ABSTRACT

Figurative language, including similes and metaphors, enriches human communication by conveying complex ideas, emotions, and relationships through creative expressions. However, detecting and understanding figurative language pose significant challenges for machine learning models due to its inherent ambiguity, contextual dependence, and cultural nuances. This paper explores the advancements in figurative intelligence—the capacity of machines to recognize and interpret figurative expressions—by leveraging state-of-the-art machine learning techniques.

The research delves into methods for simile and metaphor detection, focusing on neural network architectures such as transformers, pre-trained language models (e.g., BERT, GPT), and attention mechanisms. Techniques for feature extraction, context modeling, and semantic similarity analysis are discussed, along with datasets designed for figurative language annotation. Experimental results demonstrate that fine-tuning pre-trained models on figurative-specific datasets enhances detection accuracy. Moreover, the study emphasizes the importance of multimodal approaches, incorporating text, imagery, and other contextual clues to improve understanding.

Applications of figurative intelligence span various domains, including sentiment analysis, creative writing, language translation, and educational tools. Despite progress, challenges such as domain generalization, low-resource languages, and cultural biases persist, highlighting the need for further research. This paper contributes to bridging the gap between human creativity and machine understanding, paving the way for more intuitive human-computer interactions.

1.INTRODUCTION

1.1 OVERVIEW

Figurative language, including similes ("as brave as a lion") and metaphors ("time is a thief"), plays a critical role in human communication by conveying abstract or complex ideas through creative expressions. However, its interpretation is challenging for machine learning (ML) systems due to non-literal meanings, contextual dependencies, and cultural variations.

Figurative intelligence refers to the ability of ML models to identify, interpret, and generate figurative language, bridging the gap between literal and implied meanings. It combines linguistic analysis, contextual modelling , and semantic understanding to process similes, metaphors, and other figurative forms effectively.

1.2 PURPOSE

The primary purpose of figurative intelligence in machine learning (ML) is to enable computational systems to recognize, interpret, and generate figurative language, including similes and metaphors. This capability is essential for improving human-computer interactions, understanding creative language use, and advancing natural language processing (NLP) applications. Below are the specific purposes of this field:

1. Enhancing Language Understanding : Figurative language is pervasive in human communication, often used to express abstract ideas, emotions, and cultural nuances. By detecting similes and metaphors, ML models can better grasp non-literal meanings, leading to improved comprehension of nuanced or creative language.

2. Improving NLP Applications : Incorporating figurative intelligence improves the performance of NLP applications, such as: Sentiment Analysis,

Text Summarization , Language Translation.

3. Bridging Human-Machine Communication: For conversational AI systems, understanding figurative language is crucial for natural and intuitive interactions.

4. Supporting Creativity and Education: Figurative intelligence aids in developing tools for creative writing, helping users generate metaphors and similes for artistic or pedagogical purposes.

5. Advancing Cognitive AI: Figurative language understanding mirrors human cognitive abilities, such as abstract reasoning and contextual awareness. Developing figurative intelligence brings AI closer to replicating human-like cognition and linguistic creativity.

6. Tackling Cultural and Contextual Nuances: By interpreting similes and metaphors, ML models can adapt to cultural and domain-specific contexts, making them more effective in global applications.

2.LITERATURE SURVEY

2.1 EXISTING PROBLEM

Despite significant advancements in natural language processing (NLP), the field of figurative intelligence faces several persistent challenges in effectively detecting and interpreting similes and metaphors. These problems arise from the complexity, ambiguity, and context-dependence of figurative language. Below are the key issues:

1.Ambiguity Between Literal and Figurative Meaning:

Figurative expressions often have literal counterparts, making it difficult for machine learning models to distinguish between the two. For instance, the phrase *"she has a heart of gold"* is metaphorical, but *"the heart of gold jewelry"* is literal. Models struggle to resolve such ambiguities without deep contextual understanding.

2. Lack of Context Awareness:

Figurative language heavily relies on context for interpretation. Without proper contextual modeling, ML systems may misclassify or misinterpret expressions.

3.Data Scarcity:

Annotated datasets specifically designed for figurative language detection are limited. Creating such datasets is challenging because annotating metaphors and similes requires linguistic expertise and an understanding of context. This scarcity hampers model training and generalization.

4. Real-Time Application Challenges:

Figurative language detection in real-time applications (e.g., chatbots, virtual assistants) requires fast and accurate processing. However, the complexity of figurative language often slows down processing or reduces accuracy in dynamic environments.

5. Interpretation Beyond Detection:

While many models focus on identifying figurative expressions, interpreting their meaning in a human-like manner remains an unresolved challenge.

6. Lack of Multimodal Integration:

Some figurative expressions rely on visual, auditory, or other sensory cues to be fully understood. Current models primarily focus on text, ignoring the multimodal nature of human communication, which can lead to incomplete or incorrect interpretations.

2.2 PROPOSED SOLUTION

To address the challenges of detecting and interpreting figurative language, including similes and metaphors, researchers can adopt a combination of advanced techniques, data strategies, and contextual approaches. Below are the proposed solution.

1.Context-Aware Language Models:

Attention Mechanisms: Use attention layers to focus on the surrounding context and distinguish between literal and figurative meanings, ensuring more accurate interpretation of ambiguous expressions.

2. Multimodal Integration:

Text and Visual Contexts: Combine textual data with visual or auditory data to enhance metaphor and simile detection. For example, pairing the phrase *"a cloud of sadness"* with an image of a rainy sky can help contextualize its figurative meaning.

3. Hybrid Approaches:

Rule-Based and Machine Learning Integration: Combine rule-based methods (e.g., identifying specific linguistic patterns) with machine learning models to detect both common and novel figurative expressions.

4. Few-Shot and Zero-Shot Learning:

Transfer Learning: Transfer knowledge from high-resource languages to low-resource ones by aligning figurative patterns across languages.

5. Multilingual and Cross-Cultural Models:

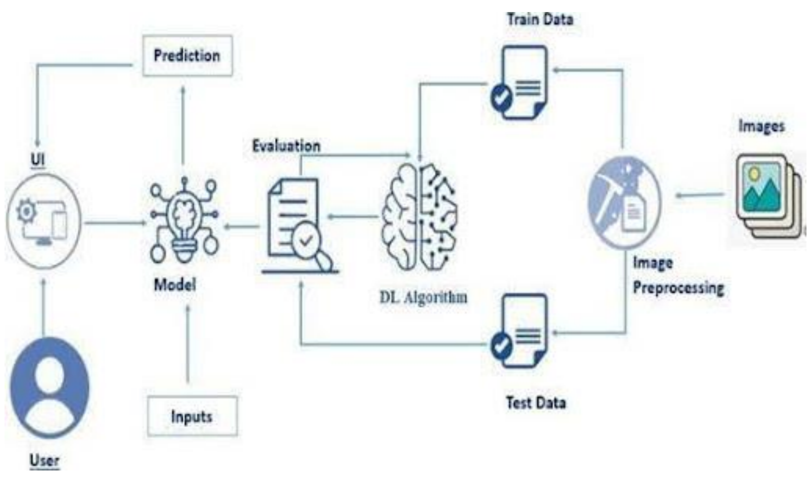
Cross-Cultural Training: Train models on multilingual corpora with cultural annotations to improve generalization across regions. For example, a metaphor common in English may have an equivalent but different phrasing in another language.

6. Real-Time Processing Enhancements:

Optimization Techniques: Optimize transformer-based models for faster inference to enable real-time detection of figurative language in conversational AI applications.

3. THEORITICAL ANALYSIS

3.1. BLOCK DIAGRAM



3.2. SOFTWARE DESIGNING

To accomplish this, we have to complete all the activities listed below:

.Data Collection & Preparation

- Collect the dataset
- Data Preparation

- Exploratory Data Analysis
    - Descriptive statistical
    - Visual Analysis

- Model Building
    - Training the model in multiple algorithms
    - Testing the model

- Model Deployment
    - Save the best model
    - Integrate with Web Framework

4.EXPERIMENTAL INVESTIGATION

1. Data Collection and Preparation:

ML depends heavily on data. It is the most crucial aspect that makes algorithm training possible. So, this section allows you to download the required dataset.

2.Exploratory Data Analysis:

. Visual analysis

. Univariate analysis

. Bivariate analysis

3. Model Building:

. Logistic regression

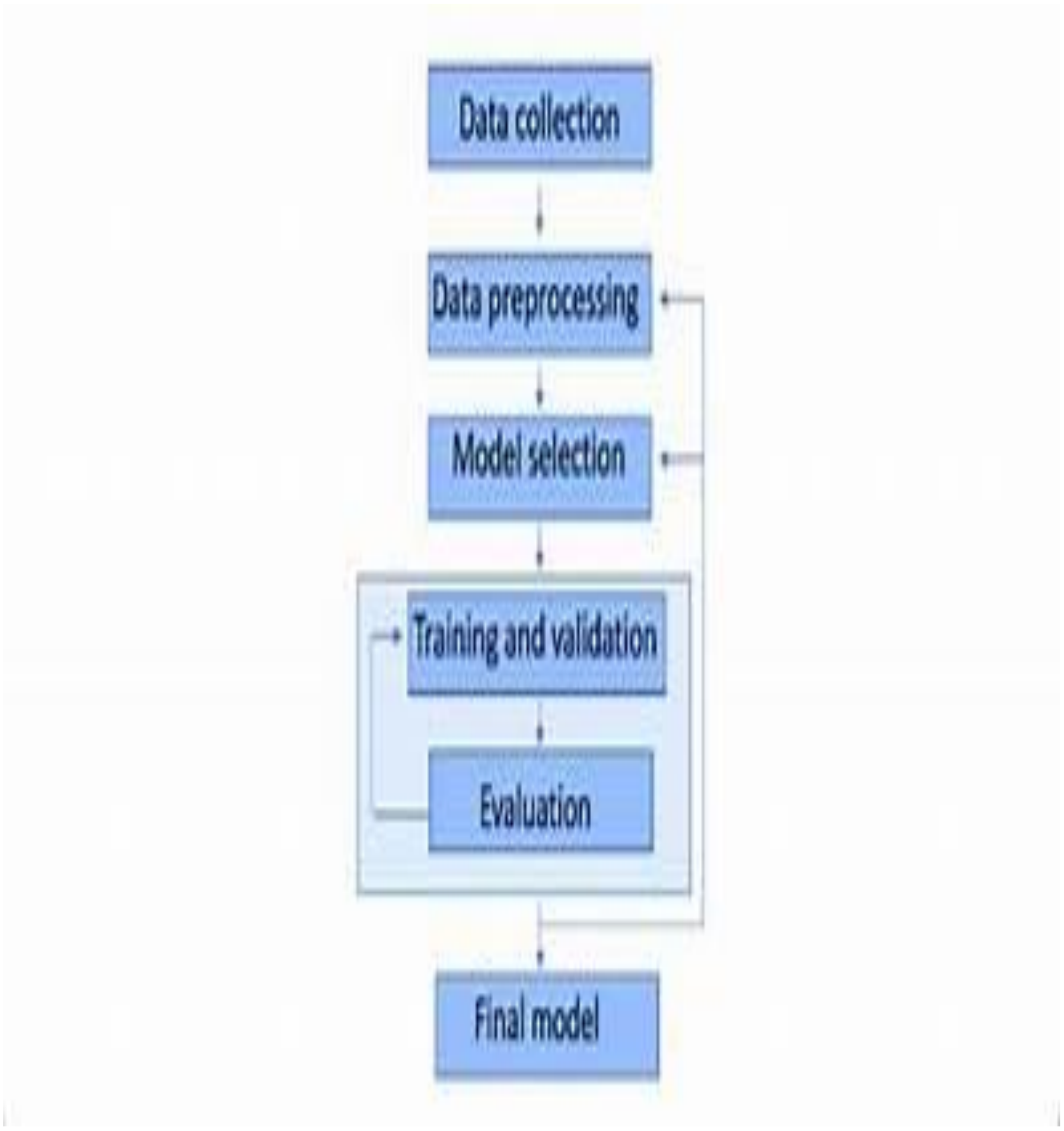
. ANN(artificial neural network)

4.Model Deployment:

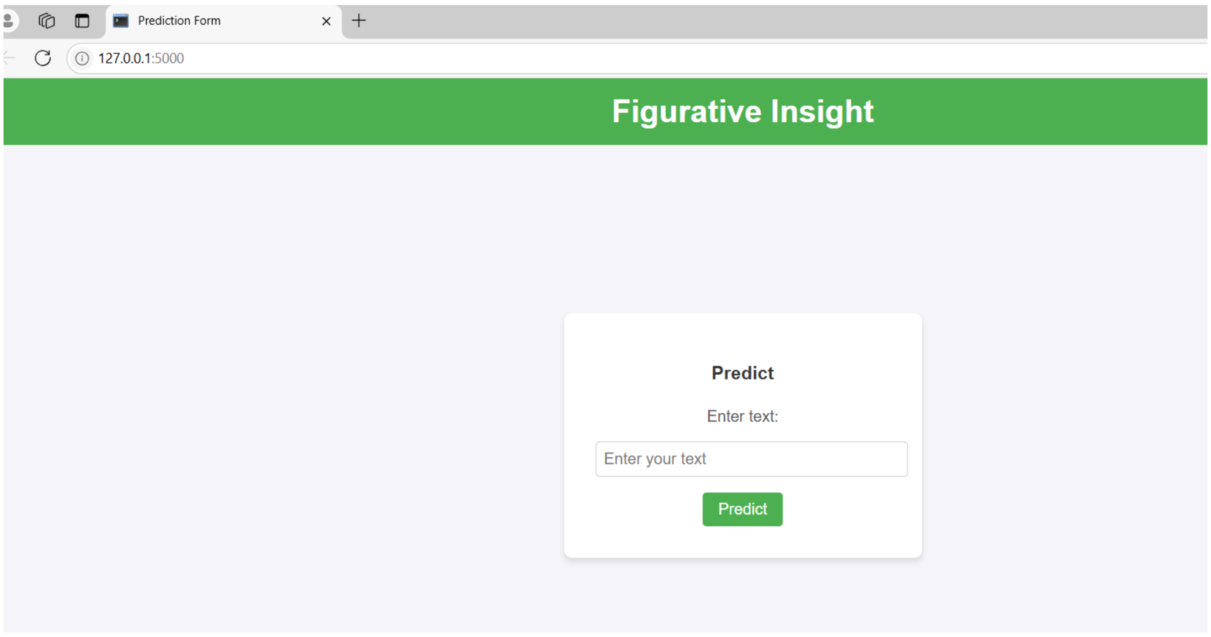
Save and load the best model.

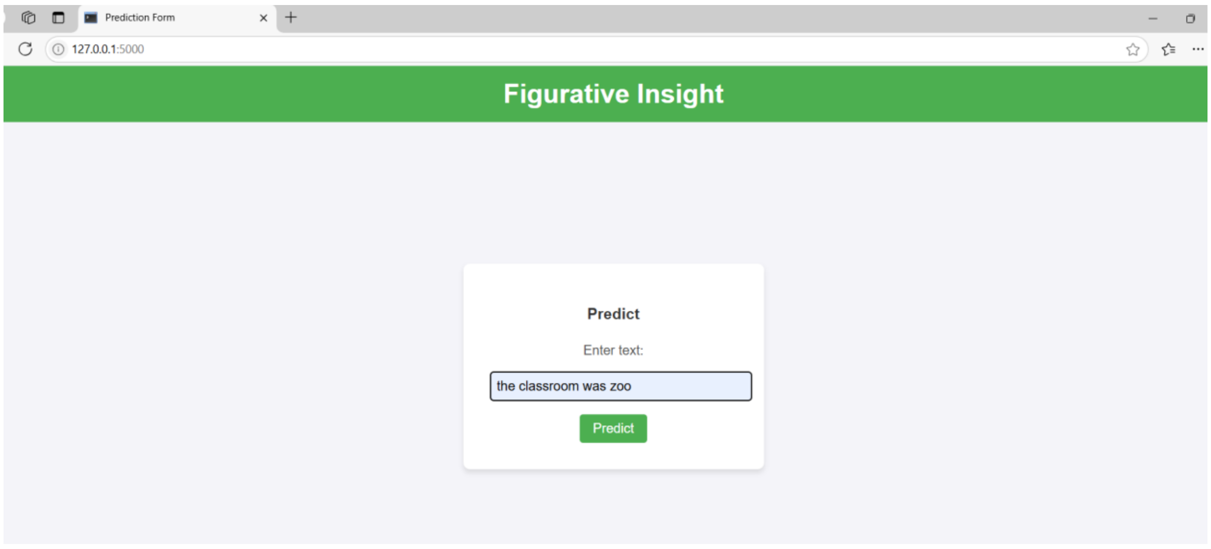
Saving the best model after comparing its performance using different evaluation metrics means selecting the model with the highest performance. This can be useful in avoiding the need to retrain the model every time it is needed and also to be able to use it in the future.

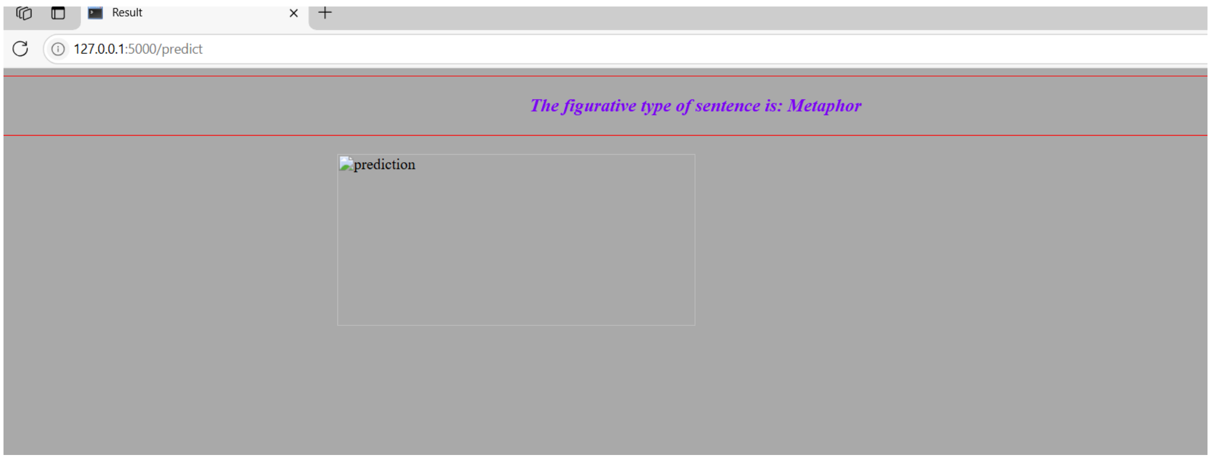
5.FLOWCHART


Data collection
Data preprocessing
Model selection
Training and validation
Evaluation
Final model

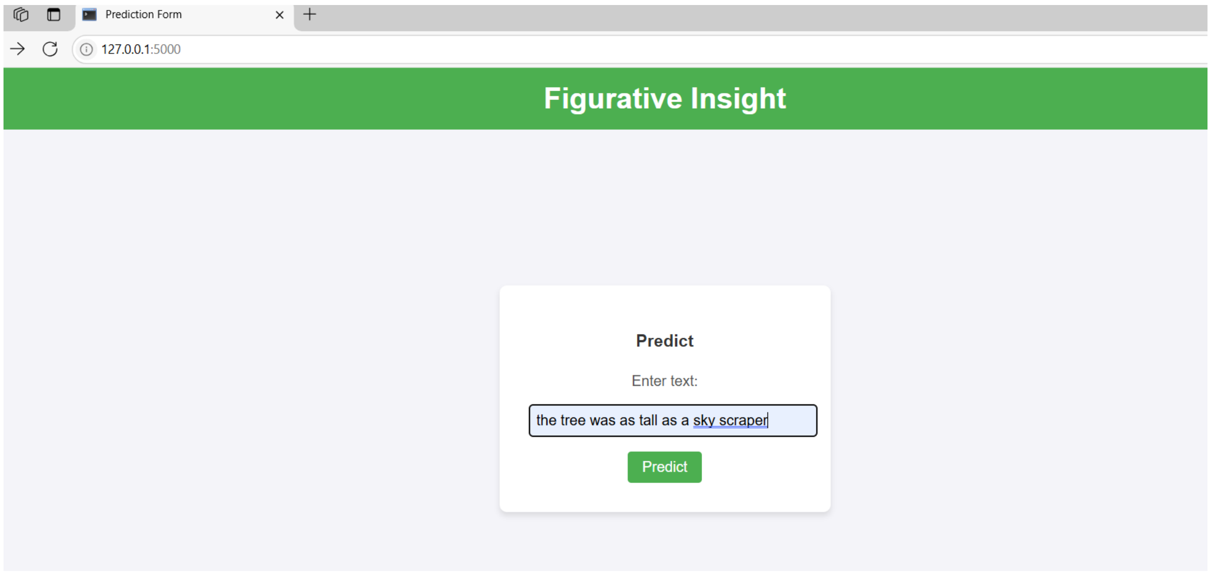
6.RESULTS







The figurative type of sentence is: Metaphor



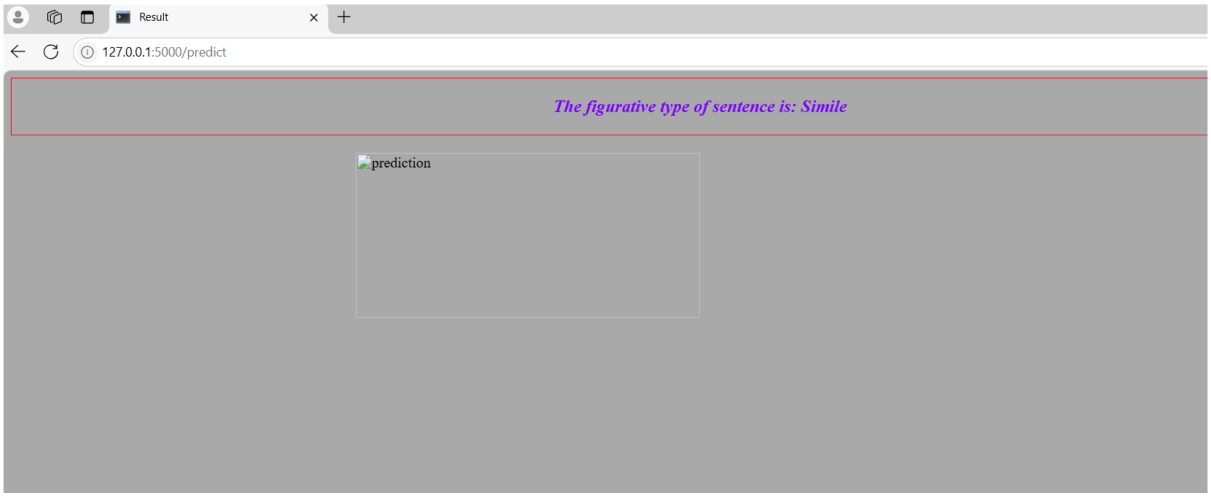
Figurative Insight

Predict

Enter text:

the tree was as tall as a sky scraper

Predict



The figurative type of sentence is: Simile

prediction

6.ADVANTAGES AND DISADVANTAGES

Advantages :

 Enhanced Language Understanding

- Improves natural language processing (NLP) systems by enabling them to interpret non-literal, creative, and abstract expressions.

 Improved NLP Applications

- Benefits tasks like sentiment analysis, machine translation, and text summarization by accurately identifying figurative expressions.

 Better Human-AI Interaction

- Makes conversational AI systems, like chatbots and virtual assistants, more intuitive and relatable by understanding and responding to figurative language.

 Applications in Creative Fields

- Assists in creative writing and educational tools by detecting or generating metaphors and similes, fostering artistic expression.

 Cultural and Contextual Adaptation

- Advances cross-cultural applications by enabling the detection of figurative expressions specific to different regions or languages.

Disadvantages:

 Complexity of Figurative Language

- Figurative expressions are context-dependent and ambiguous, making them difficult for machine learning models to detect and interpret accurately.

 Data Scarcity

- Lack of large, annotated datasets specifically for figurative language detection hinders model training and generalization.

 Cultural and Domain Challenges

- Models often fail to generalize across different cultural and domain-specific contexts due to varying interpretations of figurative language.

 High Computational Requirements

- Training sophisticated models like transformers (e.g., BERT, GPT) for figurative intelligence requires significant computational resources.

7.APPLICATIONS

Sentiment Analysis and Opinion Mining:

.Enhanced Emotion Detection: Identifies figurative expressions like *"a rollercoaster of emotions"* or *"a heart of stone"* to better capture user sentiment.

Creative Writing Assistance:

.Writing Tools: Assists writers by detecting, analyzing, or even suggesting metaphors and similes to enhance creative content.

Education and Language Learning:

.Language Teaching: Helps non-native speakers or students understand the meaning and usage of figurative language.

Machine Translation:

.Figurative Translation: Improves translation accuracy by detecting and correctly interpreting figurative expressions, such as *"raining cats and dogs"* into culturally equivalent phrases in other languages.

Marketing and Branding:

.Creative Ad Copy: Enhances the creativity of marketing content by generating or analyzing metaphors and similes to make messages more engaging.

Mental Health and Psychotherapy:

.Therapeutic Applications: Detects metaphorical expressions in conversations, such as *"I feel like I'm drowning"* to identify emotional distress or mental health issues.

Legal and Financial Document Analysis

.Ambiguity Detection: Identifies figurative language in contracts or agreements that could lead to legal ambiguity or misinterpretation.

8.CONCLUSION

Figurative intelligence, particularly through machine learning for simile and metaphor detection, represents a significant advancement in natural language processing (NLP). By enabling machines to recognize and understand figurative expressions—such as similes, metaphors, and other forms of non-literal language—this technology brings AI closer to understanding human communication in its full complexity.

The integration of figurative intelligence allows for more accurate, context-aware interpretation of language, enhancing AI's capabilities in areas like conversational AI, sentiment analysis, creative writing, and cross-cultural communication. It contributes to more relatable and sophisticated interactions with machines, as seen in applications ranging from virtual assistants to mental health support systems.

However, challenges remain in fully capturing the richness of figurative language. The context-dependent nature of metaphors and similes, the scarcity of annotated data, and the need for better reasoning abilities in AI models mean that figurative intelligence is still an evolving field. Additionally, cultural and domain-specific variations complicate the development of generalized models.

Despite these hurdles, the continued advancements in deep learning, multimodal learning, and dataset creation provide optimism for improving figurative language detection systems. As machine learning models become more adept at handling abstract and metaphorical expressions, the potential applications will expand, bringing us closer to AI that can engage with human language in a more nuanced and creative manner.

In conclusion, figurative intelligence not only holds promise for enhancing current AI applications but also paves the way for future developments in human-computer interaction, creative industries, and cross-domain understanding. As research and technology continue to evolve, the integration of figurative language processing into AI will become a cornerstone for more intuitive, effective, and emotionally intelligent systems.

9.FUTURE SCOPE

The field of figurative intelligence, particularly in detecting similes and metaphors through machine learning, holds immense potential for future advancements. As natural language processing (NLP) and machine learning technologies evolve, the scope of figurative intelligence will continue to expand, offering exciting new applications and capabilities. Below are some key areas where figurative intelligence can evolve and make a significant impact:

. Enhanced Understanding of Complex Figurative Language

. Multimodal Figurative Intelligence

. Cross-Cultural Figurative Language Understanding

. Real-Time Figurative Language Detection

. Advanced Applications in Creative Fields

. Personalized Learning and Educational Tools

. Mental Health and Emotional Intelligence

. Legal and Business Applications

. Hybrid Cognitive AI Systems

. Ethical and Bias Detection in Figurative Language.

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10.APPENDIX

SOURCE CODE:

Index.html:

```
<!DOCTYPE html>
<html lang="en">
<head>
  <meta charset="UTF-8">
  <meta name="viewport" content="width=device-width, initial-scale=1.0">
  <title>Prediction Form</title>
  <style>
    /* General Styles */
    body {
      font-family: Arial, sans-serif;
      margin: 0;
      padding: 0;
      box-sizing: border-box;
      background-color: #f4f4f9;
    }
    header {
      background-color: #4CAF50;
      color: white;
      padding: 1rem;
      text-align: center;
    }
    .logo h1 {
      margin: 0;
    }
    .container {
      display: flex;
      justify-content: center;
      align-items: center;
      height: 80vh;
    }
    .prediction-box {
      background-color: white;
      padding: 2rem;
      border-radius: 8px;
      box-shadow: 0 4px 6px rgba(0, 0, 0, 0.1);
      text-align: center;
      width: 300px;
    }
    .prediction-box h3 {
      margin-bottom: 1.5rem;
      color: #333;
    }
    label {
      font-size: 1rem;
      color: #555;
    }
    input[type="text"] {
      width: 100%;
      padding: 0.5rem;
      margin: 1rem 0;
      border: 1px solid #ccc;
      border-radius: 4px;
      font-size: 1rem;
    }
    .btn {
```

```
            background-color: #4CAF50;
            color: white;
            border: none;
            padding: 0.5rem 1rem;
            border-radius: 4px;
            font-size: 1rem;
            cursor: pointer;
            transition: background-color 0.3s;
        }
        .btn:hover {
            background-color: #45a049;
        }
    </style>

</head>
<body>
    <header>
        <div class="logo">
            <h1>Figurative Insight</h1>
        </div>
        <nav>
            <!-- Your navigation here if any -->
        </nav>
    </header>
    <div class="container">
        <div class="prediction-box">
            <h3>Predict</h3>
            <form action="{{url_for('predict')}}" method="post">
                <label for="userInput">Enter text:</label><br>
                <input type="text" id="userInput" name="userInput" placeholder="Enter your text"
required><br>
                <button class="btn" type="submit">Predict</button>
            </form>
        </div>
    </div>
</body>
</html>
```

<u>Result.html:</u>

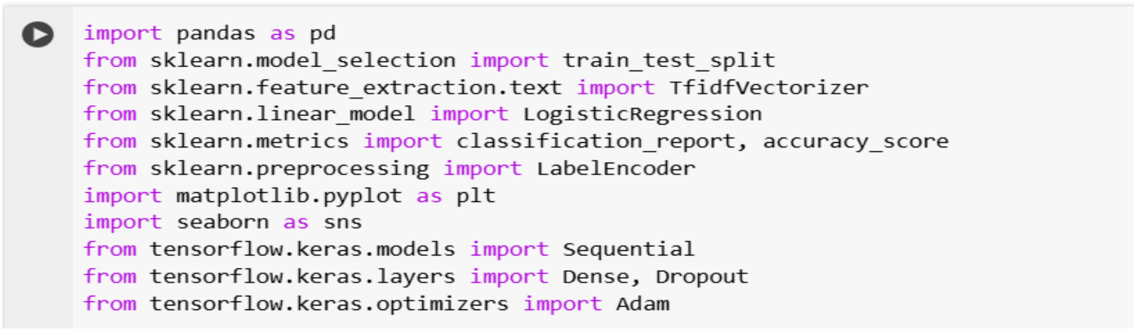
```
<html>
  <head>
    <title>Result</title>
    <style>
      body {
        background-color: darkgrey;
      }
      .output {
        padding: 20px;
        border: 1px solid red;
        text-align: center;
        color: rgb(124, 0, 241);
        font-style: italic;
        font-size: larger;
      }
      .result {
        display: block;
        margin-left: auto;
        margin-right: auto;
        width: 50%;
      }
    </style>
  </head>
  <body>
    <h3 class="output">{{ prediction_text }}</h3>
    <img class="result" src="static/fig.jpeg" alt="prediction" width="200" />
  </body>
</html>
```

App.py:

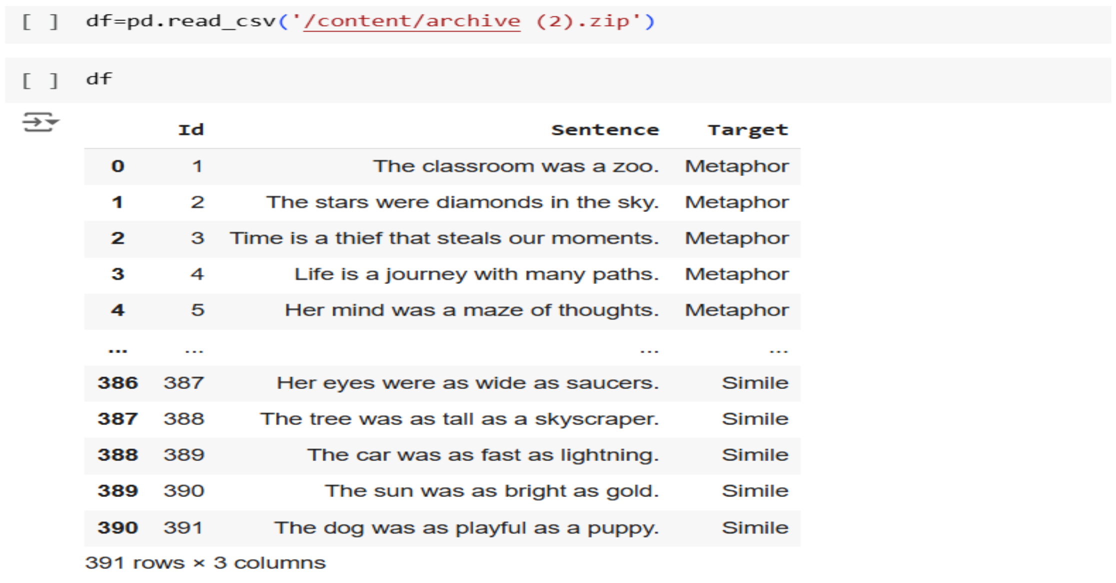
```
import numpy as np
import pickle
import os
from flask import Flask, request, render_template
from keras.models import load_model
import tensorflow as tf
app = Flask(__name__, template_folder='template')
# Load the necessary files
with open('vector_model.pkl', 'rb') as file:
    vectorizer = pickle.load(file)
   classification_model = load_model('trained_model.h5')
with open('label_encoder.pkl', 'rb') as file:
    label_encoder = pickle.load(file)
@app.route('/')
def home():
    return render_template('index.html')
@app.route('/predict', methods=['POST'])
def predict():
    if request.method == 'POST':
         text = request.form['userInput']  # Make sure this matches the name attribute in your
form
```

```
        data = [text]
        # Transform the input data using the vectorizer
        x = vectorizer.transform(data)
        print(f"x shape: {x.shape}, x type: {type(x)}")  # Fix this print statement
      # Get the model's prediction
        nn_probabilities = classification_model.predict(x)
        nn_predictions = (nn_probabilities > 0.5).astype(int).flatten()

        # Convert predictions back to labels
        nn_predicted_labels = label_encoder.inverse_transform(nn_predictions)
        result = nn_predicted_labels[0]

        # Return the result page with the prediction
        return render_template("result.html", prediction_text=f"The figurative type of sentence
is: {result}")

if __name__ == "__main__":
    app.run(debug=True)
```

Model Building



```python
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
import seaborn as sns
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.optimizers import Adam
```

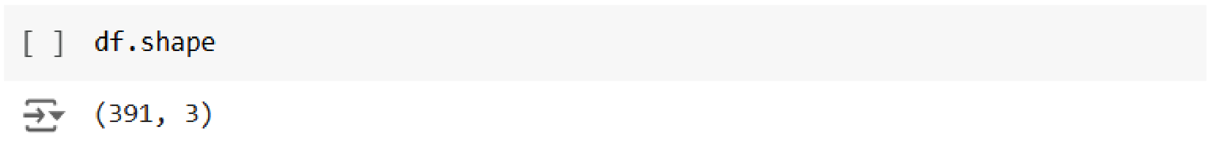


```python
df=pd.read_csv('/content/archive (2).zip')
```

```python
df
```

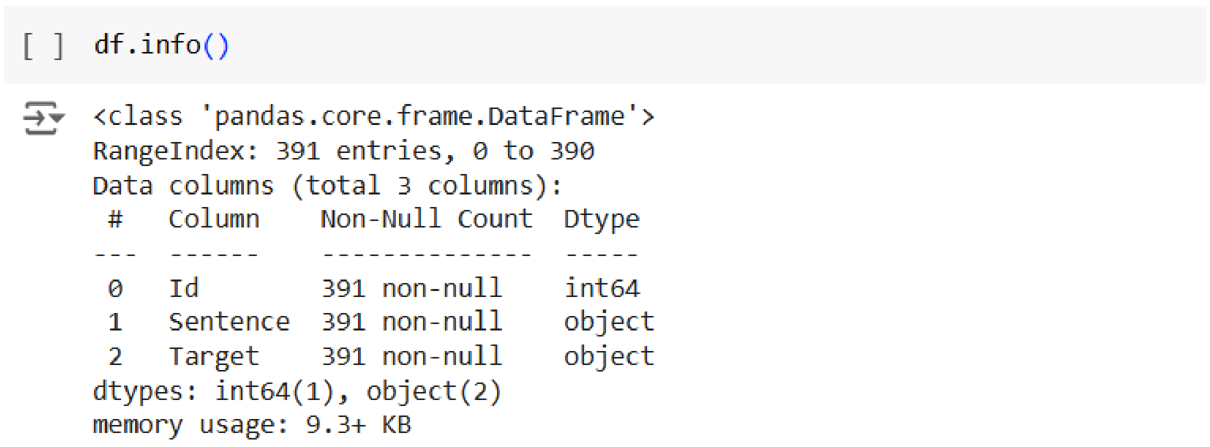
	Id	Sentence	Target
0	1	The classroom was a zoo.	Metaphor
1	2	The stars were diamonds in the sky.	Metaphor
2	3	Time is a thief that steals our moments.	Metaphor
3	4	Life is a journey with many paths.	Metaphor
4	5	Her mind was a maze of thoughts.	Metaphor
...	...	...	...
386	387	Her eyes were as wide as saucers.	Simile
387	388	The tree was as tall as a skyscraper.	Simile
388	389	The car was as fast as lightning.	Simile
389	390	The sun was as bright as gold.	Simile
390	391	The dog was as playful as a puppy.	Simile

391 rows × 3 columns



```python
df.shape
```

```
(391, 3)
```



```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 391 entries, 0 to 390
Data columns (total 3 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Id        391 non-null    int64
 1   Sentence  391 non-null    object
 2   Target    391 non-null    object
dtypes: int64(1), object(2)
memory usage: 9.3+ KB
```

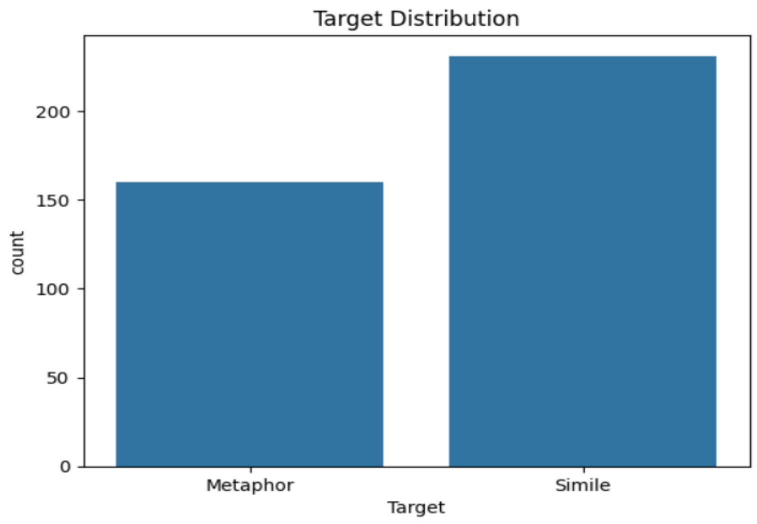
```
[ ] df.isnull().sum()
```

	0
Id	0
Sentence	0
Target	0

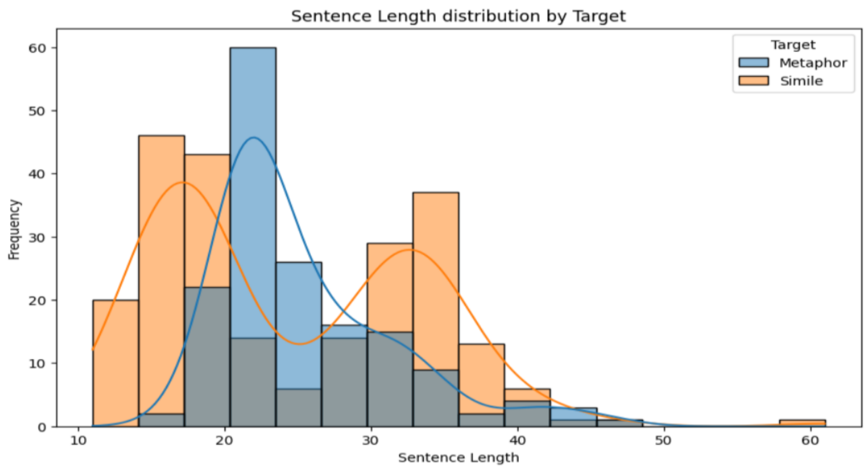
dtype: int64

```
x = df['Sentence']
y = df['Target']

label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y)
```

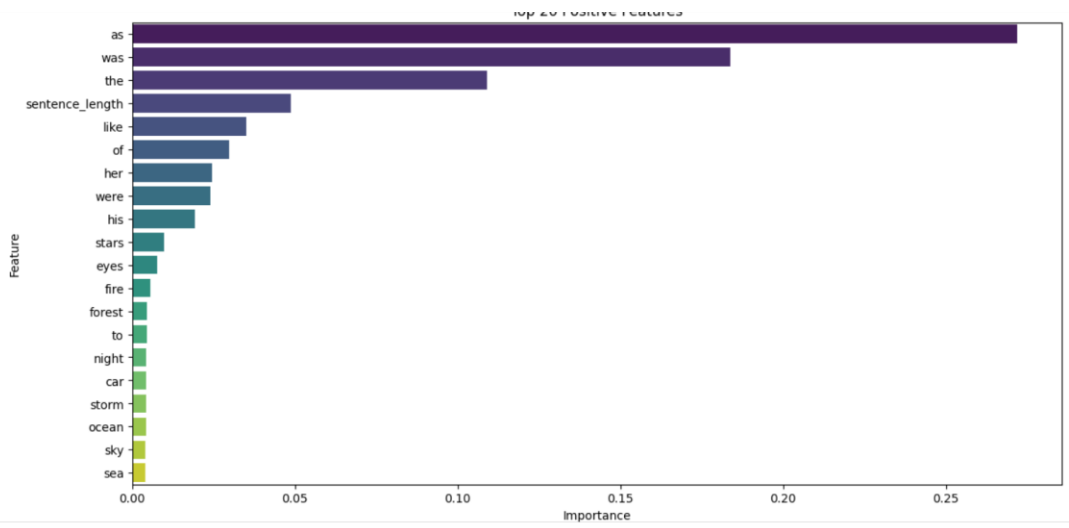
```
sns.countplot(x='Target',data=df)
plt.title('Target Distribution')
plt.show()
```



```
df['sentence_length'] = df['Sentence'].apply(len)
plt.figure(figsize=(10,6))
sns.histplot(df,x='sentence_length' , hue='Target' , kde=True)
plt.title('Sentence Length distribution by Target')
plt.xlabel('Sentence Length')
plt.ylabel('Frequency')
plt.show()
```



```
from sklearn.ensemble import RandomForestClassifier
vectorizer = TfidfVectorizer()
sentence_tfidf = vectorizer.fit_transform(X.astype(str)).toarray()

# Create DataFrame for TF-IDF features
tfidf_df = pd.DataFrame(sentence_tfidf, columns=vectorizer.get_feature_names_out())

# Combine TF-IDF features with sentence length
X_combined = pd.concat([tfidf_df, df[['sentence_length']].reset_index(drop=True)], axis=1)

# Fit Random Forest model
rf_model = RandomForestClassifier()
rf_model.fit(X_combined, y_encoded)
importances = rf_model.feature_importances_

# Create a DataFrame for feature importance
feature_names = vectorizer.get_feature_names_out().tolist() + ['sentence_length']
top_positive_features = pd.DataFrame({'feature': feature_names, 'importance': importances})
top_positive_features = top_positive_features.sort_values(by='importance', ascending=False)

# Plotting the top features
plt.figure(figsize=(14, 7))
sns.barplot(y='feature', x='importance', data=top_positive_features.head(20), palette='viridis')
plt.title('Top 20 Positive Features')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.show()
```



```
[ ] vectorizer = TfidfVectorizer()
    X_tfidf = vectorizer.fit_transform(X)

    X_train, X_test, y_train, y_test = train_test_split(X_tfidf, y_encoded, random_state=42, test_size=0.2)
```

Logistic Regression

```
[ ] model1 = LogisticRegression()
    model1.fit(X_train, y_train)
```

```
LogisticRegression
LogisticRegression()
```

```
[ ] y_pred = model1.predict(X_test)
    print("Logistic Regression Accuracy:", accuracy_score(y_test, y_pred))
    print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Logistic Regression Accuracy: 1.0

Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00        41
           1       1.00      1.00      1.00        38

    accuracy                           1.00        79
   macro avg       1.00      1.00      1.00        79
weighted avg       1.00      1.00      1.00        79
```

```
[ ] model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 512)	261,120
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 256)	131,328
dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 1)	257

```
Total params: 392,705 (1.50 MB)
Trainable params: 392,705 (1.50 MB)
Non-trainable params: 0 (0.00 B)
```

```
[ ] for ele in X_train :
        print(ele)
        break
```

```
  (0, 452)	0.24266800143272493
  (0, 478)	0.2332956009153811
  (0, 494)	0.6041349672119037
  (0, 270)	0.7222924235142234
```

```
history = model.fit(X_train.toarray(), y_train,
                    epochs=75,
                    batch_size=64,
                    validation_data=(X_test.toarray(), y_test),
                    verbose=2)


# Evaluate the neural network model
loss, accuracy = model.evaluate(X_test.toarray(), y_test)
print("Neural Network Accuracy:", accuracy)
```

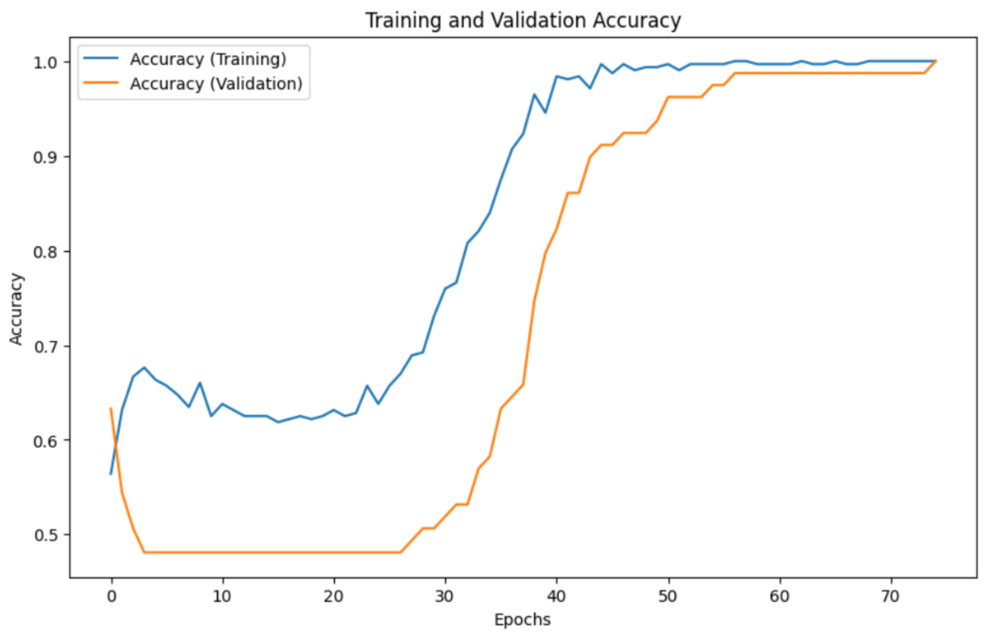
```
Epoch 1/75
5/5 - 2s - 370ms/step - accuracy: 0.5641 - loss: 0.6908 - val_accuracy: 0.6329 - val_loss: 0.6900
```

```
[ ] y_pred_prob = model.predict(X_test.toarray())
    y_pred = (y_pred_prob > 0.5).astype(int).flatten()

    print("\nClassification Report:\n", classification_report(y_test, y_pred, target_names=label_encoder.classes_))
```

```
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step

Classification Report:
               precision    recall  f1-score   support

    Metaphor       1.00      1.00      1.00        41
      Simile       1.00      1.00      1.00        38

    accuracy                           1.00        79
   macro avg       1.00      1.00      1.00        79
weighted avg       1.00      1.00      1.00        79
```

```
plt.figure(figsize=(10, 6))
plt.plot(history.history['accuracy'], label='Accuracy (Training)')
plt.plot(history.history['val_accuracy'], label='Accuracy (Validation)')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

[ ]



```
import pickle
with open('vector_model.pkl', 'wb') as file:
    pickle.dump(vectorizer, file)
```

```
[ ] with open('label_encoder.pkl', 'wb') as file:
        pickle.dump (label_encoder, file)
```

```
[ ] model.save('trained_model.h5')
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instea
```

```
[ ]  new_sentences =[
         "Her smile was as bright as the sun.",
         "The world is a stage, and we are merely players."]
     X_new = vectorizer.transform(new_sentences)
```

```
[ ]  nn_probabilities = model.predict(X_new)

     nn_predictions = (nn_probabilities > 0.5).astype(int).flatten()

     nn_predicted_labels = label_encoder.inverse_transform(nn_predictions)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 150ms/step
```

```
for i, sentence in enumerate(new_sentences):
    nn_simile_prob = nn_probabilities[i][0]
    nn_metaphor_prob = 1 - nn_simile_prob

    print(f"Sentence: {sentence}")
    print()
    print(f"Neural Network Prediction: {nn_predicted_labels[i]}")
    print()
    print(f" Probability of being a Simile: {nn_simile_prob:.4f}")
    print(f" Probability of being a Metaphor: {nn_metaphor_prob:.4f}")
    print()
```

```
Sentence: Her smile was as bright as the sun.

Neural Network Prediction: Simile

 Probability of being a Simile: 0.9213
 Probability of being a Metaphor: 0.0787

Sentence: The world is a stage, and we are merely players.

Neural Network Prediction: Metaphor

 Probability of being a Simile: 0.1772
 Probability of being a Metaphor: 0.8228
```