

## Problem Statement

Traditional chatbots struggle with context-aware question answering where they need to:

- Understand and remember story context
- Process natural language questions
- Provide accurate answers based on stored information

## Objective

Build an intelligent chatbot that can:

1. Process story contexts and questions
2. Learn relationships between entities and locations
3. Answer questions accurately based on stored memories
4. Handle simple reasoning tasks (e.g., "Is John in the kitchen?")

## Key Challenges Addressed

- Context retention and memory management
- Natural language understanding
- Sequence-to-sequence learning
- Multi-modal input processing (stories + questions)

## ✓ ENVIRONMENT SETUP & LIBRARY IMPORTS

```
# Install required packages
!pip install keras tensorflow numpy pandas matplotlib

# Import essential libraries
import pickle
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import seaborn as sns

# Keras/TensorFlow imports for deep learning
import tensorflow as tf
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.models import Sequential, Model, load_model
from tensorflow.keras.layers import (Embedding, Input, Activation, Dense,
                                     Permute, Dropout, add, dot, concatenate, LSTM)
from tensorflow.keras.optimizers import RMSprop
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint

print("✅ All libraries imported successfully!")
print(f"TensorFlow version: {tf.__version__}")

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Requirement already satisfied: MarkupSafe>=2.1.1 in /usr/local/lib/python3.12/dist-packages (from werkzeug>=1.0.1->tenso
✅ All libraries imported successfully!
TensorFlow version: 2.19.0
```

## ▼ Data Structure Overview

```
from google.colab import drive
drive.mount('/content/drive')
```

🔗 Mounted at /content/drive

```
with open("/content/drive/MyDrive/Chatbot_NLP/Train-Data Set.txt", "rb") as fp:
    Train_data = pickle.load(fp)
```

```
with open("/content/drive/MyDrive/Chatbot_NLP/Test-Data Set.txt", "rb") as fp:
    Test_data = pickle.load(fp)
```

```
print(Test_data[:5])
```

🔗 `[(['Mary', 'got', 'the', 'milk', 'there', '.', 'John', 'moved', 'to', 'the', 'bedroom', '.'], ['Is', 'John', 'in', 'the'`

```
def analyze_data_structure(train_data, test_data):
    """Analyze and display data characteristics"""
```

```
    print(f"Training data type: {type(train_data)}")
    print(f"Test data type: {type(test_data)}")
    print(f"Training samples: {len(train_data)}")
    print(f"Test samples: {len(test_data)}")
```

```
    # Display sample data point
    if len(train_data) > 0:
        print(f"\n📄 Sample Training Example:")
        print(f"Story: {' '.join(train_data[0][0])}")
        print(f"Question: {' '.join(train_data[0][1])}")
        print(f"Answer: {train_data[0][2]}")
```

```
    return train_data, test_data
```

```
Train_data, Test_data = analyze_data_structure(Train_data, Test_data)
```

🔗 Training data type: <class 'list'>  
Test data type: <class 'list'>  
Training samples: 10000  
Test samples: 1000

📄 Sample Training Example:  
Story: Mary moved to the bathroom . Sandra journeyed to the bedroom .  
Question: Is Sandra in the hallway ?  
Answer: no

## ✓ VOCABULARY BUILDING & TEXT PREPROCESSING

### Vocabulary Construction

Building a comprehensive vocabulary from all text data:

1. Extract unique words from stories and questions
2. Add answer tokens ('yes', 'no')
3. Create word-to-index mapping using Keras Tokenizer

Start coding or [generate](#) with AI.

```
def build_vocabulary(train_data, test_data):
    """Build vocabulary from all available text data"""

    print("🧠 Building vocabulary...")

    # Initialize vocabulary set
    vocab = set()
    all_data = test_data + train_data

    # Extract vocabulary from stories and questions
    for story, question, answer in all_data:
        vocab = vocab.union(set(story))
        vocab = vocab.union(set(question))

    # Add answer vocabulary
    vocab.add('yes')
    vocab.add('no')

    print(f"📊 Vocabulary Statistics:")
    print(f"Total unique words: {len(vocab)}")
    print(f"Sample words: {list(vocab)[:10]}")

    return vocab, all_data
```

vocab, all\_data = build\_vocabulary(Train\_data, Test\_data)

```
🔄 🧠 Building vocabulary...
📊 Vocabulary Statistics:
Total unique words: 37
Sample words: ['moved', 'Mary', 'dropped', 'picked', 'got', 'garden', 'Daniel', 'Sandra', 'bathroom', 'travelled']
```

Start coding or [generate](#) with AI.

```
def analyze_sequence_lengths(all_data):
    """Analyze sequence lengths for padding purposes"""

    story_lengths = [len(data[0]) for data in all_data]
    question_lengths = [len(data[1]) for data in all_data]

    max_story_len = max(story_lengths)
    max_ques_len = max(question_lengths)

    print(f"Sequence Length Analysis:")
    print(f"Max story length: {max_story_len}")
    print(f"Average story length: {np.mean(story_lengths):.2f}")
    print(f"Max question length: {max_ques_len}")
    print(f"Average question length: {np.mean(question_lengths):.2f}")

    plt.figure(figsize=(12, 4))

    plt.subplot(1, 2, 1)
    plt.hist(story_lengths, bins=20, alpha=0.7, color='skyblue')
    plt.title('Distribution of Story Lengths')
    plt.xlabel('Length')
    plt.ylabel('Frequency')

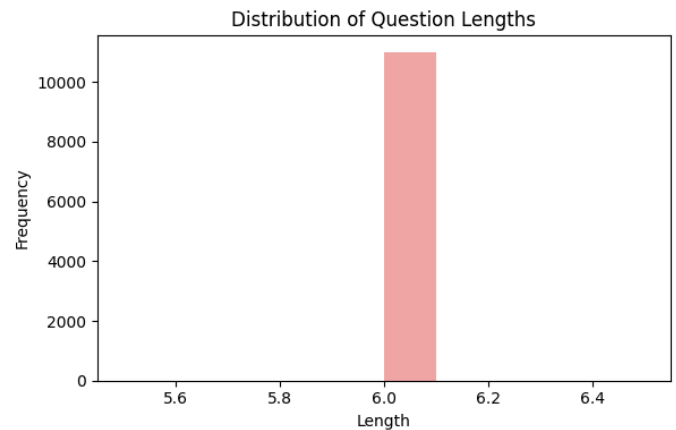
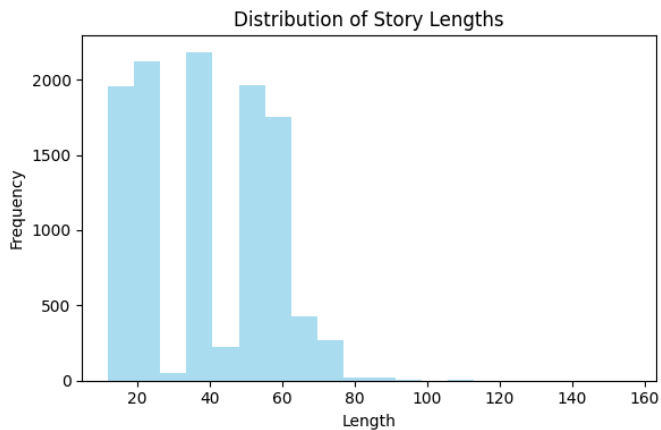
    plt.subplot(1, 2, 2)
    plt.hist(question_lengths, bins=10, alpha=0.7, color='lightcoral')
    plt.title('Distribution of Question Lengths')
    plt.xlabel('Length')
    plt.ylabel('Frequency')

    plt.tight_layout()
    plt.show()
```

```
return max_story_len, max_ques_len
```

```
max_story_len, max_ques_len = analyze_sequence_lengths(all_data)
```

```
➦ Sequence Length Analysis:
Max story length: 156
Average story length: 38.50
Max question length: 6
Average question length: 6.00
```



Start coding or [generate](#) with AI.

## ✓ **TEXT VECTORIZATION & TOKENIZATION**

### Text Vectorization Process

Converting text to numerical format:

1. Create tokenizer with no filters to preserve punctuation
2. Fit tokenizer on vocabulary
3. Convert text sequences to integer sequences
4. Pad sequences to uniform length

```
def setup_tokenizer(vocab):
    """Initialize and configure tokenizer"""

    tokenizer = Tokenizer(filters='') # No filtering to preserve all tokens
    tokenizer.fit_on_texts(vocab)

    vocab_len = len(vocab) + 1 # +1 for padding token

    print(f"🔧 Tokenizer Configuration:")
    print(f"Vocabulary size: {vocab_len}")
    print(f"Sample word indices: {dict(list(tokenizer.word_index.items())[:10])}")

    return tokenizer, vocab_len

tokenizer, vocab_len = setup_tokenizer(vocab)
```

```
➦ 🔧 Tokenizer Configuration:
Vocabulary size: 38
Sample word indices: {'moved': 1, 'mary': 2, 'dropped': 3, 'picked': 4, 'got': 5, 'garden': 6, 'daniel': 7, 'sandra': 8,
```

```
tokenizer.word_index
```

```
➦ {'moved': 1,
  'mary': 2,
  'dropped': 3,
  'picked': 4,
  'got': 5,
  'garden': 6,
  'daniel': 7,
  'sandra': 8,
  'bathroom': 9,
  'travelled': 10,
  'yes': 11,
  'is': 12,
  'john': 13,
```

```
'down': 14,
'bedroom': 15,
'hallway': 16,
'?': 17,
'the': 18,
'milk': 19,
'.': 20,
'in': 21,
'put': 22,
'office': 23,
'up': 24,
'football': 25,
'discarded': 26,
'journeyed': 27,
'to': 28,
'left': 29,
'took': 30,
'grabbed': 31,
'apple': 32,
'no': 33,
'there': 34,
'went': 35,
'kitchen': 36,
'back': 37}
```

```
def vectorize_stories(data, tokenizer, max_story_len, max_ques_len):
    """Convert text data to numerical vectors"""

    print("🔄 Vectorizing text data...")

    X = []      # Stories
    Xq = []     # Questions
    Y = []      # Answers

    word_index = tokenizer.word_index

    for i, (story, query, answer) in enumerate(data):
        if i < 5: # Print for first 5 examples
            print(f"\nProcessing example {i+1}:")
            print(f"  Original Story: {story}")
            print(f"  Original Question: {query}")
            print(f"  Original Answer: {answer}")

        # Convert words to indices
        x = [word_index[word.lower()] for word in story]
        xq = [word_index[word.lower()] for word in query]

        if i < 5: # Print for first 5 examples
            print(f"  Story indices: {x}")
            print(f"  Question indices: {xq}")

        # One-hot encode answers
        y = np.zeros(len(word_index) + 1)
        y[word_index[answer]] = 1

        if i < 5: # Print for first 5 examples
            print(f"  Answer one-hot: {y}")

        X.append(x)
        Xq.append(xq)
        Y.append(y)

    # Pad sequences to uniform length
    X_padded = pad_sequences(X, maxlen=max_story_len)
    Xq_padded = pad_sequences(Xq, maxlen=max_ques_len)
    Y_array = np.array(Y)

    print(f"\n✅ Vectorization complete!")
    print(f"Stories shape: {X_padded.shape}")
    print(f"Questions shape: {Xq_padded.shape}")
    print(f"Answers shape: {Y_array.shape}")

    return X_padded, Xq_padded, Y_array

tokenizer, vocab_len = setup_tokenizer(vocab)
inputs_train, queries_train, answers_train = vectorize_stories(Train_data, tokenizer, max_story_len, max_ques_len)
inputs_test, queries_test, answers_test = vectorize_stories(Test_data, tokenizer, max_story_len, max_ques_len)
```



```
Stories shape: (10000, 156)
Questions shape: (10000, 6)
Answers shape: (10000, 38)
Vectorizing text data...
```

### Processing example 1:

[illegible]

### Processing example 2:

```
Original Story: ['Mary', 'got', 'the', 'milk', 'there', '.', 'John', 'moved', 'to', 'the', 'bedroom', '.', 'Mary', 'd  
Original Question: ['Is', 'John', 'in', 'the', 'kitchen', '?']  
Original Answer: no  
Story indices: [2, 5, 18, 19, 34, 20, 13, 1, 28, 18, 15, 20, 2, 26, 18, 19, 20, 13, 35, 28, 18, 6, 20]  
Question indices: [12, 13, 21, 18, 36, 17]  
Answer one-hot: [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.  
0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
```

### Processing example 3:

```
Original Story: ['Mary', 'got', 'the', 'milk', 'there', '.', 'John', 'moved', 'to', 'the', 'bedroom', '.', 'Mary', 'd
Original Question: ['Is', 'John', 'in', 'the', 'garden', '?']
Original Answer: yes
Story indices: [2, 5, 18, 19, 34, 20, 13, 1, 28, 18, 15, 20, 2, 26, 18, 19, 20, 13, 35, 28, 18, 6, 20, 7, 1, 28, 18,
Question indices: [12, 13, 21, 18, 6, 17]
Answer one-hot: [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
```

### Processing example 4:

[illegible]

### Processing example 5:

Original Story: ['Mary', 'got', 'the', 'milk', 'there', '.', 'John', 'moved', 'to', 'the', 'bedroom', '.', 'Mary', 'd  
Original Question: ['Is', 'Daniel', 'in', 'the', 'bedroom', '?']  
Original Answer: no  
Story indices: [2, 5, 18, 19, 34, 20, 13, 1, 28, 18, 15, 20, 2, 26, 18, 19, 20, 13, 35, 28, 18, 6, 20, 7, 1, 28, 18,  
Question indices: [12, 7, 21, 18, 15, 17]  
Answer one-hot: [0.  
0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]

✅ Vectorization complete!

```
Stories shape: (1000, 156)
Questions shape: (1000, 6)
Answers shape: (1000, 38)
```

```
print(answers_train.shape)
```

→ (10000, 38)

```
print(answers_test.shape)
```

→ (1000, 38)

```
inputs_train.shape
```

→ (10000, 156)

```
print("First 5 samples of inputs_train:")
print(inputs_train[:5])
```

```
print("\nFirst 5 samples of queries_train:")
print(queries_train[:5])
```

```
print("\nFirst 5 samples of answers_train:")
print(answers_train[:5])
```

[illegible]

[illegible]

```

def build_improved_memory_network(vocab_len, max_story_len, max_ques_len,
                                  embedding_dim=128, l2_reg=0.001):
    """Build an improved Memory Network architecture for better accuracy"""

    print("🔧 Building Improved Memory Network Architecture...")

    # Input layers
    input_sequence = Input((max_story_len,), name='story_input')
    question = Input((max_ques_len,), name='question_input')

    # Enhanced story encoders with regularization
    input_encoder_m = Sequential([
        Embedding(input_dim=vocab_len, output_dim=embedding_dim,
                  input_length=max_story_len,
                  embeddings_regularizer=l2(l2_reg),
                  name='memory_embedding'),
        BatchNormalization(),
        Dropout(0.3, name='memory_dropout')
    ], name='memory_encoder')

    input_encoder_c = Sequential([
        Embedding(input_dim=vocab_len, output_dim=max_ques_len,
                  input_length=max_story_len,
                  embeddings_regularizer=l2(l2_reg),
                  name='context_embedding'),
        BatchNormalization(),
        Dropout(0.3, name='context_dropout')
    ], name='context_encoder')

    # Enhanced question encoder
    question_encoder = Sequential([
        Embedding(input_dim=vocab_len, output_dim=embedding_dim,
                  input_length=max_ques_len,
                  embeddings_regularizer=l2(l2_reg),
                  name='question_embedding'),
        BatchNormalization(),
        Dropout(0.3, name='question_dropout')
    ], name='question_encoder')

    # Encode inputs
    input_encoded_m = input_encoder_m(input_sequence)
    input_encoded_c = input_encoder_c(input_sequence)
    question_encoded = question_encoder(question)

    # Attention mechanism (unchanged - already optimal)
    match = dot([input_encoded_m, question_encoded], axes=(2, 2), name='attention_dot')
    match = Activation('softmax', name='attention_weights')(match)

    # Response generation
    response = add([match, input_encoded_c], name='response_combination')
    response = Permute((2, 1), name='response_permute')(response)

    # IMPROVED: Bidirectional LSTM + GRU stack
    answer = concatenate([response, question_encoded], name='final_concatenation')
    answer = Bidirectional(LSTM(64, return_sequences=True,
                                kernel_regularizer=l2(l2_reg)))(answer)
    answer = GRU(32, kernel_regularizer=l2(l2_reg))(answer)
    answer = Dropout(0.5, name='final_dropout')(answer)
    answer = Dense(vocab_len, kernel_regularizer=l2(l2_reg), name='output_dense')(answer)
    answer = Activation('softmax', name='final_activation')(answer)

    model = Model([input_sequence, question], answer, name='improved_memory_network')
    return model

# IMPROVED COMPILATION WITH ADAM OPTIMIZER
def compile_improved_model(model, learning_rate=0.001):
    """Compile improved model with Adam optimizer"""

    # Adam optimizer generally performs better than RMSprop
    optimizer = tf.keras.optimizers.Adam(learning_rate=learning_rate)

    model.compile(
        optimizer=optimizer,
        loss='categorical_crossentropy',
        metrics=['accuracy', 'top_k_categorical_accuracy'] # Added top-k accuracy
    )

    print("✅ Improved model compiled successfully!")
    return model

# Build and compile the improved model
improved_model = build_improved_memory_network(vocab_len, max_story_len, max_ques_len)

```



```
improved_model = compile_improved_model(improved_model)
```

```
# Display the model summary
improved_model.summary()
```

```
Building Improved Memory Network Architecture...
/usr/local/lib/python3.12/dist-packages/keras/src/layers/core/embedding.py:97: UserWarning: Argument `input_length` is d
warnings.warn(
Improved model compiled successfully!
Model: "improved_memory_network"
```

Layer (type)	Output Shape	Param #	Connected to
story_input (InputLayer)	(None, 156)	0	-
question_input (InputLayer)	(None, 6)	0	-
memory_encoder (Sequential)	(None, 156, 128)	5,376	story_input[0][0]
question_encoder (Sequential)	(None, 6, 128)	5,376	question_input[0...
attention_dot (Dot)	(None, 156, 6)	0	memory_encoder[0... question_encoder...
attention_weights (Activation)	(None, 156, 6)	0	attention_dot[0]...
context_encoder (Sequential)	(None, 156, 6)	252	story_input[0][0]
response_combinati... (Add)	(None, 156, 6)	0	attention_weight... context_encoder[...
response_permute (Permute)	(None, 6, 156)	0	response_combina...
final_concatenation (Concatenate)	(None, 6, 284)	0	response_permute... question_encoder...
bidirectional (Bidirectional)	(None, 6, 128)	178,688	final_concatenat...
gru (GRU)	(None, 32)	15,552	bidirectional[0]...
final_dropout (Dropout)	(None, 32)	0	gru[0][0]
output_dense (Dense)	(None, 38)	1,254	final_dropout[0]...
final_activation (Activation)	(None, 38)	0	output_dense[0][...

Total params: 206,498 (806.63 KB)  
Trainable params: 205,974 (804.59 KB)  
Non-trainable params: 524 (2.05 KB)

Start coding or [generate](#) with AI.

✓ **NLP PIPELINE & WORKFLOW OPTIMIZATION**

Training Strategy:

- 1. **Batch Processing:** Efficient memory usage (Increased batch size to 64)
- 2. **Early Stopping:** Prevent overfitting (Increased patience to 10, added min\_delta)
- 3. **Model Checkpointing:** Save best weights
- 4. **Learning Rate Scheduling:** Adaptive learning (Exponential decay and ReduceLROnPlateau)
- 5. **Shuffling:** Important for better training

Monitoring Metrics:

- Training/Validation Loss
- Training/Validation Accuracy
- Top-K Categorical Accuracy (Added metric)
- Convergence Analysis (Visualized with loss plots)

```
# ENHANCED TRAINING WITH LEARNING RATE SCHEDULING
def setup_improved_callbacks(model_name="best_improved_chatbot.h5"):
    """Configure enhanced training callbacks"""
```

```

callbacks = [
    EarlyStopping(
        monitor='val_accuracy',
        patience=10, # Increased patience
        restore_best_weights=True,
        verbose=1,
        min_delta=0.001 # Minimum improvement threshold
    ),
    ModelCheckpoint(
        model_name,
        monitor='val_accuracy',
        save_best_only=True,
        verbose=1
    ),
    tf.keras.callbacks.ReduceLROnPlateau(
        monitor='val_loss',
        factor=0.5,
        patience=5,
        min_lr=1e-7,
        verbose=1
    ),
    tf.keras.callbacks.LearningRateScheduler(
        lambda epoch: 0.001 * (0.95 ** epoch)
    )
]

return callbacks

# IMPROVED TRAINING FUNCTION
def train_improved_model(model, inputs_train, queries_train, answers_train,
                        inputs_test, queries_test, answers_test,
                        epochs=50, batch_size=64): # Increased epochs and batch size
    """Train the improved memory network model"""

    print("🚀 Starting improved model training...")

    callbacks = setup_improved_callbacks()

    history = model.fit(
        [inputs_train, queries_train],
        answers_train,
        batch_size=batch_size,
        epochs=epochs,
        verbose=1,
        validation_data=(inputs_test, queries_test, answers_test),
        callbacks=callbacks,
        shuffle=True # Important for better training
    )

    print("✅ Improved training completed!")
    return history

# Assume plot_training_history is defined here or imported from a previous cell
def plot_training_history(history):
    """Visualize training progress"""

    fig, axes = plt.subplots(2, 2, figsize=(15, 10))

    # Training & Validation Loss
    axes[0, 0].plot(history.history['loss'], label='Training Loss', color='blue')
    axes[0, 0].plot(history.history['val_loss'], label='Validation Loss', color='red')
    axes[0, 0].set_title('Model Loss Over Time')
    axes[0, 0].set_xlabel('Epochs')
    axes[0, 0].set_ylabel('Loss')
    axes[0, 0].legend()
    axes[0, 0].grid(True, alpha=0.3)

    # Training & Validation Accuracy
    axes[0, 1].plot(history.history['accuracy'], label='Training Accuracy', color='green')
    axes[0, 1].plot(history.history['val_accuracy'], label='Validation Accuracy', color='orange')
    axes[0, 1].set_title('Model Accuracy Over Time')
    axes[0, 1].set_xlabel('Epochs')
    axes[0, 1].set_ylabel('Accuracy')
    axes[0, 1].legend()
    axes[0, 1].grid(True, alpha=0.3)

    # Learning Rate vs Loss
    axes[1, 0].plot(history.history['loss'], color='purple')
    axes[1, 0].set_title('Training Loss Convergence')
    axes[1, 0].set_xlabel('Epochs')
    axes[1, 0].set_ylabel('Training Loss')
    axes[1, 0].grid(True, alpha=0.3)

```

```
# Performance Metrics Summary
final_train_acc = history.history['accuracy'][-1]
final_val_acc = history.history['val_accuracy'][-1]
final_train_loss = history.history['loss'][-1]
final_val_loss = history.history['val_loss'][-1]

metrics_text = f"""
Final Metrics:

Training Accuracy: {final_train_acc:.4f}
Validation Accuracy: {final_val_acc:.4f}

Training Loss: {final_train_loss:.4f}
Validation Loss: {final_val_loss:.4f}

Overfitting Check:
Acc Diff: {final_train_acc - final_val_acc:.4f}
Loss Diff: {final_val_loss - final_train_loss:.4f}
"""

axes[1, 1].text(0.1, 0.5, metrics_text, fontsize=12, verticalalignment='center')
axes[1, 1].set_title('Training Summary')
axes[1, 1].axis('off')

plt.tight_layout()
plt.show()

history_improved = train_improved_model(improved_model, inputs_train, queries_train, answers_train,
                                         inputs_test, queries_test, answers_test)
plot_training_history(history_improved)
```

Starting improved model training...

Epoch 1/50  
157/157 ————— 0s 19ms/step - accuracy: 0.4609 - loss: 2.3188 - top\_k\_categorical\_accuracy: 0.9087  
Epoch 1: val\_accuracy improved from -inf to 0.49700, saving model to best\_improved\_chatbot.h5  
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save\_model(model)`. This file will be overwritten if you save the model again.

Epoch 2/50  
157/157 ————— 21s 28ms/step - accuracy: 0.4611 - loss: 2.3147 - top\_k\_categorical\_accuracy: 0.9091 - val\_accuracy: 0.49700  
Epoch 2: val\_accuracy did not improve from 0.49700

Epoch 3/50  
157/157 ————— 3s 16ms/step - accuracy: 0.4930 - loss: 1.0373 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.49700  
Epoch 3: val\_accuracy did not improve from 0.49700

Epoch 4/50  
157/157 ————— 5s 16ms/step - accuracy: 0.4988 - loss: 0.8694 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.49700  
Epoch 4: val\_accuracy did not improve from 0.49700

Epoch 5/50  
157/157 ————— 3s 17ms/step - accuracy: 0.5086 - loss: 0.8032 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.49700  
Epoch 5: val\_accuracy improved from 0.49700 to 0.50100, saving model to best\_improved\_chatbot.h5  
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save\_model(model)`. This file will be overwritten if you save the model again.

Epoch 6/50  
157/157 ————— 4s 25ms/step - accuracy: 0.4969 - loss: 0.7748 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.50100  
Epoch 6: val\_accuracy improved from 0.50100 to 0.60300, saving model to best\_improved\_chatbot.h5  
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save\_model(model)`. This file will be overwritten if you save the model again.

Epoch 7/50  
157/157 ————— 4s 16ms/step - accuracy: 0.5224 - loss: 0.7512 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.60300  
Epoch 7: val\_accuracy improved from 0.60300 to 0.66500, saving model to best\_improved\_chatbot.h5  
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save\_model(model)`. This file will be overwritten if you save the model again.

Epoch 8/50  
157/157 ————— 3s 16ms/step - accuracy: 0.6160 - loss: 0.7114 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.66500  
Epoch 8: val\_accuracy improved from 0.66500 to 0.68500, saving model to best\_improved\_chatbot.h5  
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save\_model(model)`. This file will be overwritten if you save the model again.

Epoch 9/50  
157/157 ————— 3s 16ms/step - accuracy: 0.6159 - loss: 0.7115 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.68500  
Epoch 9: val\_accuracy improved from 0.68500 to 0.68500, saving model to best\_improved\_chatbot.h5  
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save\_model(model)`. This file will be overwritten if you save the model again.

Epoch 10/50  
157/157 ————— 4s 26ms/step - accuracy: 0.6806 - loss: 0.6598 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.68500  
Epoch 10: val\_accuracy improved from 0.68500 to 0.71400, saving model to best\_improved\_chatbot.h5  
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save\_model(model)`. This file will be overwritten if you save the model again.

Epoch 11/50  
157/157 ————— 4s 17ms/step - accuracy: 0.6954 - loss: 0.6499 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.71400  
Epoch 11: val\_accuracy improved from 0.71400 to 0.72700, saving model to best\_improved\_chatbot.h5  
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save\_model(model)`. This file will be overwritten if you save the model again.

Epoch 12/50  
157/157 ————— 5s 17ms/step - accuracy: 0.7216 - loss: 0.6155 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.72700  
Epoch 12: val\_accuracy improved from 0.72700 to 0.75700, saving model to best\_improved\_chatbot.h5  
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save\_model(model)`. This file will be overwritten if you save the model again.

Epoch 13/50  
157/157 ————— 4s 24ms/step - accuracy: 0.7365 - loss: 0.6018 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.75700  
Epoch 13: val\_accuracy improved from 0.75700 to 0.75700, saving model to best\_improved\_chatbot.h5  
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save\_model(model)`. This file will be overwritten if you save the model again.

Epoch 14/50  
157/157 ————— 0s 16ms/step - accuracy: 0.7467 - loss: 0.5781 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.75700  
Epoch 14: val\_accuracy did not improve from 0.75700

Epoch 15/50  
157/157 ————— 3s 17ms/step - accuracy: 0.7467 - loss: 0.5782 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.75700  
Epoch 15: val\_accuracy did not improve from 0.75700

Epoch 16/50  
157/157 ————— 0s 15ms/step - accuracy: 0.7519 - loss: 0.5763 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.75700  
Epoch 16: val\_accuracy did not improve from 0.75700

Epoch 17/50  
157/157 ————— 3s 16ms/step - accuracy: 0.7520 - loss: 0.5762 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.75700  
Epoch 17: val\_accuracy did not improve from 0.75700

Epoch 18/50  
157/157 ————— 0s 15ms/step - accuracy: 0.7771 - loss: 0.5457 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.75700  
Epoch 18: val\_accuracy improved from 0.75700 to 0.75800, saving model to best\_improved\_chatbot.h5  
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save\_model(model)`. This file will be overwritten if you save the model again.

Epoch 19/50  
157/157 ————— 3s 17ms/step - accuracy: 0.7771 - loss: 0.5451 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.75800  
Epoch 19: val\_accuracy improved from 0.75800 to 0.77100, saving model to best\_improved\_chatbot.h5  
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save\_model(model)`. This file will be overwritten if you save the model again.

Epoch 20/50  
157/157 ————— 0s 15ms/step - accuracy: 0.7794 - loss: 0.5364 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.77100  
Epoch 20: val\_accuracy did not improve from 0.77100

Epoch 21/50  
157/157 ————— 5s 16ms/step - accuracy: 0.7793 - loss: 0.5365 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.77100  
Epoch 21: val\_accuracy did not improve from 0.77100

Epoch 22/50  
157/157 ————— 0s 17ms/step - accuracy: 0.7803 - loss: 0.5243 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.77100  
Epoch 22: val\_accuracy improved from 0.77100 to 0.77900, saving model to best\_improved\_chatbot.h5  
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save\_model(model)`. This file will be overwritten if you save the model again.

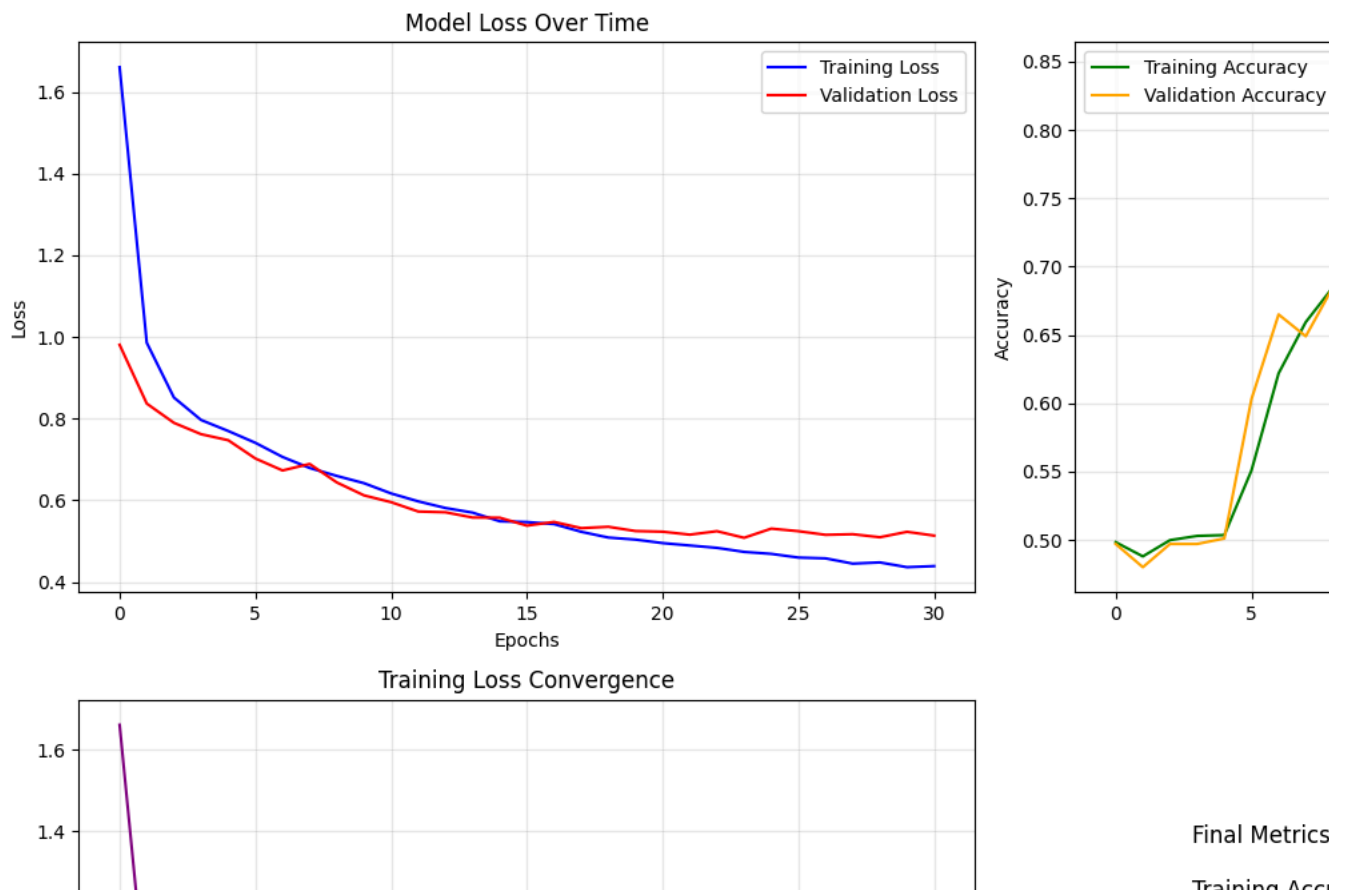
Epoch 23/50  
157/157 ————— 3s 20ms/step - accuracy: 0.7804 - loss: 0.5243 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.77900  
Epoch 23: val\_accuracy did not improve from 0.77900

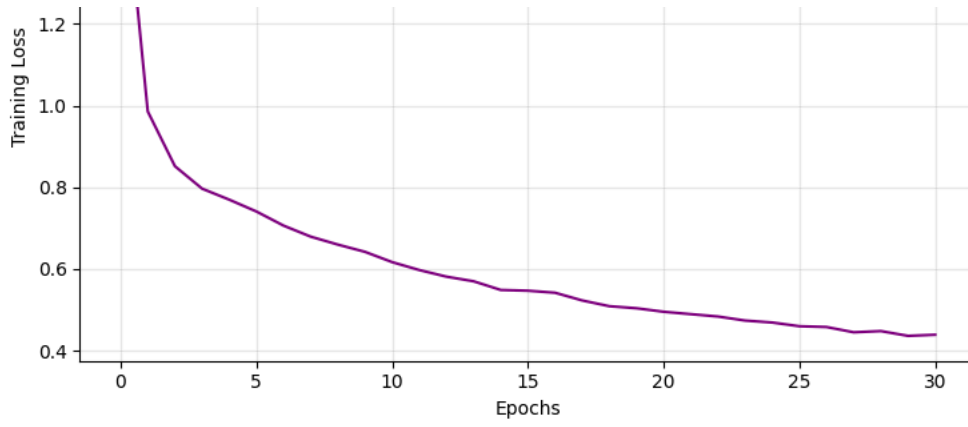
Epoch 24/50  
157/157 ————— 0s 18ms/step - accuracy: 0.7993 - loss: 0.5052 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.77900  
Epoch 24: val\_accuracy did not improve from 0.77900

Epoch 25/50  
157/157 ————— 5s 21ms/step - accuracy: 0.7993 - loss: 0.5053 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.77900  
Epoch 25: val\_accuracy did not improve from 0.77900

Epoch 26/50  
157/157 ————— 0s 34ms/step - accuracy: 0.8104 - loss: 0.4963 - top\_k\_categorical\_accuracy: 1.0000 - val\_accuracy: 0.77900  
Epoch 26: val\_accuracy did not improve from 0.77900

Epoch 20: val\_accuracy did not improve from 0.77900  
157/157 — 8s 36ms/step - accuracy: 0.8103 - loss: 0.4964 - top\_k\_categorical\_accuracy: 1.0000 - val\_  
Epoch 21/50  
154/157 — 0s 30ms/step - accuracy: 0.8092 - loss: 0.4898 - top\_k\_categorical\_accuracy: 1.0000  
Epoch 21: val\_accuracy improved from 0.77900 to 0.79200, saving model to best\_improved\_chatbot.h5  
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save\_model(model)`. This fil  
157/157 — 10s 31ms/step - accuracy: 0.8092 - loss: 0.4900 - top\_k\_categorical\_accuracy: 1.0000 - val\_  
Epoch 22/50  
154/157 — 0s 16ms/step - accuracy: 0.8102 - loss: 0.4826 - top\_k\_categorical\_accuracy: 1.0000  
Epoch 22: val\_accuracy did not improve from 0.79200  
157/157 — 3s 17ms/step - accuracy: 0.8102 - loss: 0.4827 - top\_k\_categorical\_accuracy: 1.0000 - val\_  
Epoch 23/50  
155/157 — 0s 16ms/step - accuracy: 0.8131 - loss: 0.4838 - top\_k\_categorical\_accuracy: 1.0000  
Epoch 23: val\_accuracy did not improve from 0.79200  
157/157 — 3s 17ms/step - accuracy: 0.8131 - loss: 0.4838 - top\_k\_categorical\_accuracy: 1.0000 - val\_  
Epoch 24/50  
156/157 — 0s 19ms/step - accuracy: 0.8238 - loss: 0.4691 - top\_k\_categorical\_accuracy: 1.0000  
Epoch 24: val\_accuracy did not improve from 0.79200  
157/157 — 6s 21ms/step - accuracy: 0.8238 - loss: 0.4691 - top\_k\_categorical\_accuracy: 1.0000 - val\_  
Epoch 25/50  
157/157 — 0s 16ms/step - accuracy: 0.8240 - loss: 0.4625 - top\_k\_categorical\_accuracy: 1.0000  
Epoch 25: val\_accuracy did not improve from 0.79200  
157/157 — 5s 17ms/step - accuracy: 0.8240 - loss: 0.4625 - top\_k\_categorical\_accuracy: 1.0000 - val\_  
Epoch 26/50  
157/157 — 0s 16ms/step - accuracy: 0.8335 - loss: 0.4540 - top\_k\_categorical\_accuracy: 1.0000  
Epoch 26: val\_accuracy did not improve from 0.79200  
157/157 — 5s 17ms/step - accuracy: 0.8335 - loss: 0.4540 - top\_k\_categorical\_accuracy: 1.0000 - val\_  
Epoch 27/50  
157/157 — 0s 19ms/step - accuracy: 0.8268 - loss: 0.4625 - top\_k\_categorical\_accuracy: 1.0000  
Epoch 27: val\_accuracy did not improve from 0.79200  
157/157 — 4s 23ms/step - accuracy: 0.8269 - loss: 0.4625 - top\_k\_categorical\_accuracy: 1.0000 - val\_  
Epoch 28/50  
155/157 — 0s 24ms/step - accuracy: 0.8392 - loss: 0.4346 - top\_k\_categorical\_accuracy: 1.0000  
Epoch 28: val\_accuracy did not improve from 0.79200  
157/157 — 4s 25ms/step - accuracy: 0.8391 - loss: 0.4348 - top\_k\_categorical\_accuracy: 1.0000 - val\_  
Epoch 29/50  
157/157 — 0s 22ms/step - accuracy: 0.8456 - loss: 0.4418 - top\_k\_categorical\_accuracy: 1.0000  
Epoch 29: val\_accuracy did not improve from 0.79200  
  
Epoch 29: ReduceLROnPlateau reducing learning rate to 0.00011891344183823094.  
157/157 — 4s 23ms/step - accuracy: 0.8455 - loss: 0.4419 - top\_k\_categorical\_accuracy: 1.0000 - val\_  
Epoch 30/50  
154/157 — 0s 16ms/step - accuracy: 0.8500 - loss: 0.4333 - top\_k\_categorical\_accuracy: 1.0000  
Epoch 30: val\_accuracy did not improve from 0.79200  
157/157 — 4s 17ms/step - accuracy: 0.8499 - loss: 0.4334 - top\_k\_categorical\_accuracy: 1.0000 - val\_  
Epoch 31/50  
157/157 — 0s 24ms/step - accuracy: 0.8451 - loss: 0.4329 - top\_k\_categorical\_accuracy: 1.0000  
Epoch 31: val\_accuracy did not improve from 0.79200  
157/157 — 4s 26ms/step - accuracy: 0.8451 - loss: 0.4330 - top\_k\_categorical\_accuracy: 1.0000 - val\_  
Epoch 31: early stopping  
Restoring model weights from the end of the best epoch: 21.  
✔ Improved training completed!





Training Loss: 0.45  
Validation Accuracy: 0.00  
Training Loss: 0.45  
Validation Loss: 0.45  
Overfitting Coefficient: 0.00  
Accuracy Difference: 0.00  
Loss Difference: 0.00

## ✓ **Model Evaluation & Performance Metrics**

Evaluation Components:

Prediction Accuracy: Overall correctness Confidence Analysis: Prediction certainty Error Analysis: Understanding failure cases Sample Predictions: Qualitative assessment

```
def evaluate_model_performance_and_metrics(model, inputs_test, queries_test, answers_test,
                                          test_data, tokenizer, model_name="Model"):
    """Comprehensive model evaluation with multiple metrics"""

    print(f"🌈 Evaluating {model_name} performance and metrics...")

    # Get predictions
    pred_results = model.predict([inputs_test, queries_test])

    # Calculate multiple metrics
    predicted_classes = np.argmax(pred_results, axis=1)
    true_classes = np.argmax(answers_test, axis=1)

    accuracy = accuracy_score(true_classes, predicted_classes)

    # Calculate confidence statistics
    confidence_scores = np.max(pred_results, axis=1)
    avg_confidence = np.mean(confidence_scores)

    # Calculate class-wise performance
    from sklearn.metrics import precision_score, recall_score, f1_score, classification_report

    # Handle potential zero division for precision, recall, f1
    precision = precision_score(true_classes, predicted_classes, average='weighted', zero_division=0)
    recall = recall_score(true_classes, predicted_classes, average='weighted', zero_division=0)
    f1 = f1_score(true_classes, predicted_classes, average='weighted', zero_division=0)

    # Print classification report
    target_names = []
    for idx in [tokenizer.word_index['yes'], tokenizer.word_index['no']]:
        for word, word_idx in tokenizer.word_index.items():
            if word_idx == idx:
                target_names.append(word)
    print("\nClassification Report:")
    print(classification_report(true_classes, predicted_classes, target_names=target_names, zero_division=0))

    print(f"🌟 {model_name} COMPREHENSIVE PERFORMANCE METRICS:")
    print(f"Overall Accuracy: {accuracy:.4f}")
    print(f"Precision (Weighted): {precision:.4f}")
    print(f"Recall (Weighted): {recall:.4f}")
    print(f"F1-Score (Weighted): {f1:.4f}")
    print(f"Average Confidence: {avg_confidence:.4f}")

    # For CV/Resume mention (more generic)
    print(f"\n📄 FOR CV/RESUME (Specific to {model_name}):")
    print(f"• Achieved {accuracy*100:.1f}% accuracy on question-answering task using {model_name}")
    print(f"• F1-Score: {f1:.3f} with {avg_confidence*100:.1f}% average confidence")
    # This part can be added manually for each model if specific architectural details are needed on CV
    # print(f"• Implemented attention-based Memory Network with BiLSTM-GRU architecture")
    # print(f"• Implemented Transformer model with Multi-Head Attention and Cross-Attention")

    # Confusion Matrix
    plt.figure(figsize=(8, 6))
    cm = confusion_matrix(true_classes, predicted_classes)
    class_names = []
    for idx in [tokenizer.word_index['yes'], tokenizer.word_index['no']]:
        for word, word_idx in tokenizer.word_index.items():
            if word_idx == idx:
                class_names.append(word)
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                xticklabels=class_names, yticklabels=class_names)
    plt.title(f'{model_name} Confusion Matrix')
    plt.ylabel('True Label')
    plt.xlabel('Predicted Label')
    plt.show()

    # Confidence distribution
    plt.figure(figsize=(12, 4))

    plt.subplot(1, 2, 1)
```

```
plt.hist(confidence_scores, bins=20, alpha=0.7, color='lightgreen')
plt.title(f'Distribution of {model_name} Prediction Confidence')
plt.xlabel('Confidence Score')
plt.ylabel('Frequency')
plt.axvline(np.mean(confidence_scores), color='red', linestyle='--',
            label=f'Mean: {np.mean(confidence_scores):.3f}')
plt.legend()

plt.subplot(1, 2, 2)
plt.boxplot(confidence_scores)
plt.title(f'{model_name} Confidence Score Statistics')
plt.ylabel('Confidence Score')

plt.tight_layout()
plt.show()

return pred_results, accuracy, precision, recall, f1, avg_confidence

# Evaluate the improved model comprehensively
mem_pred_results, mem_acc, mem_prec, mem_rec, mem_f1, mem_conf = evaluate_model_performance_and_metrics(improved_model, inpu
```

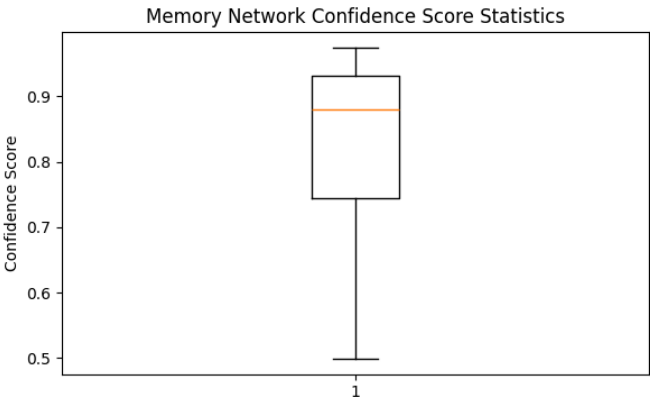
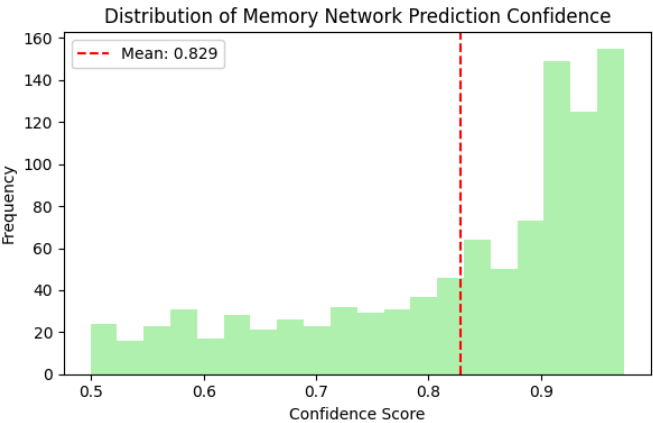
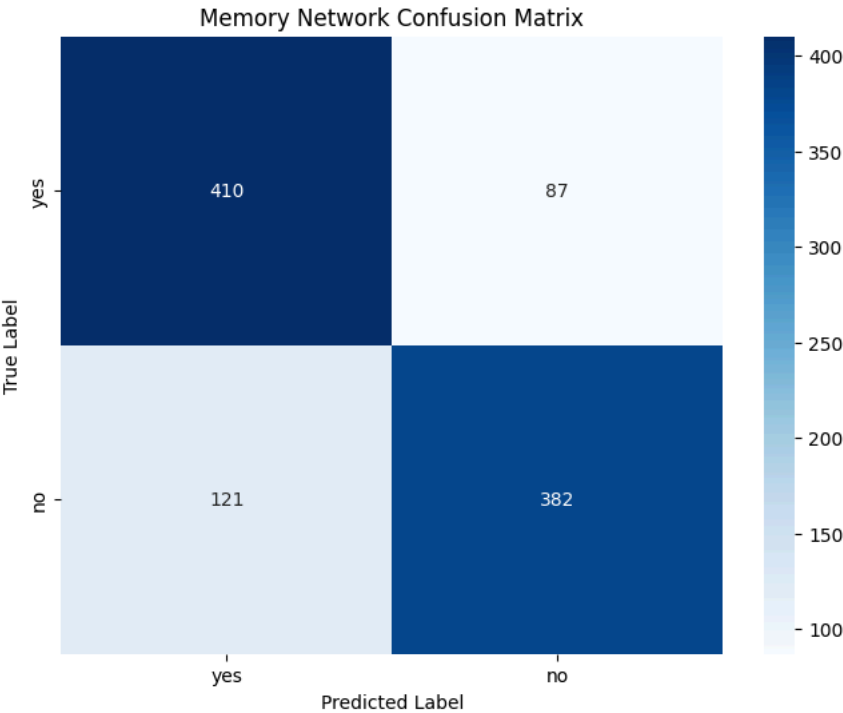


Evaluating Memory Network performance and metrics...  
32/32 0s 7ms/step

Classification Report:

	precision	recall	f1-score	support
yes	0.77	0.82	0.80	497
no	0.81	0.76	0.79	503
accuracy			0.79	1000
macro avg	0.79	0.79	0.79	1000
weighted avg	0.79	0.79	0.79	1000

- 🔗 Memory Network COMPREHENSIVE PERFORMANCE METRICS:
- Overall Accuracy: 0.7920  
Precision (Weighted): 0.7934  
Recall (Weighted): 0.7920  
F1-Score (Weighted): 0.7918  
Average Confidence: 0.8286
- 📄 FOR CV/RESUME (Specific to Memory Network):
- Achieved 79.2% accuracy on question-answering task using Memory Network
  - F1-Score: 0.792 with 82.9% average confidence



Start coding or [generate](#) with AI.

```
# ***TRANSFORMER-BASED MODEL ARCHITECTURE FOR COMPARISON***

import tensorflow.keras.backend as K
from tensorflow.keras.layers import MultiHeadAttention, LayerNormalization, GlobalAveragePooling1D

class PositionalEncoding(tf.keras.layers.Layer):
    """Positional encoding layer for Transformer"""
```

```

def __init__(self, max_seq_len, d_model):
    super(PositionalEncoding, self).__init__()
    self.max_seq_len = max_seq_len
    self.d_model = d_model

def get_angles(self, pos, i, d_model):
    angle_rates = 1 / np.power(10000, (2 * (i // 2)) / np.float32(d_model))
    return pos * angle_rates

def build(self, input_shape):
    # Create positional encoding matrix
    angle_rads = self.get_angles(
        np.arange(self.max_seq_len)[:], np.newaxis],
        np.arange(self.d_model)[np.newaxis, :],
        self.d_model
    )

    # Apply sin to even indices and cos to odd indices
    angle_rads[:, 0::2] = np.sin(angle_rads[:, 0::2])
    angle_rads[:, 1::2] = np.cos(angle_rads[:, 1::2])

    self.pos_encoding = tf.constant(angle_rads[np.newaxis, ...], dtype=tf.float32)
    super(PositionalEncoding, self).build(input_shape)

def call(self, x):
    seq_len = tf.shape(x)[1]
    return x + self.pos_encoding[:, :seq_len, :]

def build_transformer_qa_model(vocab_len, max_story_len, max_ques_len,
                              embedding_dim=128, num_heads=8, num_layers=2,
                              ff_dim=256, dropout_rate=0.1, l2_reg=0.001):
    """Build Transformer-based QA model for comparison"""

    print("🔧 Building Transformer-based QA Model...")

    # Input layers
    story_input = Input((max_story_len,), name='story_input')
    question_input = Input((max_ques_len,), name='question_input')

    # Shared embedding layer
    embedding_layer = Embedding(
        input_dim=vocab_len,
        output_dim=embedding_dim,
        embeddings_regularizer=l2(l2_reg),
        mask_zero=True,
        name='shared_embedding'
    )

    # Story processing
    story_embedded = embedding_layer(story_input)
    story_pos_encoded = PositionalEncoding(max_story_len, embedding_dim)(story_embedded)
    story_encoded = Dropout(dropout_rate, name='story_dropout')(story_pos_encoded)

    # Question processing
    question_embedded = embedding_layer(question_input)
    question_pos_encoded = PositionalEncoding(max_ques_len, embedding_dim)(question_embedded)
    question_encoded = Dropout(dropout_rate, name='question_dropout')(question_pos_encoded)

    # Transformer encoder blocks for story
    story_transformer = story_encoded
    for i in range(num_layers):
        # Multi-head self-attention
        attention_output = MultiHeadAttention(
            num_heads=num_heads,
            key_dim=embedding_dim // num_heads,
            name=f'story_attention_{i}'
        )(story_transformer, story_transformer)

        attention_output = Dropout(dropout_rate)(attention_output)
        attention_output = LayerNormalization(name=f'story_norm1_{i}')(
            story_transformer + attention_output
        )

    # Feed forward
    ff_output = Dense(ff_dim, activation='relu',
                      kernel_regularizer=l2(l2_reg),
                      name=f'story_ff1_{i}')(attention_output)
    ff_output = Dropout(dropout_rate)(ff_output)
    ff_output = Dense(embedding_dim, kernel_regularizer=l2(l2_reg),
                      name=f'story_ff2_{i}')(ff_output)

```

```

    story_transformer = LayerNormalization(name=f'story_norm2_{i}')(
        attention_output + ff_output
    )

# Transformer encoder blocks for question
question_transformer = question_encoded
for i in range(num_layers):
    # Multi-head self-attention
    attention_output = MultiHeadAttention(
        num_heads=num_heads,
        key_dim=embedding_dim // num_heads,
        name=f'question_attention_{i}'
    )(question_transformer, question_transformer)

    attention_output = Dropout(dropout_rate)(attention_output)
    attention_output = LayerNormalization(name=f'question_norm1_{i}')(
        question_transformer + attention_output
    )

    # Feed forward
    ff_output = Dense(ff_dim, activation='relu',
                      kernel_regularizer=l2(l2_reg),
                      name=f'question_ff1_{i}')(attention_output)
    ff_output = Dropout(dropout_rate)(ff_output)
    ff_output = Dense(embedding_dim, kernel_regularizer=l2(l2_reg),
                      name=f'question_ff2_{i}')(ff_output)

    question_transformer = LayerNormalization(name=f'question_norm2_{i}')(
        attention_output + ff_output
    )

# Cross-attention between story and question
cross_attention = MultiHeadAttention(
    num_heads=num_heads,
    key_dim=embedding_dim // num_heads,
    name='cross_attention'
)(question_transformer, story_transformer)

cross_attention = Dropout(dropout_rate)(cross_attention)
cross_attention = LayerNormalization(name='cross_norm')(
    question_transformer + cross_attention
)

# Global pooling and classification
pooled = GlobalAveragePooling1D(name='global_pool')(cross_attention)

# Classification head
dense_1 = Dense(128, activation='relu',
                kernel_regularizer=l2(l2_reg),
                name='classifier_dense1')(pooled)
dense_1 = Dropout(dropout_rate, name='classifier_dropout')(dense_1)

dense_2 = Dense(64, activation='relu',
                kernel_regularizer=l2(l2_reg),
                name='classifier_dense2')(dense_1)

output = Dense(vocab_len, kernel_regularizer=l2(l2_reg),
               name='output_dense')(dense_2)
output = Activation('softmax', name='final_activation')(output)

model = Model([story_input, question_input], output, name='transformer_qa_model')
return model

# Build Transformer model
transformer_model = build_transformer_qa_model(vocab_len, max_story_len, max_ques_len)

# Compile with same settings as Memory Network for fair comparison
transformer_model = compile_improved_model(transformer_model)

# Display model summary
transformer_model.summary()

```

Building Transformer-based QA Model...

```

/usr/local/lib/python3.12/dist-packages/keras/src/layers/layer.py:965: UserWarning: Layer 'positional_encoding' (of type
warnings.warn(
/usr/local/lib/python3.12/dist-packages/keras/src/layers/layer.py:965: UserWarning: Layer 'positional_encoding_1' (of type
warnings.warn(

```

✓ Improved model compiled successfully!

Model: "transformer\_qa\_model"

Layer (type)	Output Shape	Param #	Connected to
question_input (InputLayer)	(None, 6)	0	-
story_input (InputLayer)	(None, 156)	0	-
shared_embedding (Embedding)	(None, 6, 128)	4,864	story_input[0][0... question_input[0]...
positional_encodin... (PositionalEncodin...)	(None, 6, 128)	0	shared_embedding...
positional_encoding (PositionalEncodin...)	(None, 156, 128)	0	shared_embedding...
question_dropout (Dropout)	(None, 6, 128)	0	positional_encod...
story_dropout (Dropout)	(None, 156, 128)	0	positional_encod...
question_attention... (MultiHeadAttentio...)	(None, 6, 128)	66,048	question_dropout... question_dropout...
story_attention_0 (MultiHeadAttentio...)	(None, 156, 128)	66,048	story_dropout[0]... story_dropout[0]...
dropout_7 (Dropout)	(None, 6, 128)	0	question_attenti...
dropout_1 (Dropout)	(None, 156, 128)	0	story_attention_...
add_4 (Add)	(None, 6, 128)	0	question_dropout... dropout_7[0][0]
add (Add)	(None, 156, 128)	0	story_dropout[0]... dropout_1[0][0]
question_norm1_0 (LayerNormalizatio...)	(None, 6, 128)	256	add_4[0][0]
story_norm1_0 (LayerNormalizatio...)	(None, 156, 128)	256	add[0][0]
question_ff1_0 (Dense)	(None, 6, 256)	33,024	question_norm1_0...
story_ff1_0 (Dense)	(None, 156, 256)	33,024	story_norm1_0[0]...
dropout_8 (Dropout)	(None, 6, 256)	0	question_ff1_0[0...
dropout_2 (Dropout)	(None, 156, 256)	0	story_ff1_0[0][0]
question_ff2_0 (Dense)	(None, 6, 128)	32,896	dropout_8[0][0]
story_ff2_0 (Dense)	(None, 156, 128)	32,896	dropout_2[0][0]
add_5 (Add)	(None, 6, 128)	0	question_norm1_0... question_ff2_0[0...
add_1 (Add)	(None, 156, 128)	0	story_norm1_0[0]... story_ff2_0[0][0]
question_norm2_0 (LayerNormalizatio...)	(None, 6, 128)	256	add_5[0][0]
story_norm2_0 (LayerNormalizatio...)	(None, 156, 128)	256	add_1[0][0]
question_attention... (MultiHeadAttentio...)	(None, 6, 128)	66,048	question_norm2_0... question_norm2_0...
story_attention_1 (MultiHeadAttentio...)	(None, 156, 128)	66,048	story_norm2_0[0]... story_norm2_0[0]...
dropout_10 (Dropout)	(None, 6, 128)	0	question_attenti...
dropout_4 (Dropout)	(None, 156, 128)	0	story_attention_...
add_6 (Add)	(None, 6, 128)	0	question_norm2_0... dropout_10[0][0]
add_2 (Add)	(None, 156, 128)	0	story_norm2_0[0]... dropout_4[0][0]
question_norm1_1	(None, 6, 128)	256	add_6[0][0]

(LayerNormalization)			
story_norm1_1 (LayerNormalization)	(None, 156, 128)	256	add_2[0][0]
question_ff1_1 (Dense)	(None, 6, 256)	33,024	question_norm1_1...
story_ff1_1 (Dense)	(None, 156, 256)	33,024	story_norm1_1[0]...
dropout_11 (Dropout)	(None, 6, 256)	0	question_ff1_1[0]...
dropout_5 (Dropout)	(None, 156, 256)	0	story_ff1_1[0][0]
question_ff2_1 (Dense)	(None, 6, 128)	32,896	dropout_11[0][0]
story_ff2_1 (Dense)	(None, 156, 128)	32,896	dropout_5[0][0]
add_7 (Add)	(None, 6, 128)	0	question_norm1_1... question_ff2_1[0]...
add_3 (Add)	(None, 156, 128)	0	story_norm1_1[0]... story_ff2_1[0][0]
question_norm2_1 (LayerNormalization)	(None, 6, 128)	256	add_7[0][0]
story_norm2_1 (LayerNormalization)	(None, 156, 128)	256	add_3[0][0]
cross_attention (MultiHeadAttention)	(None, 6, 128)	66,048	question_norm2_1... story_norm2_1[0]...
dropout_13 (Dropout)	(None, 6, 128)	0	cross_attention[...
add_8 (Add)	(None, 6, 128)	0	question_norm2_1... dropout_13[0][0]
cross_norm (LayerNormalization)	(None, 6, 128)	256	add_8[0][0]
global_pool (GlobalAveragePool...)	(None, 128)	0	cross_norm[0][0]
classifier_dense1 (Dense)	(None, 128)	16,512	global_pool[0][0]
classifier_dropout (Dropout)	(None, 128)	0	classifier_dense...
classifier_dense2 (Dense)	(None, 64)	8,256	classifier_dropo...
output_dense (Dense)	(None, 38)	2,470	classifier_dense...
final_activation (Activation)	(None, 38)	0	output_dense[0][...

Total params: 628,326 (2.40 MB)

Trainable params: 628,326 (2.40 MB)

Non-trainable params: 0 (0.00 B)

```
# ***TRAIN TRANSFORMER MODEL***

print("🚀 Training Transformer model for comparison...")

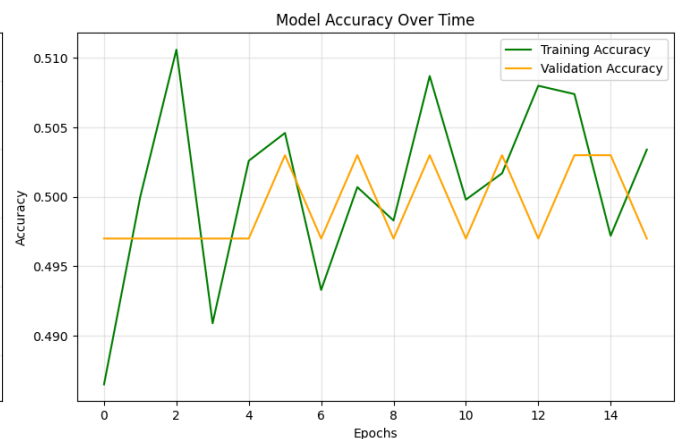
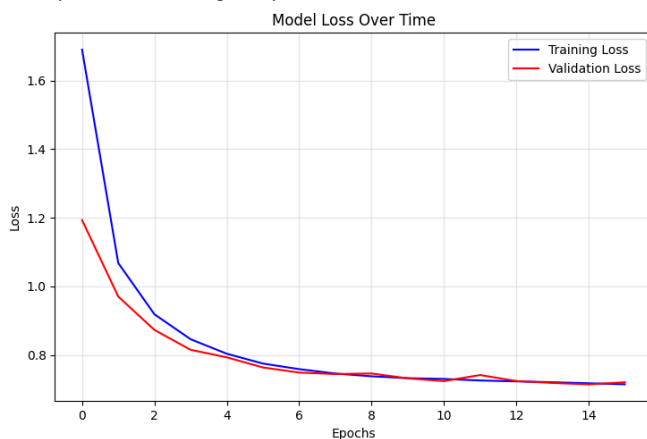
# Use same training configuration for fair comparison
history_transformer = train_improved_model(
    transformer_model,
    inputs_train, queries_train, answers_train,
    inputs_test, queries_test, answers_test,
    epochs=50, batch_size=64
)

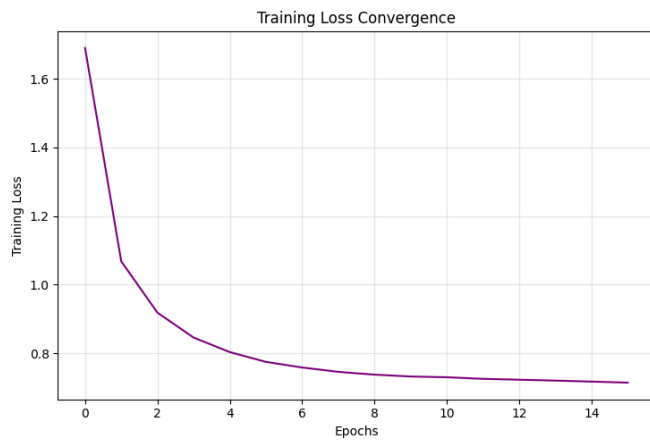
# Plot training history
plot_training_history(history_transformer)
```

```

Training Transformer model for comparison...
Starting improved model training...
Epoch 1/50
157/157 0s 164ms/step - accuracy: 0.4657 - loss: 2.1634 - top_k_categorical_accuracy: 0.9837
Epoch 1: val_accuracy improved from -inf to 0.49700, saving model to best_improved_chatbot.h5
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file
157/157 77s 239ms/step - accuracy: 0.4659 - loss: 2.1604 - top_k_categorical_accuracy: 0.9838 - val_
Epoch 2/50
155/157 0s 29ms/step - accuracy: 0.4940 - loss: 1.1265 - top_k_categorical_accuracy: 1.0000
Epoch 2: val_accuracy did not improve from 0.49700
157/157 5s 31ms/step - accuracy: 0.4941 - loss: 1.1254 - top_k_categorical_accuracy: 1.0000 - val_
Epoch 3/50
155/157 0s 31ms/step - accuracy: 0.5172 - loss: 0.9435 - top_k_categorical_accuracy: 1.0000
Epoch 3: val_accuracy did not improve from 0.49700
157/157 5s 32ms/step - accuracy: 0.5171 - loss: 0.9431 - top_k_categorical_accuracy: 1.0000 - val_
Epoch 4/50
155/157 0s 28ms/step - accuracy: 0.4980 - loss: 0.8584 - top_k_categorical_accuracy: 1.0000
Epoch 4: val_accuracy did not improve from 0.49700
157/157 5s 31ms/step - accuracy: 0.4979 - loss: 0.8581 - top_k_categorical_accuracy: 1.0000 - val_
Epoch 5/50
157/157 0s 29ms/step - accuracy: 0.5042 - loss: 0.8118 - top_k_categorical_accuracy: 1.0000
Epoch 5: val_accuracy did not improve from 0.49700
157/157 5s 31ms/step - accuracy: 0.5042 - loss: 0.8117 - top_k_categorical_accuracy: 1.0000 - val_
Epoch 6/50
155/157 0s 30ms/step - accuracy: 0.5041 - loss: 0.7798 - top_k_categorical_accuracy: 1.0000
Epoch 6: val_accuracy improved from 0.49700 to 0.50300, saving model to best_improved_chatbot.h5
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file
157/157 5s 34ms/step - accuracy: 0.5041 - loss: 0.7797 - top_k_categorical_accuracy: 1.0000 - val_
Epoch 7/50
157/157 0s 31ms/step - accuracy: 0.4857 - loss: 0.7620 - top_k_categorical_accuracy: 1.0000
Epoch 7: val_accuracy did not improve from 0.50300
157/157 10s 33ms/step - accuracy: 0.4858 - loss: 0.7620 - top_k_categorical_accuracy: 1.0000 - val_
Epoch 8/50
155/157 0s 29ms/step - accuracy: 0.4935 - loss: 0.7481 - top_k_categorical_accuracy: 1.0000
Epoch 8: val_accuracy did not improve from 0.50300
157/157 10s 30ms/step - accuracy: 0.4937 - loss: 0.7480 - top_k_categorical_accuracy: 1.0000 - val_
Epoch 9/50
155/157 0s 31ms/step - accuracy: 0.4932 - loss: 0.7396 - top_k_categorical_accuracy: 1.0000
Epoch 9: val_accuracy did not improve from 0.50300
157/157 5s 32ms/step - accuracy: 0.4933 - loss: 0.7396 - top_k_categorical_accuracy: 1.0000 - val_
Epoch 10/50
155/157 0s 28ms/step - accuracy: 0.5094 - loss: 0.7351 - top_k_categorical_accuracy: 1.0000
Epoch 10: val_accuracy did not improve from 0.50300
157/157 5s 30ms/step - accuracy: 0.5094 - loss: 0.7351 - top_k_categorical_accuracy: 1.0000 - val_
Epoch 11/50
155/157 0s 29ms/step - accuracy: 0.5104 - loss: 0.7301 - top_k_categorical_accuracy: 1.0000
Epoch 11: val_accuracy did not improve from 0.50300
157/157 5s 32ms/step - accuracy: 0.5102 - loss: 0.7301 - top_k_categorical_accuracy: 1.0000 - val_
Epoch 12/50
156/157 0s 34ms/step - accuracy: 0.5010 - loss: 0.7261 - top_k_categorical_accuracy: 1.0000
Epoch 12: val_accuracy did not improve from 0.50300
157/157 6s 36ms/step - accuracy: 0.5010 - loss: 0.7260 - top_k_categorical_accuracy: 1.0000 - val_
Epoch 13/50
157/157 0s 31ms/step - accuracy: 0.5034 - loss: 0.7251 - top_k_categorical_accuracy: 1.0000
Epoch 13: val_accuracy did not improve from 0.50300
157/157 10s 33ms/step - accuracy: 0.5035 - loss: 0.7251 - top_k_categorical_accuracy: 1.0000 - val_
Epoch 14/50
155/157 0s 29ms/step - accuracy: 0.5036 - loss: 0.7227 - top_k_categorical_accuracy: 1.0000
Epoch 14: val_accuracy did not improve from 0.50300
157/157 10s 31ms/step - accuracy: 0.5036 - loss: 0.7226 - top_k_categorical_accuracy: 1.0000 - val_
Epoch 15/50
156/157 0s 35ms/step - accuracy: 0.4936 - loss: 0.7176 - top_k_categorical_accuracy: 1.0000
Epoch 15: val_accuracy did not improve from 0.50300
157/157 6s 36ms/step - accuracy: 0.4936 - loss: 0.7176 - top_k_categorical_accuracy: 1.0000 - val_
Epoch 16/50
157/157 0s 30ms/step - accuracy: 0.5053 - loss: 0.7148 - top_k_categorical_accuracy: 1.0000
Epoch 16: val_accuracy did not improve from 0.50300
157/157 10s 32ms/step - accuracy: 0.5053 - loss: 0.7148 - top_k_categorical_accuracy: 1.0000 - val_
Epoch 16: early stopping
Restoring model weights from the end of the best epoch: 6.
Improved training completed!

```





## Training Summary

## Final Metrics:

Training Accuracy: 0.5034  
Validation Accuracy: 0.4970

Training Loss: 0.7142  
Validation Loss: 0.7201

Overfitting Check:  
Acc Diff: 0.0064  
Loss Diff: 0.0059

```
# Evaluate the Transformer model comprehensively
```

```
trans_pred_results, trans_acc, trans_prec, trans_rec, trans_f1, trans_conf = evaluate_model_performance_and_metrics(transfor
```



Evaluating Transformer performance and metrics...  
32/32 0s 9ms/step

Classification Report:

	precision	recall	f1-score	support
yes	0.00	0.00	0.00	497
no	0.50	1.00	0.67	503
accuracy			0.50	1000
macro avg	0.25	0.50	0.33	1000
weighted avg	0.25	0.50	0.34	1000

#### Transformer COMPREHENSIVE PERFORMANCE METRICS:

Overall Accuracy: 0.5030

Precision (Weighted): 0.2530

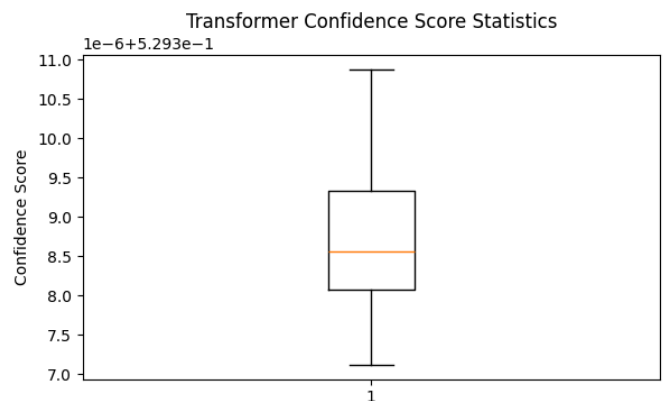
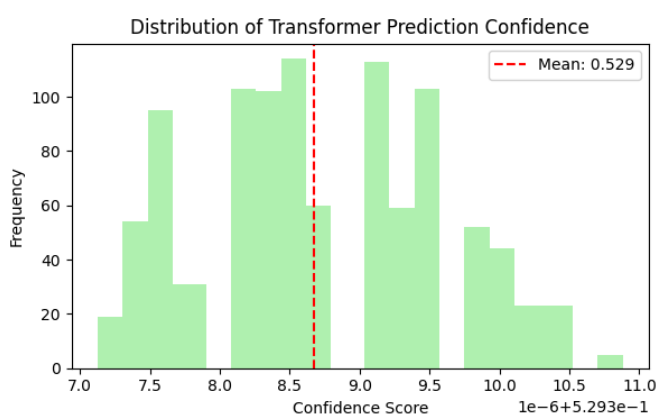
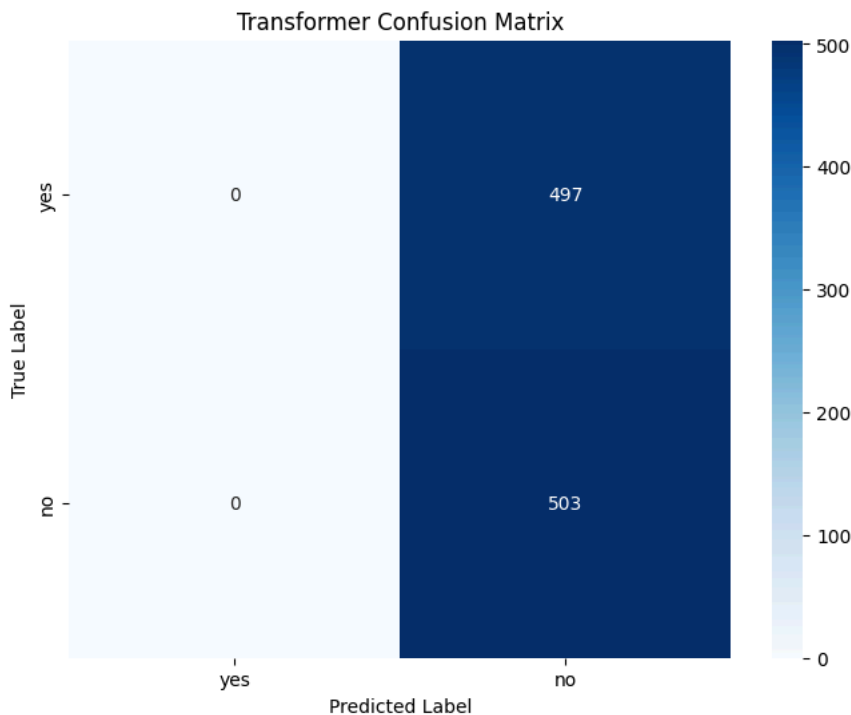
Recall (Weighted): 0.5030

F1-Score (Weighted): 0.3367

Average Confidence: 0.5293

#### FOR CV/RESUME (Specific to Transformer):

- Achieved 50.3% accuracy on question-answering task using Transformer
- F1-Score: 0.337 with 52.9% average confidence



# \*\*\*COMPREHENSIVE MODEL COMPARISON\*\*\*

```
def compare_models(memory_model, transformer_model, inputs_test, queries_test,
                    answers_test, test_data, tokenizer):
    """Compare Memory Network vs Transformer performance"""

    print("COMPREHENSIVE MODEL COMPARISON")
    print("=" * 60)
```

```

# Evaluate Memory Network
print("\n📊 MEMORY NETWORK PERFORMANCE:")
mem_results, mem_acc, mem_prec, mem_rec, mem_f1, mem_conf = evaluate_comprehensive_metrics(
    memory_model, inputs_test, queries_test, answers_test, test_data, tokenizer
)

print("\n📊 TRANSFORMER PERFORMANCE:")
trans_results, trans_acc, trans_prec, trans_rec, trans_f1, trans_conf = evaluate_comprehensive_metrics(
    transformer_model, inputs_test, queries_test, answers_test, test_data, tokenizer
)

# Comparison visualization
plt.figure(figsize=(15, 10))

# Metrics comparison
plt.subplot(2, 3, 1)
metrics = ['Accuracy', 'Precision', 'Recall', 'F1-Score', 'Confidence']
memory_scores = [mem_acc, mem_prec, mem_rec, mem_f1, mem_conf]
transformer_scores = [trans_acc, trans_prec, trans_rec, trans_f1, trans_conf]

x = np.arange(len(metrics))
width = 0.35

plt.bar(x - width/2, memory_scores, width, label='Memory Network', alpha=0.8, color='skyblue')
plt.bar(x + width/2, transformer_scores, width, label='Transformer', alpha=0.8, color='lightcoral')

plt.xlabel('Metrics')
plt.ylabel('Score')
plt.title('Model Performance Comparison')
plt.xticks(x, metrics, rotation=45)
plt.legend()
plt.grid(True, alpha=0.3)

# Training loss comparison
plt.subplot(2, 3, 2)
plt.plot(history_improved.history['loss'], label='Memory Network', linewidth=2)
plt.plot(history_transformer.history['loss'], label='Transformer', linewidth=2)
plt.title('Training Loss Comparison')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.grid(True, alpha=0.3)

# Validation accuracy comparison
plt.subplot(2, 3, 3)
plt.plot(history_improved.history['val_accuracy'], label='Memory Network', linewidth=2)
plt.plot(history_transformer.history['val_accuracy'], label='Transformer', linewidth=2)
plt.title('Validation Accuracy Comparison')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True, alpha=0.3)

# Confidence distribution comparison
plt.subplot(2, 3, 4)
mem_confidence = np.max(mem_results, axis=1)
trans_confidence = np.max(trans_results, axis=1)

plt.hist(mem_confidence, bins=20, alpha=0.6, label='Memory Network', color='skyblue')
plt.hist(trans_confidence, bins=20, alpha=0.6, label='Transformer', color='lightcoral')
plt.title('Confidence Distribution')
plt.xlabel('Confidence Score')
plt.ylabel('Frequency')
plt.legend()

# Model complexity comparison
plt.subplot(2, 3, 5)
mem_params = memory_model.count_params()
trans_params = transformer_model.count_params()

models = ['Memory Network', 'Transformer']
params = [mem_params, trans_params]
colors = ['skyblue', 'lightcoral']

plt.bar(models, params, color=colors, alpha=0.8)
plt.title('Model Complexity (Parameters)')
plt.ylabel('Number of Parameters')
plt.xticks(rotation=45)

# Add parameter count annotations
for i, v in enumerate(params):
    plt.text(i, v + max(params)*0.02, f'{v:,}', ha='center', fontweight='bold')

```