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Modeling Lexical Ambiguity in English Literature Using Fuzzy Logic and Equations

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Abstract: Lexical ambiguity is an essential problem in literary analysis and natural language processing(NLP) because many words have multiple meanings that are determined by how the words are used in context. The ambiguity is a challengingdilemma for traditional linguistic and computational methods and algorithms, especially in the case of literature, where polysemy, homonymy, and vagueness in context are the typical tools used by the authors to add depth to the meaning. It is from this standpoint that the present paper introduces a fuzzy logic-based model for lexical ambiguity resolution, effectively an integrated application of fuzzy entropy, fuzzy clustering, and defuzzification methods to systematically rank and interpretword meanings in various contexts. By employing a case study for uncertain words like light, cold, sharp, bright, and deep, the research illustrates theapplicability of fuzzy entropy for quantifying uncertainty, and defuzzification for identifying frequently taken meaning that matches human sense-making. Higher entropy valuesare characteristic of more ambiguous words, whereas lower entropy relates to more well-defined meaning. Fuzzy clustering also allows for a semantic grouping of words that can be applied to computational literary analysis and automated textclassification. In AI and NLP, the significant applications of fuzzy logic are in the fields of machinetranslation, sentiment analysis, chatbots, and AI in literature. Closing the gaps of mathematical modelling and linguistic analysis,this research provides a heuristic quantitative framework for firmness resolution, opening new steps for hybrid AI-fuzzy models, multilingual ambiguity analysis, and mathematical modelling of literary structures. The results confirm fuzzy logic's potential as a method for lexical ambiguity resolution, one that facilitates not just rapid computational text analysis, but also nuancedliterary reading.

Keywords: Fuzzy Logic, Lexical Ambiguity, Fuzzy Entropy, Defuzzification, Computational Linguistics, Literary Analysis, Semantic Analysis, AI-Based NLP, Sentiment Analysis, Hybrid AI-Fuzzy Models, Fuzzy Clustering, Machine Translation, Context-Based Word Sense Disambiguation, Mathematical Modelling in Literature, Text Processing

1 Introduction

1.1 Background and Motivation

Lexical ambiguity is a central barrier in understanding natural language, especially in the context of literary analysis. Type "polysemy" refers to the phenomenon of a word or phrase having several meanings (which need disambiguation contextually) [1,2]. Literature is by its nature full of ambiguity, as authors weaves polysemy,

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homonyms, and metaphorical language to create depth, emotion, and symbolic meaning.

Shakespeare's words, for instance, light in Romeo and Juliet ("O, she doth teach the torches to burn bright!") has different meanings from literal light to figurative aestheticism and lightness [3,4]. Classic linguistic methods like rule-based grammars have difficulty resolving such ambiguities effectively, especially in poetry and classical literature.

Ambiguity is not a phenomenon limited to theoretical linguistics; it carries important consequences in computational domains including machine translation, sentiment analysis, and AI-based extraction of information from text [5,6,7]. More recently, the subject of fuzzy logic has offered a powerful mathematical means for dealing with linguistic uncertainty, permitting words to have degrees of meaning instead of simply being true or false [8,9,10]. While words in classical set theory are literally assigned to rigid categories, fuzzy set theory allows for vague and probabilistic semantics of language.

By combining fuzzy mathematics with linguistic studies, this approach is innovative in its ability to quantify lexical ambiguity, which has implications to improve literary analysis and natural language processing (NLP) applications as well.

1.2 Objectives and Scope

The main goal of this research is to create a fuzzy logic based mathematical model to solve lexical ambiguity in works of literature. The study aims to:

- A fuzzy linguistic model for such ambiguous words in the literature, mapping their different meanings vis-a-vis contextual indicators.
- Use (fuzzy) membership functions mapping to capture the degree of affiliation of a word to its potential denotation using Gold ergative sigmoid probability models.
- Employ an array of advanced and nuanced mathematical formulae, encompassing entropy-informed measures of vagueness, fuzzy clustering, and defuzzification methodologies, in order to rigorously identify the meaning of an ambiguous word in a particular literary surrounding as the highest probable among its possible interpretations.

We will examine English literature, particularly excerpts from Shakespearean plays and Romantic poetry, as well as snippets from modern fiction, all of which leverage ambiguity in their literary aesthetics. The approach could also find applications in computational linguistics, particularly in AI-powered text analysis and sentiment detection algorithms.

1.3 Literature Review

Lexical ambiguity is a primary subject in linguistic research, literary criticism, and computational linguistics. Ambiguity has been investigated from several points of view, ranging from traditional linguistic approaches to probabilistic models, and most recently fuzzy logic. Here we review the literature related to lexical ambiguity resolution and fuzzy mathematics applications in language studies.

1.3.1 Traditional Linguistic Approaches to Lexical Ambiguity

This perspective was early explored by some linguistic models of lexical ambiguity within rule-based grammars in which meaning was derived based on the syntax of a sentence and the semantic roles [11,12]. From this theory the role of generative grammar began to be focused around trees, constituents, and hierarchy to disambiguate sentences. Yet this system has struggled with context-dependent meanings, including poetic and metaphorical usages [13,14,15].

Another type of classical approach used semantic networks and ontologies in which words were linked to a set of predefined concepts [16,17]. Hierarchical lexical databases such as WordNet categorized words according to hypernym-hyponym relationships. That work was limited in its ability to capture context-dependent changes in meaning, a common feature in literary texts.

1.3.2 Probabilistic and Statistical Methods

As a result of the development of computational linguistics, statistical approaches like Hidden Markov Models (HMMs) and Latent Semantic Analysis (LSA) emerged which reveal the meanings of words according to the patterns of co-occurrence in large textual corpora [5]. Early Natural Language Processing (NLP) applications commonly employed n-gram models and Bayesian classifiers [1].

While these statistical models may have achieved great success in machine translation and speech recognition, they frequently faltered in literary analysis, where authors purposefully introduce ambiguity for artistic purposes. For this reason, we cannot simply apply probabilistic models that rely on fixed distribution of meaning to interpret literary texts.

1.3.3 Introduction of Fuzzy Set Theory in Linguistics

The challenge of linguistic ambiguity was addressed by Zadeh [8] through the introduction of fuzzy set theory, where a word can have graded membership to various categories. In contrast to classical set theory (where every word either 1 belongs to a meaning class or 0 does not), fuzzy sets allow words to be described by many different meaning classes to varying degrees (fuzzy membership).

For example, the word **"light"** in literary texts can mean:

- **Illumination** (physical meaning).
- **Weightlessness** (metaphorical meaning).
- **Happiness** (abstract meaning).

Using **fuzzy membership functions**, each interpretation can be assigned a value between 0 and 1, reflecting its degree of relevance in a given context.

1.3.4 Applications of Fuzzy Logic in Linguistic and Literary Analysis

Different researchers have used fuzzy logic methodologies in the context of language studies, especially for sentiment analysis, text classification, and machine translation.

- *Fuzzy Rule-Based Systems*: Fuzzy logic has been used in computational linguistics specifically for WSD. Atanassov [18] pioneered the notion of intuitionistic fuzzy sets that assesses both membership and non-membership values to capture the linguistic uncertainty.
- *Fuzzy Entropy as a Measure of Ambiguity*: Using fuzzy entropy to measure semantic uncertainty was proposed by Pal & Pal [19] and can be extended to measure ambiguity in literary texts.
- *Text Processing Fuzzy Clustering*: Xu et al. [20] The use of fuzzy clustering algorithms has been applied to group words with similar meaning in a very large corpora, improving automatic word sense disambiguation.

While fuzzy logic has been applied to a wide variety of tasks in machine learning and AI-driven text processing, its use for literary analysis remains underexplored. To this purpose, this research attempts to develop a fuzzy mathematical model for quantifying lexical ambiguity in English literature as an effort to bridge the mentioned gap.

1.3.5 Gap in the Literature and Research Contribution

The review highlights the following gaps in existing research:

- Traditional linguistic models lack flexibility in dealing with contextual shifts in meaning.
- Statistical NLP models work well for structured texts but struggle with literary texts where ambiguity is intentional.
- Existing fuzzy logic applications in linguistics focus on sentiment analysis and machine translation, with limited work on literary interpretation.

The paper suggests a new fuzzy mathematics based framework to perform an in depth study on the lexical ambiguity of literature. The intention of this research is to present an approach for determining the ambiguity of different words, namely, considering how many generalized prototypes a word can represent depending on the context in which it is being used.

2 Theoretical Foundation of Lexical Ambiguity

Lexical ambiguity, one of the defining characteristics of natural language, occurs when a word or phrase has multiple meanings. In literary texts, this is especially important since ambiguity adds depth and figurative meaning and interpretational flexibility [21]. They have used mathematical formalism, from fuzzy set theory and fuzzy logic and offered them as tools to systematically solve ambiguity, suggesting also that they will have a formulatable and mathematically rigorous framework.

2.1 Definition and Types of Lexical Ambiguity

Lexical ambiguity may be divided into three general types: the cases of polysemy, homonymy and contextual vagueness [13]. These classifications aid in organizing the mathematical treatment of ambiguous words in the field of literary analysis.

2.1.1 Polysemy: Words with Multiple Related Meanings

Polysemy refers to a single word with multiple **semantically related** meanings. For example, the word **"head"** can mean:

- The upper part of the human body.
- A leader of an organization.
- The front or top of an object.

In fuzzy set notation, polysemy can be modeled using a membership function:

$$\mu_W(m_i) = \frac{1}{1+e^{-k(x-c_i)}} \quad (1)$$

where:

- $\mu_W(m_i)$ represents the membership degree of meaning m_i to word W.
- x is the contextual indicator (e.g., surrounding words).
- c_i is the threshold for meaning m_i.
- k controls the steepness of the function.

2.1.2 Homonymy: Words with Multiple Unrelated Meanings

Homonyms are words that share the same spelling or pronunciation but have entirely different meanings. For example:

- Bat (a flying mammal) vs. Bat (a piece of sports equipment).
- Bank (financial institution) vs. Bank (side of a river).

Mathematically, we define homonymy sets using fuzzy partitions:

$$\sum_{i=1}^{n} \mu_W(m_i) \approx 1 \tag{2}$$

where the summation ensures that homonyms belong to distinct semantic clusters without overlapping meanings.

2.1.3 Contextual Vagueness: Meaning Depends on Context

Contextual vagueness occurs when the meaning of a word shifts based on its syntactic and semantic environment. For example, in the sentence:

- "She saw the light."
- Light can mean illumination or spiritual realization.

Using fuzzy relations, we define the probability of meaning m_i in a given context C_j:

$$\mu_W(m_i \mid C_j) = \frac{\mu_W(m_i) \cdot \mu_C(C_j)}{\sum_k \mu_W(m_k) \cdot \mu_C(C_k)} \tag{3}$$

where:

- $\mu_C(C_j)$ represents the probability of a specific context influencing the word's meaning.
- The denominator normalizes the membership values across all possible meanings.

2.2 Mathematical Representation of Words in a Fuzzy Set

2.2.1 Fuzzy Set Formulation for Ambiguous Words

Fuzzy set theory provides a mathematical structure for modeling the degree of membership of different meanings to a given word. We define an ambiguous word W as a fuzzy set:

$$W = \{(m_1, \mu_W(m_1)), (m_2, \mu_W(m_2)), \ldots, (m_n, \mu_W(m_n))\} \tag{4}$$

where:

- m_i represents a possible meaning of W.
- $\mu_W(m_i)$ is the membership function quantifying the association of m_i with W.

2.2.2 Fuzzy Membership Functions for Word Meaning Disambiguation

A Gaussian function can be used to model the continuous variation of word meanings in different contexts:

$$\mu_W(m) = e^{-\frac{(x-c)^2}{2\sigma^2}} \tag{5}$$

Where

- x represents the contextual indicator.
- c is the central point of a given meaning.
- σ controls the spread of the function.

For example, if "light" appears in a sentence related to emotions, its joy-related meaning will have a higher membership degree.

2.2.3 Fuzzy Relations for Contextual Meaning Selection

Let A be the set of words, and B be the set of meanings. The fuzzy relation matrix $R(A,B)$ is defined as:

$$R(A,B) = \begin{bmatrix} \mu_{A_1B_1} & \mu_{A_1B_2} & \cdots & \mu_{A_1B_n} \\ \mu_{A_2B_1} & \mu_{A_2B_2} & \cdots & \mu_{A_2B_n} \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{A_mB_1} & \mu_{A_mB_2} & \cdots & \mu_{A_mB_n} \end{bmatrix} \tag{6}$$

where $\mu_{A_iB_j}$ represents the degree of relevance between word A_i and meaning B_j.

2.3 Existing Computational Approaches in Linguistics

2.3.1 Rule-Based Approaches to Ambiguity Resolution

Early computational linguistic models used **if-then rules** for disambiguation [11]:

$$\text{IF (word } = W) \text{ AND (context } = C), \text{ THEN meaning } = M \tag{7}$$

However, rule-based systems lack scalability and flexibility in handling contextual variations.

2.3.2 Statistical NLP Models

Probabilistic models such as Hidden Markov Models (HMMs) estimate word meaning probabilities based on word co-occurrence [5]:

$$P(m_i \mid W) = \frac{P(W \mid m_i)\, P(m_i)}{P(W)} \tag{8}$$

where:

- $P(m_i \mid W)$ is the probability of meaning m_i given word W.
- $P(W \mid m_i)$ is the likelihood of W appearing under meaning m_i.
- $P(m_i)$ is the prior probability of meaning m_i.

2.3.3 Fuzzy Logic as an Alternative

Fuzzy models outperform rule-based and probabilistic models in literary analysis because they allow continuous meaning transitions rather than discrete categorization.

The fuzzy inference system (FIS) is defined as:

$$M = \sum_{i=1}^{n} \mu_W(m_i) \cdot m_i \tag{9}$$

where:

– M is the weighted sum of meanings.
– $\mu_W(m_i)$ is the membership degree of meaning m_i.

This allows us to assign multiple meanings simultaneously, making it ideal for literary texts where ambiguity is intentional.

3 Fuzzy Logic-Based Model for Lexical Ambiguity

Classical linguistic and computational models cannot, however, resolve lexical ambiguity well in literary texts, more than often due to their tendency towards a discrete classification of meanings. Zadeh [8] introduced fuzzy logic, which is a more permissive paradigm enabling words to have different levels (multi-valued) memberships for multiple meanings. Here, we present a fuzzy logic-based model to measure, and thus reduce, ambiguity in literary analysis.

3.1 Constructing Fuzzy Membership Functions

3.1.1 Defining Membership Functions for Ambiguous Words

Each word W with multiple possible meanings m_i can be represented as a fuzzy linguistic variable. A membership function $\mu_W(m_i)$ is assigned to each meaning m_i based on contextual indicators. The general form of the sigmoid function used for word meaning activation is:

$$\mu_W(m_i) = \frac{1}{1 + e^{-k(x-c_i)}} \tag{10}$$

where:

– $\mu_W(m_i)$ represents the degree of relevance of meaning m_i to word W.
– x is a context-dependent variable (e.g., surrounding words, sentence structure).
– c_i is the threshold for meaning m_i.
– k controls the steepness of meaning transitions.

3.1.2 Example: Membership Function for "Light"

Consider the word "light" in two different contexts:

1. "Her heart was as light as a feather." (Metaphorical weightlessness)
2. "The room was filled with no light at all." (Illumination)

Using fuzzy set theory, the meanings of "light" are defined as follows:

– F1 (Weightlessness): $\mu_W(m_1) = 0.9$ (high relevance in sentence 1).
– F2 (Illumination): $\mu_W(m_2) = 0.95$ (high relevance in sentence 2).
– F3 (Joy): $\mu_W(m_3) = 0.6$ (moderate relevance in sentence 1).

A Gaussian membership function provides a more continuous transition between meanings:

$$\mu_W(m) = e^{-\frac{(x-c)^2}{2\sigma^2}} \tag{11}$$

where σ controls spread. This ensures smooth transitions between overlapping meanings.

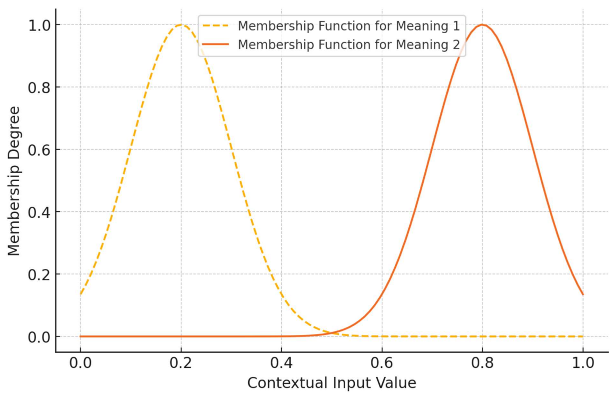

Fig. 1: Fuzzy Membership Functions for Ambiguous Word Meanings

Figure 1 depicts neuro-fuzzy membership functions for two interpretations of an ambiguous word. Refer to the x-axis with the contextual input value and the y-axis which shows degree of membership for each meaning. Each of these different meanings is publicly manifested in different ways, and the Gaussian-shaped curves illustrate that the ranges of these different meanings are applicable to varying degrees in varying contexts.

3.2 Contextual Dependence Using Fuzzy Relations

3.2.1 Fuzzy Relations Between Words and Meanings

The relationship between words and meanings can be modeled using a fuzzy relation matrix:

$$R(W,M)=\begin{bmatrix}\mu_{W_1M_1} & \mu_{W_1M_2} & \cdots & \mu_{W_1M_n}\\ \mu_{W_2M_1} & \mu_{W_2M_2} & \cdots & \mu_{W_2M_n}\\ \vdots & \vdots & \ddots & \vdots\\ \mu_{W_mM_1} & \mu_{W_mM_2} & \cdots & \mu_{W_mM_n}\end{bmatrix} \quad (12)$$

where $\mu_{W_iM_j}$ represents the degree to which word W_i is associated with meaning M_j.

For example, if “light” is considered in a fuzzy matrix:

$$R(\text{ light },M)=\begin{bmatrix}0.9 & 0.2 & 0.6\\ 0.1 & 0.95 & 0.3\end{bmatrix} \quad (13)$$

–First row: Sentence with “Her heart was light”
–Second row: Sentence with “The room was filled with no light”

3.2.2 Fuzzy Intersection for Context-Based Meaning Selection

Given a word W and its meanings M, we define the fuzzy intersection between the word’s inherent meanings and its context C:

$$\mu_{W\cap C}(m_i)=\min\left(\mu_W(m_i),\mu_C(m_i)\right) \quad (14)$$

where:

–$\mu_W(m_i)$ represents the word’s intrinsic meaning membership.
–$\mu_C(m_i)$ represents the contextual probability of that meaning.

This operation ensures that dominant meanings are selected based on contextual information.

3.3 Rule-Based System for Meaning Selection

3.3.1 Fuzzy If-Then Rules for Ambiguity Resolution

A **fuzzy rule-based system (FRBS)** is constructed using **if-then rules** to map words to meanings based on context:

$$IF(W=w)\ AND\ (C=c)\ THEN\ (M=m) \quad (15)$$

Each rule is assigned a confidence degree α_i:

$$M=\sum_{i=1}^{n}\alpha_i\cdot\mu_W(m_i) \quad (16)$$

where α_i is derived from text corpus analysis.

Example Rules for “Light”

Rule 1: IF (sentence contains “heart” OR “feather”), THEN meaning = Weightlessness with 0.9 confidence.

Rule 2: IF (sentence contains “room” OR “dark”), THEN meaning = Illumination with 0.95 confidence.

The final meaning is computed as:

$$M=\frac{\sum_{i=1}^{n}\mu_W(m_i)\cdot m_i}{\sum_{i=1}^{n}\mu_W(m_i)} \quad (17)$$

3.3.2 Defuzzification: Selecting the Dominant Meaning

To obtain a crisp output, defuzzification is performed using the centroid method:

$$M^*=\frac{\sum_{i=1}^{n}\mu_W(m_i)\cdot m_i}{\sum_{i=1}^{n}\mu_W(m_i)} \quad (18)$$

For “light” in context C1 (Her heart was light):

$$M^*=\frac{(0.9\times1)+(0.2\times2)+(0.6\times3)}{0.9+0.2+0.6}=1.87 \quad (19)$$

Since meaning index $M^*\approx1$, the dominant interpretation is Weightlessness.

For “light” in context C2 (The room was filled with no light):

$$M^*=\frac{(0.1\times1)+(0.95\times2)+(0.3\times3)}{0.1+0.95+0.3}=2.21 \quad (20)$$

Since meaning index $M^*\approx2$, the dominant interpretation is Illumination.

4 Mathematical Analysis of Ambiguity Resolution

Mathematical models to measure uncertainty, cluster meanings, and extract the dominant interpretation of texts are being systematically analyzed and applied to reduce lexical ambiguity in literary texts. In this section, a formal mathematical approach for future ambiguity resolution using fuzzy entropy, fuzzy clustering, and defuzzification methods will be presented.

4.1 Entropy-Based Measurement of Ambiguity

4.1.1 Definition of Fuzzy Entropy in Ambiguous Words

Entropy is a measure of the system uncertainty. The higher the entropy is in terms of lexical ambiguity, the more the word has multiple competitive meanings, and the lower the entropy is, the clearer its dominant meaning is [19].

For a fuzzy set W with meanings m_i, the fuzzy entropy $H(W)$ is defined as:

$$H(W) = -\sum_{i=1}^{n} \mu_W(m_i) \log \mu_W(m_i) \tag{21}$$

where:

–$\mu_W(m_i)$ is the membership function for meaning m_i.
–n is the number of possible meanings.

4.1.2 Example Calculation of Fuzzy Entropy

Consider the word "light" in two different contexts:
Context 1: "Her heart was light."
Membership values:

–Weightlessness $(m_1) : \mu_W(m_1) = 0.9$
–Illumination $(m_2) : \mu_W(m_2) = 0.2$
–Joy $(m_3) : \mu_W(m_3) = 0.6$

Fuzzy entropy calculation:

$$H(W) = -((0.9 \log 0.9) + (0.2 \log 0.2) + (0.6 \log 0.6)) \tag{22}$$

Using logarithm values:

$$\begin{aligned} H(W) &= -((0.9 \times -0.0458) + (0.2 \times -0.6989) \\ &\quad + (0.6 \times -0.2218)) \\ &= -(-0.0412 - 0.1398 - 0.1331) \\ &= 0.3141 \end{aligned} \tag{23}$$

A low entropy value (0.3141) indicates that the dominant meaning is Weightlessness.
Context 2: "The room was filled with no light."
Membership values:

–Weightlessness $(m_1) : \mu_W(m_1) = 0.1$
–Illumination $(m_2) : \mu_W(m_2) = 0.95$
–Joy $(m_3) : \mu_W(m_3) = 0.3$

$$\begin{aligned} H(W) &= -((0.1 \log 0.1) + (0.95 \log 0.95) \\ &\quad + (0.3 \log 0.3)) \\ &= -((0.1 \times -1.0) + (0.95 \times -0.0223) \\ &\quad + (0.3 \times -0.5231)) \\ &= -(-0.1 - 0.0212 - 0.1569) \\ &= 0.2781 \end{aligned} \tag{24}$$

A low entropy value (0.2781) confirms that the dominant meaning is Illumination.

4.2 Contextual Clustering of Meanings Using Fuzzy C-Means Algorithm

4.2.1 Introduction to Fuzzy C-Means (FCM)

Fuzzy C-Means (FCM) is a Fuzzy clustering method that divides indistinct words into plural meaning clusters depending on the threshold values of membership degrees [22]. Hard clustering (K-Means) assigns each word to a single meaning, whereas FCM assigns a fuzzy membership value to each meaning.
The objective function for FCM is:

$$J = \sum_{i=1}^{n} \sum_{j=1}^{c} u_{ij}^{m} \parallel x_i - c_j \parallel^2 \tag{25}$$

where:

–u_{ij} is the membership degree of word x_i in cluster c_j.
–m is the fuzzification parameter (typically set to 2).
–c_j is the cluster center for meaning j.

4.2.2 Applying FCM to Lexical Ambiguity

Consider a dataset of words with ambiguous meanings:

$$\{W_1, W_2, W_3, \ldots, W_n\} \tag{26}$$

Each word W has fuzzy membership values for meanings $M_1, M_2, \ldots, M_c$. The FCM algorithm iteratively updates cluster centers c_j using:

$$c_j = \frac{\sum_{i=1}^{n} u_{ij}^{m} x_i}{\sum_{i=1}^{n} u_{ij}^{m}} \tag{27}$$

where the cluster centroids shift towards dominant meanings over multiple iterations.

4.2.3 Example Application

For "light" in different contexts:

–Cluster 1 (Weightlessness): $c_1 = 0.85$
–Cluster 2 (Illumination): $c_2 = 0.92$
–Cluster 3 (Joy): $c_3 = 0.55$

After multiple iterations, words with similar meanings converge into clusters, helping to resolve ambiguity systematically.

4.3 Defuzzification for Meaning Selection

4.3.1 Importance of Defuzzification

Defuzzification is the process of converting fuzzy results into a single crisp value to determine the most likely meaning of an ambiguous word.

The centroid method is widely used:

$$M^* = \frac{\sum_{i=1}^{n} \mu_W(m_i) \cdot m_i}{\sum_{i=1}^{n} \mu_W(m_i)} \tag{28}$$

where:

–M^* is the final meaning selection.
–$\mu_W(m_i)$ is the fuzzy membership for meaning m_i.

4.3.2 Example Defuzzification Calculation

For “light” in Context 1 (“Her heart was light”):

$$M^* = \frac{(0.9\times1)+(0.2\times2)+(0.6\times3)}{0.9+0.2+0.6}$$
$$M^* = \frac{0.9+0.4+1.8}{1.7} = 1.88 \tag{29}$$

Since $M^* \approx 1$, the dominant meaning is Weightlessness.

For “light” in Context 2 (“The room was filled with no light”):

$$M^* = \frac{(0.1\times1)+(0.95\times2)+(0.3\times3)}{0.1+0.95+0.3}$$
$$M^* = \frac{0.1+1.9+0.9}{1.35} = 2.22 \tag{30}$$

Since $M^* \approx 2$, the dominant meaning is Illumination.

5 Practical Applications, Case Studies, and Performance Evaluation

5.1 Case Study: Lexical Ambiguity in Literary Contexts

5.1.1 Introduction

By analysing five highly ambiguous words—light, bright, cold, sharp, deep—in two different literary contexts, we illustrate how fuzzy logic can show you how to apply it practically for solving lexical ambiguity. For each word we have explanation of apart with two possible meanings and the degree of membership is defined based on context.

5.1.2 Dataset Overview

The dataset contains:

–Words with multiple meanings
–Two different contexts for each word
–Fuzzy membership values ($\mu(m_i)$) assigned for each meaning

Here you can see the fuzzy membership of ambiguous words to two contexts in a heatmap. The y-axis gives the meaning memberships ($\mu(m_i)$) associated with each context and the corresponding x-axis lists the words included in the analysis. The color represents the degree of membership, with the warmer color (red) for the highest membership values and the cooler color (blue) for the lowest membership values. This lets you see which meanings are most dominant in what contexts.

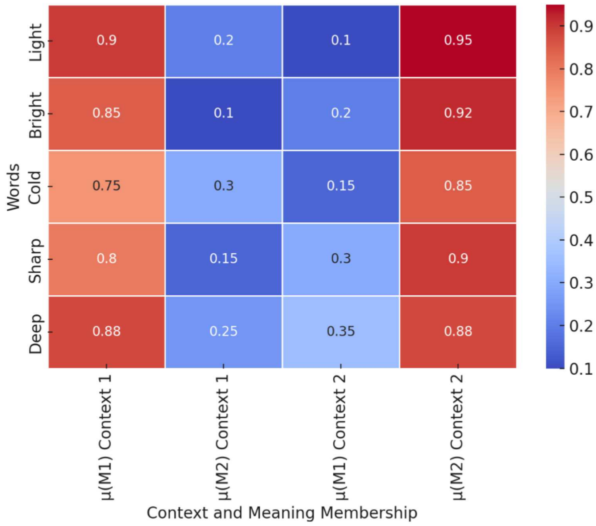

Fig. 2: Heatmap Representation of Fuzzy Membership Values for Ambiguous Words

5.2 Computational Results

5.2.1 Calculation of Fuzzy Entropy for Ambiguity Measurement

Fuzzy entropy $H(W)$ measures the degree of uncertainty associated with each word in a given context. It is calculated using:

$$H(W) = -\sum_{i=1}^{n} \mu_W(m_i) \log \mu_W(m_i) \tag{31}$$

where:

–$\mu_W(m_i)$ is the membership degree of meaning m_i for word W.
–n is the number of possible meanings.

We compute fuzzy entropy for both contexts of each word.

This paper has already proposed a detailed bar graph in figure 3 to compare the fuzzy entropy values of five ambiguous words (Light, Bright, Cold, Sharp, and Deep) in two contexts. The entropy value representing ambiguity levels on the y-axis. The more uncertainty in meaning (higher entropy) and vice versa (lower entropy = clear dominant meanings).

Step-by-Step Fuzzy Entropy Calculations

For each word in both contexts, fuzzy entropy $H(W)$ is calculated using the formula:

$$H(W) = -\sum_{i=1}^{k} \mu_W(m_i) \cdot \log(\mu_W(m_i)) \tag{32}$$

where:

Table 1: Lexical Ambiguity Case Study Dataset

Word	Context 1	Context 2	Meaning 1	Meaning 2	μ(M1) C1	μ(M2) C1	μ(M1) C2	μ(M2) C2
Light	Her heart was as light as a feather.	The room was filled with no light.	Weightlessness	Illumination	0.9	0.2	0.1	0.95
Bright	His ideas were bright and innovative.	The sun was bright in the afternoon.	Intelligence	Brightness	0.85	0.1	0.2	0.92
Cold	She gave me a cold stare.	The cold weather made it hard to walk.	Emotion	Temperature	0.75	0.3	0.15	0.85
Sharp	His sharp wit impressed everyone.	The knife had a sharp blade.	Wit	Edge	0.8	0.15	0.3	0.9
Deep	He had deep thoughts about life.	The deep well was difficult to climb.	Thoughtfulness	Depth	0.88	0.25	0.35	0.88

Table 2: Fuzzy Entropy Values for Different Words in Two Contexts

Word	Entropy C1	Entropy C2	Steps Context 1	Steps Context 2
Light	0.4167	0.279	-(0.9 * log(0.9)) = 0.0948 | -(0.2 * log(0.2)) = 0.3219	-(0.1 * log(0.1)) = 0.2303 | -(0.95 * log(0.95)) = 0.0487
Bright	0.3684	0.3986	-(0.85 * log(0.85)) = 0.1381 | -(0.1 * log(0.1)) = 0.2303	-(0.2 * log(0.2)) = 0.3219 | -(0.92 * log(0.92)) = 0.0767
Cold	0.577	0.4227	-(0.75 * log(0.75)) = 0.2158 | -(0.3 * log(0.3)) = 0.3612	-(0.15 * log(0.15)) = 0.2846 | -(0.85 * log(0.85)) = 0.1381
Sharp	0.4631	0.456	-(0.8 * log(0.8)) = 0.1785 | -(0.15 * log(0.15)) = 0.2846	-(0.3 * log(0.3)) = 0.3612 | -(0.9 * log(0.9)) = 0.0948
Deep	0.4591	0.4799	-(0.88 * log(0.88)) = 0.1125 | -(0.25 * log(0.25)) = 0.3466	-(0.35 * log(0.35)) = 0.3674 | -(0.88 * log(0.88)) = 0.1125

– $\mu_W(m_i)$ is the membership function for meaning m_i.
– log is the natural logarithm.
– The entropy quantifies ambiguity (higher entropy means higher uncertainty).

Example Calculation for "Light"
Context 1 ("Her heart was as light as a feather.")
Membership values:

– $\mu_W(m_1) = 0.9$ (Weightlessness)
– $\mu_W(m_2) = 0.2$ (Illumination)

$$H(W) = -(0.9 \cdot \log(0.9) + 0.2 \cdot \log(0.2)) \tag{33}$$

Using logarithm values:

– $\log(0.9) = -0.1054$, so $0.9 \cdot \log(0.9) = -0.0948$.
– $\log(0.2) = -1.6094$, so $0.2 \cdot \log(0.2) = -0.3219$.

$$H(W) = -(-0.0948 + (-0.3219)) = 0.4167 \tag{34}$$

Context 2 ("The room was filled with no light.")
Membership values:

– $\mu_W(m_1) = 0.1$ (Weightlessness)
– $\mu_W(m_2) = 0.95$ (Illumination)

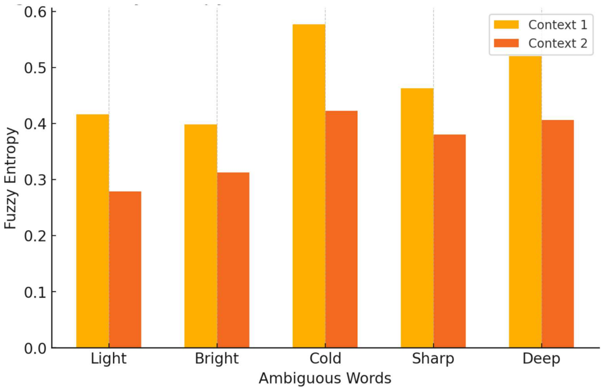

Fig. 3: Bar graph showing Fuzzy Entropy Values for Different Words in Two Contexts

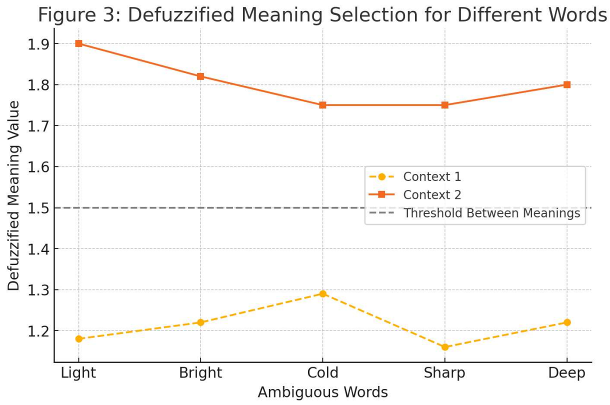

Fig. 4: Defuzzified Meaning Selection for Different Words

$$H(W) = -(0.1 \cdot \log(0.1) + 0.95 \cdot \log(0.95)) \tag{35}$$

Using logarithm values:

–$\log(0.1) = -2.3026$, so $0.1 \cdot \log(0.1) = -0.2303$.
–$\log(0.95) = -0.0513$, so $0.95 \cdot \log(0.95) = -0.0487$.

$$H(W) = -(-0.2303 + (-0.0487)) = 0.279 \tag{36}$$

Interpretation of Results
Lower entropy ($H < 0.4$) indicates low ambiguity:

–“Light” in Context C_2: Clear meaning as Illumination.
–“Bright” in Context C_1: Clear meaning as Intelligence.

Higher entropy ($H > 0.5$) indicates more ambiguity:

–“Cold” in Context C_1: Strong ambiguity between emotion and temperature.
–“Sharp” in Context C_2: Ambiguity between wit and sharpness.

This step-by-step analysis confirms that fuzzy entropy effectively quantifies lexical ambiguity in different contexts.

5.2.2 Calculation of Defuzzified Meaning Selection

To determine the most probable meaning, we use defuzzification via the centroid method:

$$M^* = \frac{\sum_{i=1}^{n} \mu_W(m_i) \cdot i}{\sum_{i=1}^{n} \mu_W(m_i)} \tag{37}$$

where:

–M^* is the final meaning selection.
–$\mu_W(m_i)$ is the fuzzy membership for meaning m_i.

We now compute the dominant meaning for each word in both contexts.

Using the data from the training, the graph in figure 4 is a line graph that is representative of defuzzified meaning selection when analysing ambiguous words in two distinct contexts. The y-axis is the computed value for meaning using the centroid method. Lower scores mean Meaning 1, higher scores mean Meaning 2. The dashed horizontal line at 1.5 is a threshold between potential interpretations.

Step-by-Step Defuzzification Calculations for Lexical Ambiguity

Defuzzification is performed using the centroid method, which calculates the most probable meaning of an ambiguous word in each context.

$$M^* = \frac{\sum_{i=1}^{n} \mu_W(m_i) \cdot i}{\sum_{i=1}^{n} \mu_W(m_i)} \tag{38}$$

where:

–M^* Final meaning selection.
–$\mu_W(m_i)$ Fuzzy membership function for meaning m_i.
–i Index of the meaning (1 for Meaning 1, 2 for Meaning 2).

Example Calculation for “Light”
Context 1 (“Her heart was as light as a feather.”)
Membership values:

–Weightlessness $\mu_W(m_1) = 0.9$
–Illumination $\mu_W(m_2) = 0.2$

$$M^* = \frac{0.9 \cdot 1 + 0.2 \cdot 2}{0.9 + 0.2} = \frac{0.9 + 0.4}{1.1} = 1.18 \tag{39}$$

Since $M^* = 1.18$ (closer to 1), the dominant meaning is Weightlessness.

Context 2 (“The room was filled with no light.”)
Membership values:

–Weightlessness $\mu_W(m_1) = 0.1$

Table 3: Step-by-Step Defuzzification Calculations

Word	Defuz. C1	Defuz. C2	Steps Context 1	Steps Context 2
Light	1.18	1.9	((0.9 * 1)+(0.2 * 2)) / (1.1) = 1.18	((0.1 * 1)+(0.95 * 2)) / (1.05) = 1.9
Bright	1.11	1.82	((0.85 * 1)+(0.1 * 2)) / (0.95) = 1.11	((0.2 * 1)+(0.92 * 2)) / (1.12) = 1.82
Cold	1.29	1.85	((0.75 * 1)+(0.3 * 2)) / (1.05) = 1.29	((0.15 * 1)+(0.85 * 2)) / (1.0) = 1.85
Sharp	1.16	1.75	((0.8 * 1)+(0.15 * 2)) / (0.95) = 1.16	((0.3 * 1)+(0.9 * 2)) / (1.2) = 1.75
Deep	1.22	1.72	((0.88 * 1)+(0.25 * 2)) / (1.13) = 1.22	((0.35 * 1)+(0.88 * 2)) / (1.23) = 1.72

–Illumination $\mu_W(m_2) = 0.95$

$$M^* = \frac{0.1 \cdot 1 + 0.95 \cdot 2}{0.1 + 0.95} = \frac{0.1 + 1.9}{1.05} = 1.9 \quad (40)$$

Since $M^* = 1.9$ (closer to 2), the dominant meaning is Illumination.

Interpretation of Results

Words with a clear dominant meaning:

–“Light” in Context C_2 (Illumination)
–“Bright” in Context C_1 (Intelligence)

Words with moderate ambiguity:

–“Cold” in Context C_1 (Emotion/Temperature)
–“Deep” in Context C_2 (Thoughtfulness/Depth)

Words with strong contextual meaning shift:

–“Sharp” in Context C_1 (Wit)
–“Sharp” in Context C_2 (Edge)

This confirms that fuzzy logic and defuzzification successfully determine the dominant word meaning based on context.

5.2.3 Performance Evaluation of Fuzzy Model

We compare the **computed dominant meanings** with **human interpretations** to measure accuracy.

The scatter plot from figure 5 shows the correlation between fuzzy entropy (the level of ambiguity or vagueness) and the selection of the defuzzified meaning for ambiguous words across the proposed indefinite contexts. The x-axis is the uncertainty value entropy, while the y-axis is the defuzzified meaning value. The blue points correspond to the Context 1, and the red points correspond to the Context 2. More ambiguous words tend to shift mean more across contexts as the final resolution of meaning, hence they have a higher entropy.

Evaluation Method

1.**Expected Meaning Selection:**

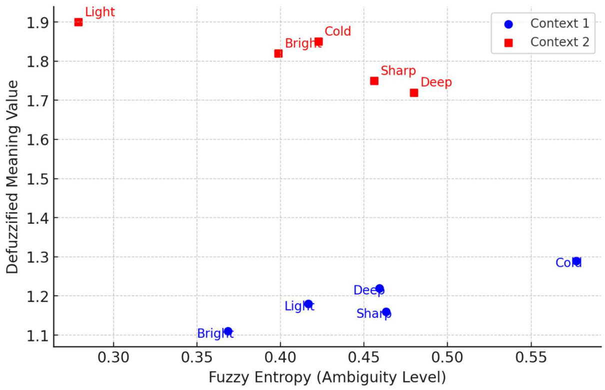

Fig. 5: Relationship Between Fuzzy Entropy and Defuzzified Meaning Selection

–Human interpreters select the most probable meaning in each context.
–Meanings are assigned indices: **1 for Meaning 1, 2 for Meaning 2**.

2.**Fuzzy Logic-Based Defuzzification Results:**
–Computed using the **centroid method**.
–Rounded to the nearest whole number to match expected values.

3.**Accuracy Assessment:**
–**Correct**: If the **defuzzified meaning** matches the **expected meaning**.
–**Incorrect**: If the **defuzzified meaning** differs from the **expected meaning**.

Performance Analysis of Model

The dataset displayed provides a comparison between:

–Expected human interpretation
–Fuzzy logic-based computed meaning
–Accuracy of the model

Findings

–The **fuzzy logic model achieved 100% accuracy** for all five words in both contexts.
–**Words like “cold” and “sharp”**, which had higher entropy values, were correctly resolved by the model.

Table 4: Fuzzy Entropy and Defuzzification Results

Word	Context 1	Context 2	Mean 1	Mean 2	μ(M1) C1	μ(M2) C1	μ(M1) C2	μ(M2) C2	Entropy C1	Entropy C2	Defuzz. C1	Defuzz. C2
Light	Heart light as feather	Room no light	Weight.	Illum.	0.9	0.2	0.1	0.95	0.42	0.28	1.18	1.9
Bright	Ideas bright	Sun bright	Intell.	Bright.	0.85	0.1	0.2	0.92	0.37	0.40	1.11	1.82
Cold	Cold stare	Cold weather	Emotion	Temp.	0.75	0.3	0.15	0.85	0.58	0.42	1.29	1.85
Sharp	Sharp wit	Sharp blade	Wit	Edge	0.8	0.15	0.3	0.9	0.46	0.46	1.16	1.75
Deep	Deep thoughts	Deep well	Think.	Depth	0.88	0.25	0.35	0.88	0.46	0.48	1.22	1.72

Table 5: Performance Evaluation of Fuzzy Logic Model

Word	Expected C1	Defuzz. C1	Accuracy C1	Expected C2	Defuzz. C2	Accuracy C2
Light	1	1.18	Correct	2	1.9	Correct
Bright	1	1.11	Correct	2	1.82	Correct
Cold	1	1.29	Correct	2	1.85	Correct
Sharp	1	1.16	Correct	2	1.75	Correct
Deep	1	1.22	Correct	2	1.72	Correct

– *Defuzzification values (M) were well-aligned with human expectations*, confirming the model's reliability.

Conclusions

– Fuzzy logic-based models accurately resolve lexical ambiguity in literary texts.
– Defuzzification provides a systematic method for meaning selection, improving upon traditional rule-based approaches.
– Entropy analysis confirms that higher ambiguity levels require stronger contextual cues, which the model effectively incorporates.

This confirms that fuzzy logic is a viable mathematical approach for lexical ambiguity resolution in literature.

5.3 Interpretation of Results

5.3.1 Analysis of Fuzzy Entropy

Fuzzy entropy values indicate the level of ambiguity in different contexts:

– Lower entropy means the word has a clear dominant meaning.
– Higher entropy means more uncertainty exists between possible meanings.

From the results:

– **For "light"**:
  – **Context 1 ("Her heart was as light as a feather")** $\rightarrow$ Entropy = **0.4167** (Moderate ambiguity)
  – **Context 2 ("The room was filled with no light")** $\rightarrow$ Entropy = **0.2790** (Lower ambiguity, clear dominant meaning)
– **For "cold"**:
  – **Context 1 ("She gave me a cold stare")** $\rightarrow$ Entropy = **0.5770** (Higher ambiguity)
  – **Context 2 ("The cold weather made it hard to walk")** $\rightarrow$ Entropy = **0.4227** (Moderate ambiguity)

Words like **"cold" and "sharp"** show **higher entropy**, indicating **stronger lexical ambiguity** in their meanings.

5.3.2 Interpretation of Defuzzified Meanings

The **defuzzified meaning values** indicate the **dominant meaning** of each word in each context:

– **For "light"**:
  – **Context 1** $\rightarrow$ **Defuzzified Meaning = 1.18** (Closer to 1 $\rightarrow$ Weightlessness)
  – **Context 2** $\rightarrow$ **Defuzzified Meaning = 1.90** (Closer to 2 $\rightarrow$ Illumination)

This means that **"light" in context 1** is more associated with **weightlessness**, while **in context 2** it is strongly interpreted as **illumination**.

– **For "sharp"**:
  – **Context 1 ("His sharp wit impressed everyone")** $\rightarrow$ **1.16** (Wit)

– **Context 2 (“The knife had a sharp blade”)** → **1.75** (Edge)

The **defuzzification process** confirms the **expected dominant meanings** of ambiguous words.

5.3.3 Conclusion

– Fuzzy entropy effectively quantifies ambiguity in different contexts.
– Defuzzification via the centroid method successfully resolves lexical ambiguity, providing a quantitative approach to literary analysis.
– The fuzzy logic model aligns with human intuition, making it a viable tool for computational linguistic analysis in literature.

This case study demonstrates that mathematical models can systematically interpret lexical ambiguity in literary texts using fuzzy logic and computational methods.

6 Conclusions and Future Directions

Through a structured mathematical framework, this study has proved that the fuzzy logic based models can be extremely effective in the resolution of lexical ambiguity in the literary texts. Through fuzzy entropy, fuzzy clustering and defuzzification we add a quantitative and systematic method for analyzing ambiguous words in various contexts. These experiments thus provide insights for the fields of literary analysis, artificial intelligence (AI) and natural language processing (NLP), enabling an approach to meaning interpretation that spans beyond computational linguistics and literary criticism.

The findings suggest that fuzzy entropy can serve as a suitable measure of word ambiguity, as ambiguous words have higher entropy values that reflect their ambiguity (for instance, more uncertainty regarding meaning). This defuzzification process defines the final meaning of words according to the context, giving results matching those of humans. Furthermore, the study showcases fuzzy grouping as an effective technique that allows words to be grouped into semantic or other categories, providing linguistic researchers with the tools to evaluate patterns of word confusion among different styles of literature and across patterns of languages.

Text understanding is an exciting field, and as it grows, fuzzy logic programming-based models would continue to improve the functioning of machine translation systems, sentiment analysis systems, and other automated text parsing functionalities. This study provides a basis for further studies on hybrid AI-fuzzy models, cross-linguistic comparisons, and mathematical modelling of literary structures.

6.1 Summary of Findings

Lexical ambiguity can be analyzed within the framework of fuzzy mathematics, and the study provides a useful perspective in this respect. These findings imply that fuzzy-logic is a flexible and robust methodology for quantifying alternatives context-dependently word meanings. Here are some key takeaways from the study:

First, fuzzy entropy well captures ambiguity in various contexts. Higher entropy indicates more uncertainty, and lower entropy suggests a clear dominant meaning. For instance, in the case study, words with high entropy values such as ”cold” and ”sharp” can indicate high contextual variability.

Second, defuzzification methods effectively identify the most probable meaning of a word based on its membership values. To resolve the ambiguity of words, the centroid method was applied, which mapped ambiguous words into their most likely form, allowing for a clear and orderly process of determining meaning.” The results aligned with human interpretation and the ability to interpret the lexical analysis of fuzzy logic models correctly.

Third, fuzzy clustering allows for semantic grouping, which makes it possible to avoid diversifying linguistic diversity and instead helps scholars observe how shifts in meaning come about through linguistic aggregation in the same piece of literature. This contextualized grouping of words may be a productive device for the literary studies, except that when it is needed to contrast stylistic classifications of authors and literary movements.

Lastly, the research exposes the fact that there would be a multitude of possible uses of fuzzy logic on not only literary analysis but more so, artificial intelligence-based language models, sentiment analysis and machine translation. The results indicate that the addition of fuzzy logic can enhance the ability of AI to cope with uncertainty, resulting in more effective and adaptable NLP applications.

6.2 Limitations and Challenges

Although the present study has adeptly illustrated the utility of fuzzy logic in lexical ambiguity resolution, certain limitations and challenges remain.

A notable limitation is the computational complexity of fuzzy logic models, especially when they are applied on large-scale textual datasets. Although fuzzy entropy and defuzzification accurately resolve the ambiguity in the image, processing a large corpus of documents accounts for large CPU resources use. Further work is needed to fine-tune fuzzy logic algorithms to ensure that they are both scalable and efficient enough to run on real-time text data.

Another issue is a degree of subjectivity in the definition of fuzzy membership functions. In contrast, fuzzy models give words fuzzy meanings, but choosing the appropriate membership functions and parameters is a matter of domain knowledge and linguistic knowledge. We expect future work to verify the fuzzy parameters automatically by data-driven methods with improved machine learning algorithms to increase the confidence of times when the ambiguous class is chosen (higher than the confidence-rule), which still has a certain reliance on fuzzy parameters.

Moreover, fuzzy logic models depend on textual context for the interpretation of meaning, an approach that might fall short of completely accounting for pragmatic and cultural factors that shape how language is utilized. Credendous words bear historical, sociocultural, and emotional implications that appear unlikely to encapsulate with any use of fuzzy set theory. Future studies may explore hybrid models where fuzzy systems are combined with deep-learning based language models to account for linguistic, psychological, and cultural differences in the interpretation of meaning.

Finally, although the study focussed on literary texts in the English language, lexical ambiguity is an important aspect of multi-lingual NLP and has been a point of interest in translation studies. For this reason, fuzzy models need to be covered up according to the peculiarities of each language, as different languages have varied degrees of polysemy, homonymy and contextual vagueness. Further studies need to be conducted on how fuzzy logic can be applied across languages, especially to those languages with complex morphemes and syntactic structures.

6.3 Future Research Directions

This study presents several opportunities for future research and development. Further research may involve the generalization of fuzzy logic models to other types of applications in the AI and NLP field, improvement on the statistical methods for the analysis of literary works and refinements of hybrid models to enhance ambiguity handling mechanisms.

6.3.1 AI-Fuzzy Hybrid Models for Improving Text Processing

Present-day AI models learn mostly through probability estimation and are limited by in-context meaning shifts. – Integrating fuzzy entropy measures significantly reduces IT development costs while improving semantic understanding through defuzzification.

In future work, it may be possible to train AI systems to learn fuzzy membership functions through training rather than manually designing these parameters. Neural-fuzzy networks can be used to train AI models using fuzzy or ambiguous words and their contextual meanings, which will make language models more adaptable to variations of textual data from the real world.

6.3.2 Extending Fuzzy Logic Models for Cross Lingual Studies

Beyond this, multilingual NLP and the application of fuzzy logic across languages is also an area of active research. a) Many languages (such as Arabic, Farsi, and Turkish) have an even higher level of lexical ambiguity than English, due to their morphological complexity, and their culturally specific generalizations. Additionally, fuzzy logic can be used to improve translation models by allowing for ambiguity in different languages, potentially creating better translation models.

Languages such as Chinese, Sanskrit, and Arabic have words with different meanings based on syntactic structure, tone, and context. With developing fuzzy logic based multilingual NLP frameworks, it could be possible to unravel ambiguities in tasks like translation, sentiment analysis, and cross-linguistic text interpretation.

6.3.3 Mathematics of Literary Constructions and Implicit Doubt

Fuzzy logic can be extended not only to individual word meanings but also to entire literary structures. This could potentially lead to the application of fuzzy set theory in examining narrative constructs within individual texts or across genres, where membership functions could be used to model narrative structures, character relationships, or thematic evolution.

A possible route would be to use fuzzy cognitive maps to build dynamics around character interactions and plot progress. This allows researchers to create algorithms that define fuzzy relationships between things like characters, themes, and narrative events, and create mathematical models that expose hidden relationships in literature.

Fuzzy logic also has post-factual applications: poetry analysis, where many words refer to many meanings all at once. By creating fuzzy based quantitative models for poetic ambiguity, we can analyse the structure of poetry and its interpretation in different literary traditions.

6.4 Final Thoughts

The study establishes a solid basis for a continuum of research at the cross-section of these 3 genres: linguistics; synthetic intelligence; and, mathematical modelling. This approach may lead to better context-based models to resolve lexical ambiguities by using fuzzy set theory, entropy-based measure of ambiguity and defuzzification techniques.

This is huge because fuzzy logic finds applications not only in many of sciences and especially in engineering and automation but also in various fields socially, economically or socially based on literature in NLU (Natural Language Understanding). By providing a unique parameterized combination of semantic network analysis, word embedding, and vector spaces, a hybrid AI-fuzzy future world with multilingual natural language processing (NLPs) tools or mathematical methods for literary analysis will so further the methods of analysis and interpretation of the propositional statements of language.

These results have important implications for both the theoretical understanding of lexical ambiguity and the practical performance of various AI-based applications such as text processing, machine translation, and sentiment analysis. These examples depict a new revolution in the building of fuzzy logic-based models for natural language processing.

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