deep Learning networks mimic human brain neurons.

---

6. Linguistics

- Language is a key part of intelligence.
- Helps in Natural Language Processing (NLP).
- Enables AI to:
  - Understand speech
  - Translate languages
  - Generate human-like responses
- Example: Google Translate, Chatbots, Alexa.

---

7. Engineering

- Provides physical machines and devices to apply AI.
- Fields: Robotics, electronics, chip design.
- Example: AI-powered robots, drones, autonomous vehicles.

❖Domain – base and Knowledge – base Database

1. Domain-base Database (DBD)

A **Domain-base Database** is a type of database that stores, organizes, and manages data related to a **specific application area or subject field**. The word *domain* refers to a particular area of knowledge, industry, or discipline, such as medical science, banking, education, engineering, business management, etc. In a domain-base database, all the data elements, attributes, and relationships are directly connected to that single domain only, which makes it highly specialized and suitable for performing tasks related to that area.

Unlike a general-purpose database, which may hold different types of data, a domain-base database restricts itself to one field, ensuring accuracy, consistency, and relevance of the data. The structure of such databases is designed according to the requirements of the domain.

- **Purpose:** To manage domain-specific information efficiently.
- **Usage:** Mostly in management systems or specialized applications.
- **Example:**
    - In a **Hospital Management System**, the database stores patients' medical records, doctors' schedules, prescriptions, test results, etc. All the data belongs to the *medical domain*.
    - In a **Library Management System**, it stores books, authors, members, issue-return records, etc., which all belong to the *education domain*.

---

2. Knowledge-base Database (KBD)

A **Knowledge-base Database** is a special kind of database used primarily in **Artificial Intelligence (AI) and Expert Systems**. Unlike a normal database that only stores raw facts or data, a knowledge-based database stores **facts, rules, relationships, and reasoning strategies**. This enables the system to perform **inference (logical reasoning)** and make intelligent decisions.

It is a combination of two important components:

1. **Facts (Data):** Basic information about the world or a problem domain (e.g., symptoms of diseases).
2. **Rules (Knowledge):** Logical conditions and relationships that describe how to use facts (e.g., *If a patient has a fever and cough, then it may indicate flu*).

By combining facts with rules, a knowledge-based database becomes capable of **problem-solving, decision-making, and providing expert-level advice**. This is why it is widely used in expert systems, intelligent tutoring systems, medical diagnosis systems, and other AI-based applications.

- **Purpose:** To simulate human-like reasoning and provide intelligent decision support.
- **Usage:** Mostly in AI applications and decision-support systems.
- **Example:**
  - In a **Medical Expert System**, the system stores patient symptoms as data and medical rules as knowledge. When a query is given, it uses both to suggest possible diagnoses or treatments.
  - In a **Chess-playing AI**, the knowledge-base database stores the rules of the game and strategies, which allows the AI to decide the best move.

Difference Between

Aspect	Domain-base Database	Knowledge-base Database
Definition	A database focused on storing information related to a specific field/domain.	A database that stores facts + rules and can perform reasoning for decision-making.
Nature	Data-oriented	Knowledge + reasoning oriented
Capability	Only stores and retrieves domain-specific data	Stores data and applies logic to make intelligent decisions
Application	Management systems (hospital, library, banking, education, etc.)	AI systems, Expert systems (medical diagnosis, chess AI, intelligent tutoring)
Decision Support	Cannot provide decisions	Can reason and provide expert-level advice

---

❖History of Artificial Intelligence (AI) –

The **history of Artificial Intelligence (AI)** refers to the gradual development of intelligent systems, theories, and technologies aimed at creating machines capable of simulating human-like thinking, reasoning, learning, and decision-making. AI's history is marked by a combination of **philosophical foundations, mathematical models, computer science breakthroughs, and practical applications**. The journey of AI can be traced back to ancient myths of intelligent beings, but its formal scientific foundation began in the mid-20th century with the rise of digital computers. The history of AI is generally divided into important **eras, milestones, and generations of development**, which are described below:

---

1. Early Foundations (Before 1950s)

- Ancient philosophers like **Aristotle** introduced the concept of formal reasoning and logic.
- Myths and stories across cultures (e.g., Greek myths of mechanical men, Chinese automata) showed the human imagination about artificial beings.
- In the 17th–19th centuries, mathematicians like **Leibniz, Boole, and Frege** developed formal logic and symbolic reasoning systems.
- By the early 20th century, **Alan Turing** proposed the idea of a universal computing machine (Turing Machine) and later suggested the **Turing Test (1950)** to measure machine intelligence.

---

2. Birth of AI as a Discipline (1950s–1960s)

- **1956 Dartmouth Conference** (organized by John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon) is considered the **birthplace of AI** as an academic field.
- Term **"Artificial Intelligence"** was officially coined by **John McCarthy**.
- Early AI research focused on **symbolic AI**, logic-based problem solving, and rule-based reasoning.
- Notable works:
  - **Logic Theorist (1955)** by Allen Newell and Herbert Simon, considered the first AI program.
  - **General Problem Solver (GPS)** (1957) attempted to solve a wide range of problems using rules.

    - **ELIZA (1966)**, an early natural language processing program by Joseph Weizenbaum.

---

3. The First AI Boom and Optimism (1960s–1970s)

- AI received heavy funding from governments and research institutions, especially in the US and UK.
- Development of **expert systems** (programs that mimic human experts in narrow domains).
- Early success in solving algebra problems, proving theorems, and playing games like chess.
- Key milestones:
    - **Shakey the Robot (1969)**: first mobile robot with reasoning ability.
    - Early natural language systems that could understand restricted English sentences.

---

4. AI Winter (1974–1980 and 1987–1993)

- Over-optimism led to **unrealistic expectations**, but the computing power and algorithms of the time were insufficient.
- Funding was reduced, leading to what is called **AI Winter** (a period of reduced research and interest).
- Limitations of symbolic reasoning and expert systems became apparent.

---

5. Rise of Expert Systems and Second AI Boom (1980s)

- The introduction of **expert systems** like **MYCIN (medical diagnosis system)** revived interest in AI.
- Companies adopted AI systems for business, finance, and industry.
- Development of specialized AI programming languages like **LISP and PROLOG**.
- However, these systems were expensive, required heavy maintenance, and lacked adaptability, leading to the second AI winter.

---

6. The Modern AI Era (1990s–2010s)

- Shift from symbolic AI to **statistical methods, machine learning, and data-driven approaches**.
- Breakthroughs:
  - **Deep Blue (1997)**: IBM's chess computer defeated world champion Garry Kasparov.
  - **Autonomous robotics** advanced, with robots like Honda's **ASIMO (2000)**.
  - **Speech recognition systems** and **search engines** began using AI.
- **Machine Learning (ML)**, **neural networks**, and **support vector machines (SVMs)** gained popularity.
- AI research moved towards practical applications like data mining, fraud detection, and recommendation systems.

---

7. Deep Learning and AI Revolution (2010s–Present)

- Availability of **big data**, powerful **GPUs**, and improved algorithms led to rapid progress in **deep learning**.
- Breakthrough achievements:
  - **Google's DeepMind AlphaGo (2016)** defeated the world champion in the complex game of Go.
  - **Image recognition** and **speech recognition systems** reached human-level accuracy.
  - **Virtual assistants** like Siri, Alexa, and Google Assistant became mainstream.
  - **Generative AI** (e.g., GPT series, DALL·E, ChatGPT) transformed natural language processing, text generation, and creative applications.
- AI became widely applied in healthcare, education, autonomous vehicles, robotics, finance, and entertainment.

---

8. Present and Future of AI (2020s and beyond)

Current focus areas include **Explainable AI (XAI)**, **Ethical AI**, **Artificial General Intelligence (AGI)**, and **AI Governance**.

AI is becoming more integrated into daily life through smart homes, personalized learning, self-driving cars, and medical diagnostics.

Future challenges include ensuring **fairness, accountability, transparency, and safety** of AI systems.

❖ Areas and state-of-the-art in Artificial Intelligence

Artificial Intelligence (AI) is the scientific and engineering discipline that builds algorithms and systems that perceive, reason, learn, plan, and act — often by automatically extracting patterns from data and (increasingly) by using large, general-purpose models that can be adapted to many tasks. The *state of the art* today is dominated by data-driven learning (especially deep neural networks), foundation/multimodal models, and powerful generative methods — together with growing attention to safety, explainability, and real-world deployment constraints.

---

1) High-level map — major areas of AI (what people mean when they say "AI")

Below I list the principal subfields, what they aim to do, and the current state-of-the-art approaches.

A. Machine Learning (ML) — supervised, unsupervised, self-supervised

Goal: learn mappings or representations from data.
SOTA: large neural networks trained with **self-supervised** objectives (masked modeling, contrastive losses) that produce transferable representations; these are now the backbone of many downstream systems.

B. Deep Learning (DL)

Goal: use multi-layer neural networks (CNNs, RNNs, Transformers) to automatically learn hierarchical features.
SOTA: **Transformers** have become the dominant architecture across modalities (text, images, audio, video) because of scale and parallelism; vision transformers and hybrid CNN–transformer architectures are now common.

C. Natural Language Processing (NLP) & Large Language Models (LLMs)

Goal: understanding and generating human language.
SOTA: Very large pretrained transformer models (GPT family, PaLM, LLaMA derivatives) fine-tuned or used through prompting or RLHF; these are now “foundation models” used for chat, summarization, code generation, retrieval-augmented generation, etc.

D. Computer Vision (CV)

Goal: perceive and understand images / video (classification, detection, segmentation).
SOTA: Vision foundation models such as **Segment Anything (SAM)**, vision transformers, and large pretraining on massive image datasets that enable strong zero-shot transfer and promptable vision tasks.

E. Speech & Audio

Goal: transcribe, understand, synthesize speech; separate sources; sound event detection.
SOTA: end-to-end models (transformer and convolutional) trained with self-supervision (e.g., wav2vec family) and large multimodal models that fuse audio with text and vision.

F. Generative Models (images, audio, video, code, molecules)

Goal: create novel, high-quality samples matching the distribution of training data.
SOTA: **Diffusion models** (Stable Diffusion family, other diffusion-based approaches) and large autoregressive/generative transformers are state-of-the-art for high-fidelity image/audio/video/text generation. These models power image generation, text-to-image, and many creative tools.

G. Reinforcement Learning (RL) & Control

Goal: learn policies to maximize cumulative reward in sequential environments (games, robotics, resource allocation).
SOTA: scalable RL (model-based and model-free), RL combined with large models and self-play (AlphaZero, AlphaStar, etc.), sim-to-real techniques for robotics. RL remains strong for decision problems with clear rewards.

H. Robotics & Perception-to-Action

Goal: integrate perception, planning, and control for physical interaction.
SOTA: combining simulators, large perception models, and learning-based policies for manipulation and navigation; research focuses on robustness and sim-to-real transfer.

I. Knowledge Representation, Symbolic Reasoning, & Neuro-Symbolic AI

Goal: represent structured knowledge and do logical, causal, or symbolic reasoning.
SOTA: hybrid systems that combine neural perception/learning with symbolic modules or retrieval reasoning pipelines; retrieval-augmented generation is a common practical pattern.

J. Causality, Explainability, Fairness, Safety, and Alignment

Goal: make models reliable, interpretable, and aligned with human values.
SOTA: active field — methods for causal inference, counterfactual explanations, model interpretability, robust evaluation, adversarial testing, and governance frameworks.

K. Privacy-preserving, Federated & Edge AI

Goal: run learning with privacy (federated learning, differential privacy) and on-device (tinyML, NPUs).
SOTA: on-device inference and specialized hardware stacks (NPUs), privacy guarantees via DP/federated algorithms, and optimizations for model compression/quantization. News in 2025 highlight improved on-device generative models for consumer laptops.

L. Scientific & Domain-Specific AI (bio, chemistry, materials)

Goal: accelerate discovery and design in science and engineering.
SOTA: protein folding and molecular design via models like **AlphaFold** and follow-ons (AlphaFold 3 and diffusion-based protein complex prediction) that have transformed structural biology. These are prime examples of AI achieving domain-changing impact.

---

2) What "state-of-the-art" means now (common patterns)

1. **Scale + Data + Compute** — larger models trained on diverse, massive datasets (text, images, code, multimodal) produce surprisingly general capabilities (foundation models).
2. **Multimodality** — models that jointly reason across text, images, audio, and video are rapidly becoming central (multimodal LLMs / MLLMs).
3. **Promptability / Few-shot / In-context learning** — models can be adapted by prompts and few examples instead of traditional fine-tuning.

4. **Generative creativity** — diffusion and transformer generative models now produce near-photorealistic images, coherent text, and realistic audio/video.
5. **Foundation models + adaptation** — large pretrained models (vision or language) serve as bases for downstream fine-tuning, prompting, retrieval augmentation, or chaining with symbolic components.

---

3) Examples of recent state-of-the-art milestones (concrete)

- **Multimodal large models** that can read text, look at images and answer or generate grounded outputs — reviewed in recent surveys.
- **Diffusion-based generative models** dominate high-quality image synthesis and are expanding into video and 3D.
- **SAM (Segment Anything Model)** — a promptable vision foundation model that provides universal image segmentation capabilities (wide zero-shot transfer), showing how vision foundation models generalize. It's widely used as a building block in vision pipelines.
- **AlphaFold and successors** — AI models that predict protein structures and complexes at scale, revolutionizing structural biology and earning major scientific recognition

---

4) Practical trends in industry / deployment

- **Retrieval-augmented systems**: combine a pretrained generative model with a search/retrieval layer for factual grounding.
- **On-device AI & specialized NPUs**: companies are shipping consumer hardware optimized for running generative or inference models locally.
- **Tooling and safety stacks**: production systems integrate content filters, grounding, human-in-the-loop validation, and monitoring.

---

5) Current limitations and active research challenges

- **Robustness & generalization**: models can hallucinate, fail under distribution shift, or be brittle in safety-critical settings.
- **Data and compute costs**: training and maintaining large models is costly and environmentally heavy.

- **Explainability & causality**: neural nets remain hard to interpret; causal reasoning is still immature compared to pattern recognition.
- **Ethics, bias, and governance**: models can encode societal biases; regulation, auditing, and governance are urgent research and policy needs.
- **Real-world embodied intelligence**: sim-to-real and safe robot learning remain difficult for open environments.

---

6) Where the field is heading (near future directions)

- **More capable multimodal foundation models** that can plan, reason, and act across modalities.
- **Efficient scaling and alignment**: research into making models smaller, faster, and safer (distillation, quantization, alignment techniques).
- **Scientific AI**: deeper integration of AI in biology, chemistry, climate, and materials (AlphaFold-class progress is a proof point).
- **Human-AI collaboration tools**: AI increasingly used as copilots for coding, design, research, and education.
- **Regulation & standards**: robust evaluation benchmarks, transparency, and oversight will shape technology adoption.

❖AI Problems –

The term **AI Problems** refers to the range of tasks, challenges, and computational questions that Artificial Intelligence systems aim to solve in order to simulate human intelligence. An **AI problem** is any situation where a computer or machine must use **knowledge representation, reasoning, learning, perception, or decision-making** to achieve a goal that would typically require human intelligence. These problems include diverse areas such as search, pattern recognition, natural language understanding, vision, planning, and robotics. Solving AI problems often requires algorithms that can handle incomplete or uncertain information, adapt through experience, and operate in dynamic environments.

AI problems can be broadly classified into **categories and levels**, each with different complexities. Below is a detailed explanation:

---

1. Search and Problem-Solving

- Many AI problems can be formulated as a **search problem**, where the system explores possible states to reach a goal.
- Example: finding the shortest route in a map, solving a puzzle, playing chess.
- **Techniques used:**
  - Uninformed Search (Breadth-First, Depth-First)
  - Informed Search (A*, Heuristic search)
- **Challenge:** search spaces are often very large, leading to the **combinatorial explosion** problem.

---

2. Knowledge Representation and Reasoning

- AI systems must represent knowledge about the world in a way machines can process.
- **Problems include:**
  - Representing facts, objects, events, and rules.
  - Using logic to make inferences (e.g., predicate logic, semantic networks, ontologies).
- Example: An expert system diagnosing diseases needs to represent medical knowledge and reason about symptoms.
- **Challenges:** incomplete information, uncertain reasoning, and real-world ambiguity.

---

3. Natural Language Processing (NLP)

- Machines need to understand, interpret, and generate human language.
- **Problems include:**
  - Speech recognition (converting spoken words into text)
  - Syntax and semantic analysis (understanding meaning)
  - Machine translation (one language to another)
  - Text summarization, sentiment analysis, and chatbot conversation.
- **Challenges:** ambiguity of words, slang, cultural context, and multiple languages.

---

4. Perception and Computer Vision

- AI must be able to **perceive the environment** through sensors such as cameras and microphones.
- **Problems include:**
    - Object detection and recognition.
    - Image classification, segmentation, and scene understanding.
    - Facial recognition, gesture recognition.
- **Challenges:** handling noise, different lighting conditions, occlusion (hidden objects), and variations in data.

---

5. Planning and Decision-Making

- AI must plan sequences of actions to achieve specific goals.
- **Problems include:**
    - Automated planning (robots deciding steps to reach a target).
    - Decision-making under uncertainty.
    - Game strategies.
- **Challenges:** real-time planning in complex environments, limited resources, and unpredictable conditions.

---

6. Learning and Adaptation

- A central AI problem is enabling machines to **learn from data and experience**.
- **Problems include:**
    - Supervised, unsupervised, and reinforcement learning.
    - Generalization (performing well on unseen data).
    - Online learning (continuous adaptation).
- Example: spam email classification, recommendation systems.
- **Challenges:** overfitting, data scarcity, noisy or biased datasets.

---

7. Robotics and Physical Interaction

- AI must control physical agents (robots, drones) to interact with the real world.
- **Problems include:**
  - Navigation and mapping (SLAM – Simultaneous Localization and Mapping).
  - Grasping and manipulation of objects.
  - Coordination between multiple robots.
- **Challenges:** uncertainty in physical environments, safety, and real-time decision-making.

---

8. Common AI Challenges Across Problems

- **Ambiguity:** human tasks are often vague and imprecise.
- **Uncertainty:** real-world data is incomplete or noisy.
- **Scalability:** algorithms may work on small examples but fail with large datasets.
- **Ethics and Bias:** AI systems may inherit human biases or behave unfairly.
- **Interpretability:** AI solutions often act as "black boxes," making their decisions hard to explain.

❖Introduction to Knowledge in AI

In Artificial Intelligence, **knowledge** refers to the information, facts, concepts, rules, and relationships about the world that an intelligent system must possess in order to understand situations, make decisions, and solve problems effectively. Knowledge in AI is the key element that differentiates simple data processing from **intelligent reasoning**. Without knowledge, AI systems can only perform mechanical computations, but with knowledge, they can interpret inputs, infer new information, adapt to different contexts, and act rationally.

The study of **Knowledge in AI** is closely related to **Knowledge Representation (KR)** and **Knowledge Reasoning**, which deal with how to represent real-world information in a computer and how to use it to draw conclusions. AI systems rely on knowledge to **perceive the**

environment, understand goals, plan actions, and learn from experience.

---

1. Importance of Knowledge in AI

- Knowledge allows AI systems to **simulate human intelligence** by using facts, rules, and experiences.
- It enables reasoning beyond raw data — for example, a system can diagnose a disease not just by matching symptoms, but by applying **medical knowledge and causal reasoning**.
- Knowledge helps AI in:
  - **Understanding natural language**
  - **Making decisions under uncertainty**
  - **Problem-solving and planning**
  - **Learning and adapting in real-time**

---

2. Characteristics of Knowledge

For knowledge to be useful in AI, it should have the following properties:

1. **Representational Adequacy** – Ability to represent different types of knowledge (facts, rules, relationships).
2. **Inferential Adequacy** – Ability to infer new knowledge from existing facts.
3. **Inferential Efficiency** – Ability to direct the reasoning process towards useful conclusions.
4. **Acquisitional Efficiency** – Ability to acquire new knowledge easily and update old knowledge.

---

3. Types of Knowledge in AI

AI uses different forms of knowledge depending on the domain:

1. **Declarative Knowledge** – "Knowing that" (facts and objects). Example: Paris is the capital of France.
2. **Procedural Knowledge** – "Knowing how" (steps and procedures). Example: how to solve an equation.

3. **Meta-Knowledge** – "Knowledge about knowledge," i.e., strategies for using knowledge effectively.
4. **Heuristic Knowledge** – Rules of thumb or practical approaches (approximate reasoning).
5. **Structural Knowledge** – Relationships between concepts, useful in building ontologies and semantic networks.

---

4. Knowledge Representation in AI

Knowledge must be represented in a machine-readable way. Some common methods are:

- **Logical Representation** (Propositional and Predicate Logic)
- **Semantic Networks**
- **Frames**
- **Production Rules (If-Then rules)**
- **Ontologies**
- **Probabilistic Representation** (Bayesian Networks for uncertain knowledge)

---

5. Role of Knowledge in Problem Solving

- Helps AI understand the **state of the problem** and possible solutions.
- Provides context for making decisions.
- Allows AI systems to explain their reasoning and actions (important in expert systems).
- Supports generalization — applying old knowledge to new situations.

---

6. Example of Knowledge in AI

- **Medical Expert System:** Stores knowledge about diseases, symptoms, and treatments, then reasons about a patient's condition.
- **Self-driving Car:** Uses knowledge of road rules, object recognition, and traffic patterns to navigate safely.

- **Chatbots:** Store and apply knowledge about language, grammar, and user intent to generate meaningful responses.

❖Knowledge Base System (KBS) in AI

A **Knowledge Base System (KBS)** in Artificial Intelligence is a computer-based system that uses a **knowledge base (repository of facts and rules)** and an **inference engine (reasoning mechanism)** to solve problems, make decisions, and provide intelligent responses similar to a human expert. It is one of the most important applications of AI, widely used in **expert systems, decision support systems, and intelligent agents**.

The purpose of a Knowledge Base System is to store, organize, and utilize knowledge in such a way that a machine can reason about it, draw logical conclusions, and offer solutions to real-world problems.

---

1. Components of a Knowledge Base System

A KBS generally consists of **two main parts**:

A) Knowledge Base (KB)

- The **knowledge repository** that contains:
    - **Facts** → basic information about the world.
    - **Rules** → logical statements or conditions (IF–THEN statements) used for reasoning.
- Example:
    - Fact: "Fever is a symptom of infection."
    - Rule: "IF a patient has fever AND cough → THEN possibility of flu."

B) Inference Engine

- The reasoning mechanism that **applies rules to known facts** in order to infer new knowledge.
- Works like the “brain” of the system.
- Performs **deduction, induction, and reasoning**.

- Example: If KB has "All birds can fly" and Fact "Parrot is a bird," the inference engine concludes: "Parrot can fly."

---

2. Working of a Knowledge Base System

1. User provides input (problem description or query).
2. Knowledge Base stores relevant facts and rules.
3. Inference Engine applies reasoning techniques (forward chaining, backward chaining).
4. System generates conclusions, recommendations, or decisions.

---

3. Features of a Knowledge Base System

- **Knowledge storage**: maintains domain-specific facts and rules.
- **Reasoning capability**: derives new information from existing knowledge.
- **Explanation facility**: explains how a conclusion was reached (important in expert systems).
- **Flexibility**: allows updates and expansion of the knowledge base.

---

4. Types of Knowledge Used in KBS

- **Declarative Knowledge** → descriptive facts (e.g., “Paris is capital of France”).
- **Procedural Knowledge** → how-to rules (e.g., steps to solve an equation).
- **Heuristic Knowledge** → practical rules of thumb (used in expert systems).

---

5. Advantages of Knowledge Base Systems

- Provides **expert-level decision-making** in specific domains.
- Stores **large volumes of knowledge** in structured form.
- Improves **efficiency and accuracy** of problem-solving.

- Can be used in **medicine, education, engineering, business, and robotics**.
- Offers **explanation and justification** for decisions.

❖Knowledge Representation Techniques in AI

Introduction

In Artificial Intelligence (AI), **Knowledge Representation (KR)** refers to the way knowledge about the world is **structured, stored, and organized** in a computer system so that it can be used for reasoning, decision-making, and problem-solving. Since AI systems need to "understand" and "think" like humans, the method of representing knowledge plays a central role in their effectiveness.

A **Knowledge Representation Technique** is the formal method or approach used to encode facts, concepts, relationships, and rules about a domain in a format that machines can process and humans can interpret. The ultimate goal of KR is to bridge the gap between **human cognitive abilities** and **machine processing capabilities**.

---

1. Properties of a Good Knowledge Representation Technique

A good KR technique should satisfy the following:

1. **Representational Adequacy** → Ability to represent all necessary kinds of knowledge.
2. **Inferential Adequacy** → Ability to derive new knowledge from existing information.
3. **Inferential Efficiency** → Ability to direct reasoning efficiently without unnecessary complexity.
4. **Acquisitional Efficiency** → Ability to easily acquire, update, and modify knowledge.

---

2. Major Knowledge Representation Techniques in AI

A) Logical Representation

- Uses **mathematical logic** to represent knowledge.
- Two main types:

- **Propositional Logic**: Deals with simple statements (true/false).
- **Predicate Logic**: More powerful; represents objects, properties, and relationships.

- Example:
  - "All humans are mortal" → $\forall x\ (Human(x) \rightarrow Mortal(x))$
  - "Socrates is human" → Human(Socrates)
  - Inference: Mortal(Socrates)
- **Advantages**: Precise, supports automated reasoning.
- **Limitations**: Cannot easily handle uncertainty or incomplete knowledge.

B) Semantic Networks

- Represents knowledge in the form of a **graph**: nodes represent concepts/objects and edges represent relationships.
- Example:
  - Node: "Cat"
  - Link: "is-a" → "Animal"
  - Node: "Has" → "Fur"
- **Advantages**: Easy visualization, hierarchical representation, good for inheritance.
- **Limitations**: Becomes complex with large networks, reasoning may be slow.

C) Frames Representation

- Organizes knowledge into **structures called frames**, similar to objects in programming.
- Each frame has **slots** (attributes) and **values**.
- Example: Frame for "Car"
  - Slots: {Color: Red, Engine: Petrol, Wheels: 4}
- **Advantages**: Easy to group related properties, supports default reasoning (if value not specified, use default).
- **Limitations**: May not handle complex or dynamic relationships well.

D) Production Rules (Rule-Based Representation)

- Knowledge is represented as a set of **IF–THEN rules**.
- Example:
  - IF “Temperature > 38°C AND Cough”
  - THEN “Patient may have fever.”
- Uses **Forward Chaining (data-driven)** or **Backward Chaining (goal-driven)** for reasoning.
- **Advantages**: Simple, modular, and widely used in expert systems.
- **Limitations**: Rule explosion (too many rules in large systems), difficulty in handling uncertainty.

E) Ontologies

- Provides a **structured, formal vocabulary** for a domain.
- Defines **concepts, relationships, and constraints** in a machine-readable way.
- Example: In medical domain → “Disease,” “Symptom,” “Treatment,” and their relations.
- Widely used in **Semantic Web, Knowledge Graphs, and AI assistants**.
- **Advantages**: Supports interoperability, reasoning across domains.
- **Limitations**: Complex to build and maintain.

F) Probabilistic & Fuzzy Representation

- Used to handle **uncertain, incomplete, or imprecise knowledge**.
- **Bayesian Networks**: Represent probabilistic dependencies among variables.
- **Fuzzy Logic**: Deals with partial truths (e.g., “Tall” may be 0.7 true).
- Example: Probability of “Rain” given “Cloudy” conditions.
- **Advantages**: Realistic handling of uncertainty, widely used in robotics and decision-making.

- **Limitations**: Requires large amounts of data and probability distributions.