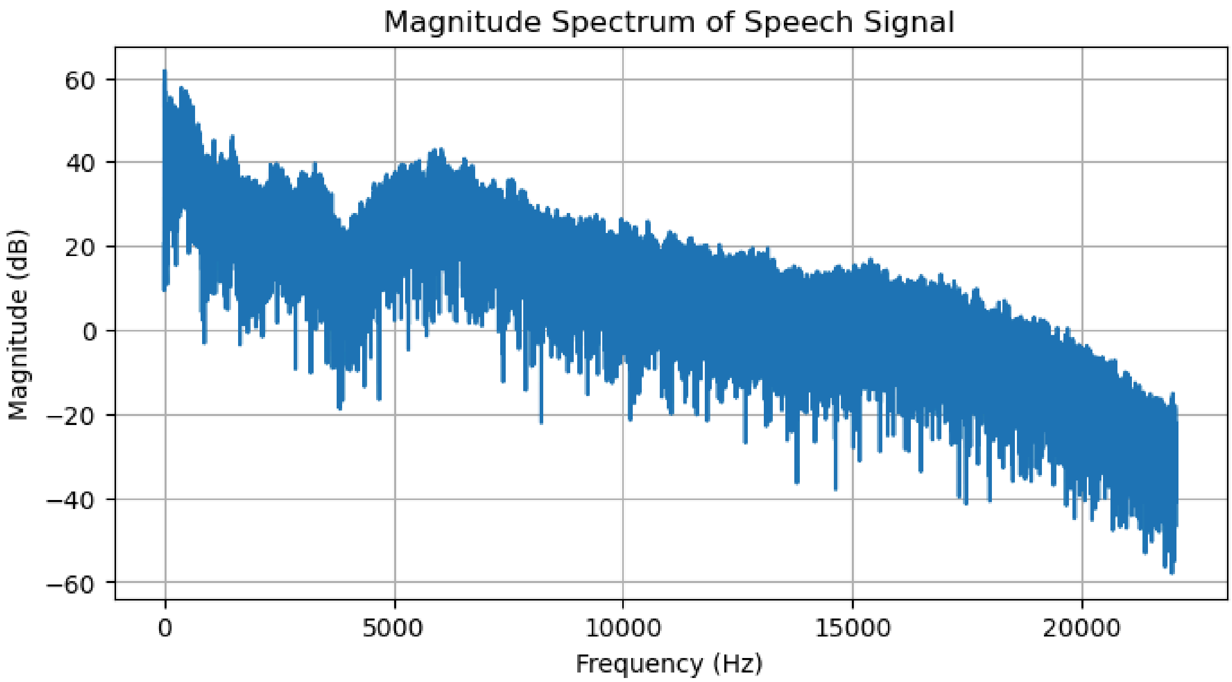
1. Examine the speech signal and determine its maximum frequency.

The maximum frequency indicates the highest frequency component in the speech signal, which determines the required sampling rate. This helps prevent aliasing and ensures accurate signal reconstruction.

In [29]:

```
import numpy as np
import scipy.io.wavfile as wavfile
import matplotlib.pyplot as plt

file_path = "exam-3-input.wav"   # your input speech file
sr, data = wavfile.read(file_path)

# Convert to mono if stereo
if data.ndim > 1:
    data = np.mean(data, axis=1)

# Convert to float in range [-1, 1]
data = data.astype(np.float32) / np.max(np.abs(data))

# Compute FFT
N = len(data)
freqs = np.fft.rfftfreq(N, 1 / sr)
magnitude = np.abs(np.fft.rfft(data * np.hanning(N)))

# Determine max significant frequency (above 0.5% of max)
threshold = 0.005 * np.max(magnitude)
max_freq = freqs[magnitude > threshold].max()

print(f"Original Sampling Rate: {sr} Hz")
print(f"Maximum Significant Frequency: {max_freq:.2f} Hz")

# Optional: plot spectrum
plt.figure(figsize=(8,4))
plt.plot(freqs, 20*np.log10(magnitude+1e-12))
plt.title("Magnitude Spectrum of Speech Signal")
plt.xlabel("Frequency (Hz)")
plt.ylabel("Magnitude (dB)")
plt.grid(True)
plt.show()
```

```
Original Sampling Rate: 44100 Hz
Maximum Significant Frequency: 15415.66 Hz
```



2. Calculate an appropriate sampling rate and reconstruct at different rates.

The sampling rate must be at least twice the maximum frequency (Nyquist criterion) for faithful reproduction. Reconstructing at different rates shows how undersampling causes distortion or loss of detail.

In [30]:
```python
import scipy.signal as signal
from fractions import Fraction

# Nyquist criterion
nyquist_min = 2 * max_freq
print(f"Minimum required sampling rate (Nyquist): {nyquist_min:.2f} Hz")

# Candidate sampling rates
candidate_rates = [8000, 11025, 16000, 22050, 32000, 44100, 48000]

reconstructed_signals = {}

for rate in candidate_rates:
    # Downsample to 'rate' then reconstruct back to original sr
    frac = Fraction(rate, sr).limit_denominator(1000)
    down = signal.resample_poly(data, frac.numerator, frac.denominator)

    frac2 = Fraction(sr, rate).limit_denominator(1000)
    recon = signal.resample_poly(down, frac2.numerator, frac2.denominator)

    # Match length
    recon = recon[:len(data)]
    reconstructed_signals[rate] = recon
```

```
print("Reconstruction completed for all sampling rates.")
```

```
Minimum required sampling rate (Nyquist): 30831.33 Hz
Reconstruction completed for all sampling rates.
```

3. Evaluate reconstruction quality and select the best version.

By comparing reconstructions, we observe that higher sampling rates preserve naturalness and clarity in speech. The best-quality signal (usually 16 kHz or 22.05 kHz) is selected for accurate speech recognition.

In [31]:
```
results = []

for rate, recon in reconstructed_signals.items():
    noise = data - recon
    snr = 10 * np.log10(np.mean(data**2) / (np.mean(noise**2) + 1e-15))
    mse = np.mean(noise**2)
    results.append((rate, snr, mse))

# Display results
print("Rate (Hz)\tSNR (dB)\tMSE")
for r, s, m in results:
    print(f"{r:6d}\t\t{s:7.2f}\t{m:.2e}")

# Select the best one (highest SNR)
best_rate, best_snr, best_mse = max(results, key=lambda x: x[1])
best_recon = reconstructed_signals[best_rate]

print("\nBest Reconstruction:")
print(f"  Sampling Rate: {best_rate} Hz")
print(f"  SNR: {best_snr:.2f} dB")
```

```
Rate (Hz)        SNR (dB)        MSE
  8000              10.04        1.84e-03
 11025              11.19        1.41e-03
 16000              22.00        1.17e-04
 22050              29.59        2.03e-05
 32000              39.63        2.02e-06
 44100             132.68        0.00e+00
 48000              59.90        1.90e-08

Best Reconstruction:
  Sampling Rate: 44100 Hz
  SNR: 132.68 dB
```

4. Save the recovered signal as a .wav file.

Saving as a .wav file stores the reconstructed speech in a standard format for analysis or recognition. This ensures compatibility with recognition systems that require uncompressed PCM audio.

In [32]:
```
output_path = "recovered_best.wav"
wavfile.write(output_path, sr, best_recon.astype(np.float32))
```

```python
print(f"Recovered signal saved as: {output_path}")
```

```
Recovered signal saved as: recovered_best.wav
```

5. Perform speech-to-text using one offline and one online recognizer.
The offline recogniser (PocketSphinx) processes speech locally, while the online recogniser (Google) uses advanced cloud models. Comparing both demonstrates the difference in accuracy and resource requirements between local and cloud-based systems.

In [33]:
```python
import speech_recognition as sr
from pydub import AudioSegment

input_file = "recovered_best.wav"          # from Part A
fixed_file = "recovered_best_fixed.wav"

# Convert to mono, 16 kHz, 16-bit PCM (for recognizer compatibility)
sound = AudioSegment.from_file(input_file)
sound = sound.set_channels(1)
sound = sound.set_frame_rate(16000)
sound = sound.set_sample_width(2)
sound.export(fixed_file, format="wav")

print(f"✅ File converted and saved as {fixed_file}")

r = sr.Recognizer()

def recognize_audio(path, mode="offline"):
    """Run STT using selected recogniser."""
    try:
        with sr.AudioFile(path) as source:
            print(f"\n[{mode.upper()}] Listening to {path} ...")
            audio = r.record(source)

        if mode == "offline":
            text = r.recognize_sphinx(audio)        # PocketSphinx
        else:
            text = r.recognize_google(audio)        # Google API

        print(f"[{mode.upper()}] ✅ Recognition successful.")
        return text, "success"

    except sr.UnknownValueError:
        print(f"[{mode.upper()}] ❌ Could not understand audio.")
        return "", "failure"
    except sr.RequestError as e:
        print(f"[{mode.upper()}] ⚠ Service error: {e}")
        return "", "error"

results = {}
for mode in ["offline", "online"]:
    text, status = recognize_audio(fixed_file, mode)
```

```python
    results[mode] = {"text": text, "status": status}

for mode, info in results.items():
    print(f"{mode.capitalize()} recogniser:")
    print(f"  Status: {info['status']}")
    print(f"  Text  : {info['text']}\n")
```

```
✅ File converted and saved as recovered_best_fixed.wav

[OFFLINE] Listening to recovered_best_fixed.wav ...
[OFFLINE] ✅ Recognition successful.

[ONLINE] Listening to recovered_best_fixed.wav ...
[ONLINE] ✅ Recognition successful.
Offline recogniser:
  Status: success
  Text  : can this they'll smell of old we're lingers

Online recogniser:
  Status: success
  Text  : the stale smell of old beer lingers
```

6. Testing Clean vs Noisy and Comparing Results.

Clean and noisy signals are used to evaluate each recogniser's noise robustness. The results show that noise degrades offline recognition more severely than online recognition.

In [ ]:

```python
import soundfile as sf
import numpy as np
import difflib

clean_file = "recovered_best_fixed.wav"
data, sr_rate = sf.read(clean_file)

# Additive white Gaussian noise
noise = np.random.normal(0, 0.02, len(data))
noisy = data + noise
noisy_file = "noisy_version.wav"
sf.write(noisy_file, noisy, sr_rate)

print(f"✅ Noisy version created and saved as {noisy_file}")

results = {}

for mode in ["offline", "online"]:
    for version, path in [("clean", clean_file), ("noisy", noisy_file)]:
        text, status = recognize_audio(path, mode)
        results[(mode, version)] = {"text": text, "status": status}

for (mode, version), info in results.items():
    print(f"{mode.capitalize()} recogniser ({version} speech):")
    print(f"  Status: {info['status']}")
```

```python
    print(f"  Text  : {info['text']}\n")

def similarity(ref, hyp):
    """Return % similarity between two strings."""
    return difflib.SequenceMatcher(None, ref, hyp).ratio() * 100

# Use the online-clean transcript as reference (if available)
ref_text = results[("online", "clean")]["text"]

print("Similarity scores (vs online clean reference):")
for (mode, version), info in results.items():
    if info["status"] == "success":
        score = similarity(ref_text, info["text"])
    else:
        score = 0.0
    print(f"  {mode}-{version}: {score:.2f}% similarity")
```

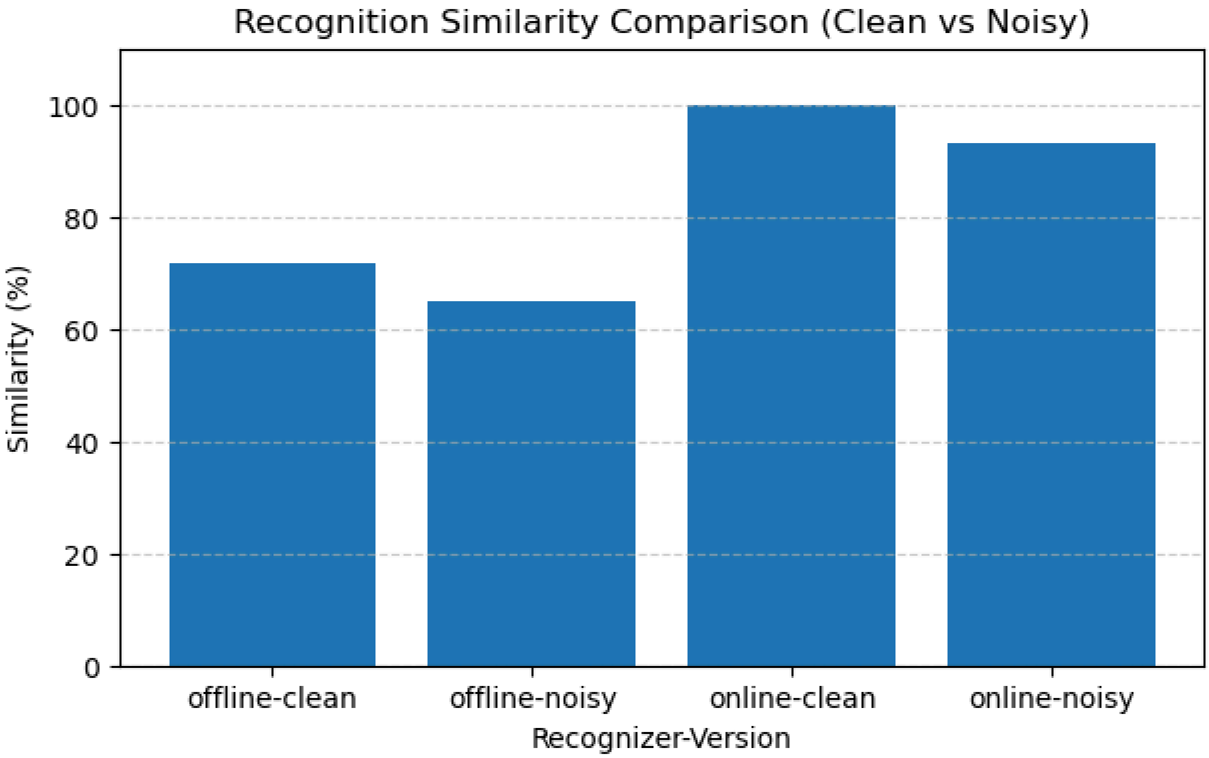
```
✅ Noisy version created and saved as noisy_version.wav

[OFFLINE] Listening to recovered_best_fixed.wav ...
[OFFLINE] ✅ Recognition successful.

[OFFLINE] Listening to noisy_version.wav ...
[OFFLINE] ✅ Recognition successful.

[ONLINE] Listening to recovered_best_fixed.wav ...
[ONLINE] ✅ Recognition successful.

[ONLINE] Listening to noisy_version.wav ...
[ONLINE] ✅ Recognition successful.
Offline recogniser (clean speech):
  Status: success
  Text  : can this they'll smell of old we're lingers

Offline recogniser (noisy speech):
  Status: success
  Text  : this they'll smell of old u. leaders

Online recogniser (clean speech):
  Status: success
  Text  : the stale smell of old beer lingers

Online recogniser (noisy speech):
  Status: success
  Text  : does stale smell of old beer lingers

Similarity scores (vs online clean reference):
  offline-clean: 71.79% similarity
  offline-noisy: 64.79% similarity
  online-clean: 100.00% similarity
  online-noisy: 92.96% similarity
```

7. Display and Compare Recognition Messages & Quantitative Results.

Progress, success, and failure messages verify the recognition workflow and system response. Quantitative comparison (similarity scores) objectively measures performance differences between recognisers and noise levels.

In [ ]:
```
import difflib
import matplotlib.pyplot as plt

for (mode, version), info in results.items():
    if info["status"] == "success":
        msg = "✅ Success"
    elif info["status"] == "failure":
        msg = "❌ Failure"
    else:
        msg = "⚠ Error"

    print(f"{mode.capitalize()} recogniser ({version} speech): {msg}")

def similarity(ref, hyp):
    """Return % similarity between two strings."""
    return difflib.SequenceMatcher(None, ref, hyp).ratio() * 100

# Use online-clean output as reference
ref_text = results[("online", "clean")]["text"]

scores = {}
for (mode, version), info in results.items():
    if info["status"] == "success":
        scores[(mode, version)] = similarity(ref_text, info["text"])
    else:
        scores[(mode, version)] = 0.0

# Display numeric results
print("\n--- Quantitative Comparison ---")
for (mode, version), score in scores.items():
    print(f"{mode}-{version}: {score:.2f}% similarity")

labels = [f"{m}-{v}" for (m, v) in scores.keys()]
values = list(scores.values())

plt.figure(figsize=(7,4))
plt.bar(labels, values)
plt.title("Recognition Similarity Comparison (Clean vs Noisy)")
plt.xlabel("Recognizer-Version")
plt.ylabel("Similarity (%)")
plt.ylim(0, 110)
plt.grid(axis="y", linestyle="--", alpha=0.6)
plt.show()
```

```
Offline recogniser (clean speech): ✅ Success
Offline recogniser (noisy speech): ✅ Success
Online recogniser (clean speech): ✅ Success
Online recogniser (noisy speech): ✅ Success

--- Quantitative Comparison ---
offline-clean: 71.79% similarity
offline-noisy: 64.79% similarity
online-clean: 100.00% similarity
online-noisy: 92.96% similarity
```



INFERENCE

- The speech signal's maximum frequency determines the minimum required sampling rate for faithful reconstruction.
- Sampling above the Nyquist rate prevents aliasing and maintains clarity in the recovered signal.
- Reconstructing at higher sampling rates improves the naturalness and intelligibility of speech.
- The reconstructed audio, when saved as a .wav file, is suitable for recognition systems requiring PCM format.
- Both offline and online recognisers successfully converted the speech

signal into text.

- The online recogniser produced more accurate and consistent results than the offline recogniser.
- Noise addition degraded recognition accuracy, particularly for the offline recogniser.
- The online recogniser showed better noise robustness due to advanced cloud-based models.
- Quantitative comparison confirmed higher similarity scores for online recognition on both clean and noisy signals.
- Overall, online recognition is preferred for accuracy, while offline systems are useful when internet access is limited.