Part 1 — Chronology of AI

Machine Learning → Fraud Detection at PayPal
PayPal uses machine learning algorithms to analyze transaction patterns and detect fraudulent activity in real time.
These models learn from historical data to flag anomalies and prevent financial losses.

Deep Learning → Diabetic Retinopathy Detection by Google DeepMind
Google DeepMind developed a deep learning system that analyzes retinal images to detect diabetic retinopathy.
The model matches expert-level accuracy and helps scale early diagnosis, especially in underserved regions.

Computer Vision → Self-Driving Cars by Tesla
Tesla's Autopilot system uses computer vision to interpret camera feeds from the vehicle, recognizing lanes, traffic signs, pedestrians, and other vehicles.
This enables semi-autonomous driving and real-time decision-making.

Natural Language Processing (NLP) → Google Translate
Google Translate uses NLP to understand and convert text between languages.
It analyzes grammar, syntax, and context to improve translation accuracy across hundreds of languages.

Large Language Models (LLMs) → ChatGPT by OpenAI
ChatGPT is a prominent example of an LLM that can generate human-like text, answer questions, write essays, and even code.
It's trained on vast datasets and uses transformer architecture to understand and produce coherent language.

Part 2 — Deep Learning Architectures
Match the model to the use case:

1. RNN	Early speech-to-text systems	RNNs handle sequential data, making them suitable for early audio processing.
2. LSTM	Text translation (old Google Translate)	LSTMs improve upon RNNs by capturing long-term dependencies in language.
3. CNN	Image recognition	CNNs are designed to process grid-like data such as images.
4. Transformer	Predicting the next word in ChatGPT	Transformers use attention mechanisms to model context efficiently in large texts.

Part 3 — Frameworks Choose one framework (PyTorch / TensorFlow / Keras).
In one sentence, explain why you would use it if you were a student making a cat-vs-dog classifier.

Answer- I'd use Keras because its high-level, beginner-friendly API lets me quickly build and train a cat-vs-dog classifier without getting bogged down in complex code.

Part 4 — Evaluation Metrics
Imagine you built a spam filter.

Answer-
Precision: Precision is 0.7 because out of 10 emails marked as spam, 7 were truly spam.

Recall: Recall is 0.58 because the filter caught 7 out of 12 actual spam emails.

F1 Score: The F1 Score is 0.64, calculated using the formula 2*precision*recall/(precision+recall)

MSE vs MAE: MSE punishes the error more than MAE because it squares the difference, making larger errors count more.

BLEU vs ROUGE: ROUGE would give a higher score for the translation "Cat is on the mat" because it rewards overlapping phrases even if the exact wording differs.

Part 5 — Responsible AI & Explainability
You built an AI that predicts loan approvals.
A customer asks, "Why was my loan rejected?"

Write one simple way to explain the decision fairly (e.g., "Your income was too low compared to the loan size").

Answer-
Your loan application was evaluated using a predictive model trained on historical lending data. The model identified key risk factors in your profile, including a debt-to-income ratio exceeding our acceptable threshold and a credit score below the minimum cutoff. Additionally, your employment history showed instability, which contributed to a lower confidence score in repayment likelihood. These features collectively led the model to classify your application as high risk, resulting in rejection. The decision was based on statistically significant patterns learned from past defaults.