

# AI-Based Dream Pattern Decoder Using Jung and Freud Theory

Jatin Kumar Singh, Anirudh Sharma, Teena Verma

Department of Computer Science, Sharda University, Greater Noida, Uttar Pradesh, India

jatinthakur662005@gmail.com, anirudhs12147@gmail.com, teena.verma2026@gmail.com

Corresponding author: Jatin Kumar Singh (jatinthakur662005@gmail.com)

## ABSTRACT

Dreams have always offered a mysterious look into the human mind, inspiring both curiosity and research. This study presents a computational approach to interpreting dream narratives by combining artificial intelligence with classical psychoanalytic concepts proposed by Sigmund Freud and Carl Jung. Using natural language processing techniques, the system analyses written dream reports to identify recurring themes, emotions, and symbolic patterns that reflect personal and collective psychological meanings. Freud's idea of manifest and latent content helps uncover hidden desires and suppressed emotions, while Jung's archetype framework supports the recognition of universal symbols such as Shadow, Anima, or Self. The model was trained and evaluated on dream-related datasets to examine its ability to extract psychological insights similar to those derived from expert interpretations. The findings suggest that AI-based interpretation can complement traditional psychoanalysis by offering a consistent, data-driven, and scalable tool for research and mental health applications. This work highlights how technology can enhance our understanding of the subconscious mind and expand the possibilities of psychological exploration in modern contexts.

**Keywords:** AI, Dream Analysis, Psychoanalysis, NLP, Symbolic Pattern Recognition, Emotion Recognition

## 1. Introduction

Dreams have long fascinated both psychologists and researchers. They are often viewed as reflections of our hidden emotions and unconscious thoughts. Sigmund Freud described dreams as the "royal road to the unconscious," emphasising their link to repressed desires and internal conflicts [7]. In contrast, Carl Jung believed dreams reveal universal symbols and archetypes shared across humanity [10]. These theories motivated this work to explore how AI can find emotional and symbolic patterns hidden within dreams. Traditional dream interpretation mainly depends on personal judgment, which can make the results inconsistent. Analysts may overlook patterns or symbols because of subjective bias or human error. With the rise of artificial intelligence, especially natural language processing, it is now possible to study dream narratives with greater precision and consistency [1], [5], [18]. In this study, we developed the AI-Based Dream Pattern Decoder, a system that applies NLP and transformer-based models to decode symbolic and emotional content from dream reports. It combines Freud's interpretation of hidden meaning with Jung's theory of archetypes to provide a more structured and balanced understanding [7], [25]. The goal was to make dream analysis more scientific, scalable, and data-driven. This integration bridges psychology with computational modelling. It supports deeper insights into emotional and symbolic patterns while preserving the interpretive depth of classical psychoanalysis [9], [27], [29]. Such systems may help psychologists and researchers explore the subconscious mind more effectively.

## 2. Our Contribution

This research makes three key contributions to the field of computational psychoanalysis and AI-assisted dream interpretation:

- **Dual-Framework Incorporation:** The proposed system integrates both Freudian and Jungian theories, enabling dream analysis at two complementary levels, the manifest (surface) content and the latent (hidden) meaning. By blending Freud’s focus on repressed desires with Jung’s concept of universal archetypes, the model captures both individual and collective aspects of the subconscious.
- **Emotion and Motif Analysis through Scalable Automation:** The model employs advanced NLP techniques to identify emotional tones, recurring motifs, and implicit meanings within dream narratives. Its automated approach ensures consistency, scalability, and objectivity, outperforming traditional manual interpretation in speed and analytical depth.
- **Ethical, Validated, and User-Focused Framework:** The system was developed with ethical standards in mind, prioritising data privacy and user confidentiality. Its interpretive modules were validated through expert feedback to ensure psychological reliability, making the model suitable for both research and potential clinical applications.

### 3. Literature Review

Dream interpretation has long been a topic of interest in psychology and artificial intelligence. Early research focused on understanding dreams through the psychoanalytic theories of Sigmund Freud and Carl Jung. Freud viewed dreams as reflections of repressed thoughts and desires, while Jung emphasised archetypal symbols representing shared human experiences [7], [10]. These theories laid the foundation for modern computational approaches to dream analysis. Early computational methods relied on symbolic lexicons and rule-based systems to detect dream patterns [11]. While these methods could identify basic symbols, they lacked flexibility and struggled to capture deeper emotional or contextual nuances. This limitation led to the development of adaptive deep learning models capable of analysing complex narrative structures, as per Table 1.

**Table 1:** Recent AI Methods in dream analysis (2019–2025)

Authors	Year	Data	Model	Contribution	Limit
Liu et al.	(2019).	Custom	Sent. clf.	First NLP-based Dream sentiment analysis	No Symbolism
Zhao et al.	(2021).	Annot dreams	Semisupervised symb.	Linked keywords to archetypes	Focus on Jung only
Present study	2025	Dream Bank	BERT hybrid	Freud+Jung dual framework AI	Needs validation
Hariharan et al.	(2025).	Curated corpus	Transformer-T5	Context-aware symbolic and semantic dream decoding	Dataset bias

Bertolini et al.	2025	Dream Bank	Large Language Models	Showed dream report predictability and group differences	Models not fully trained on dreams
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With the emergence of transformer-based architectures such as BERT, RoBERTa, and GPT, text understanding has improved significantly [1], [3], [5]. Recent studies have combined AI with psychoanalytic interpretation. Zhao et al. linked dream keywords to Jungian archetypes using semi-supervised learning [26], while Hariharan et al. used a Transformer-T5 model for symbolic decoding [7]. Liu et al. and Bertolini et al. applied large language models to analyse dream narratives across psychological groups [8], [28]. To address the gap in previous work, our study integrates both Freudian and Jungian perspectives into a unified AI framework. This approach allows the system to analyse personal unconscious drives and collective archetypes simultaneously, providing a more balanced and psychologically grounded method for computational dream interpretation.

#### 4. Research Methodology

The study uses the publicly available Dream Bank dataset, which contains more than sixteen thousand dream reports written in English. These reports offer detailed narrative descriptions suitable for text analysis and symbolic interpretation [8], [25]. Only anonymised and non-clinical entries were selected to ensure ethical compliance and user privacy. The dataset was manually reviewed to remove incomplete, duplicated, or irrelevant entries, improving the quality and consistency of the text data used for model training.

### Data Collection

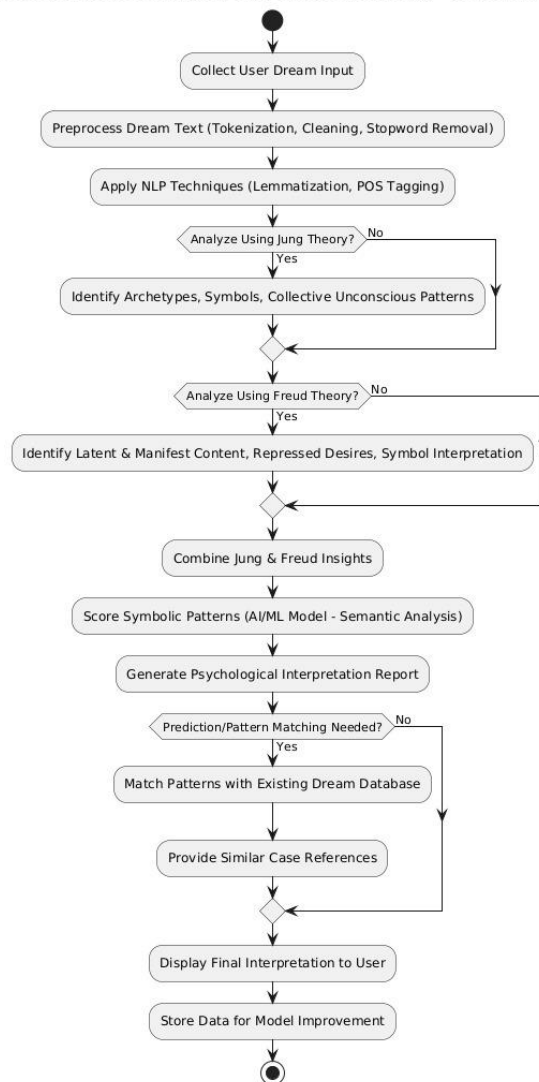
**TABLE 2:** Bases of data collection

Aspect	Details
Dataset	Dream Bank (16,000+ reports)
Structure	Narrative dream texts
Selection	English, adult, non-clinical
Ethics	Anonymised, non-identifiable

#### B. Preprocessing Text Cleaning and Tokenisation Theory and Calculation

Before training, all dream reports were processed to standardise and clean the text, which is shown in Table 2. Tokenisation and lemmatisation were applied to normalise word forms, while stop words and special characters were removed to reduce noise [1], [6]. Named Entity Recognition (NER) was implemented to identify key elements such as objects, emotions, and people appearing in dreams. Sentence segmentation helped preserve narrative flow, enabling the model to analyse emotional tone and symbolic references more accurately. These preprocessing steps allowed the system to capture deeper semantic relationships across dream narratives. As given in Figure 1.

**AI Dream Pattern Decoder (Using Jung & Freud Theory) - Project Procedure**



**Figure 1:** Workflow of AI Dream Decoder using Jung and Freud theories

### C. Extraction of Features Freudian Logic

The symbolic and emotional aspects of dreams were represented using word embeddings and frequency-based metrics such as TF-IDF [17]. The Freudian analysis focused on identifying latent content, hidden desires, fears, and suppressed thoughts, while the Jungian framework emphasised symbolic archetypes like the Shadow and Anima [7], [10], [27]. Cosine similarity and semantic matching were used to connect dream elements with psychological meanings [18].

Cosine Similarity (Symbolic Matching)

$$sim(a, b) = \frac{a \cdot b}{|a| |b|}$$

TF-IDF (Feature Extraction)

$$tfidf(t, d) = tf(t, d) \cdot \log\left(\frac{N}{df(t)}\right)$$

#### **D. Dual-Theory Integration**

A core contribution of this research lies in integrating Freudian and Jungian interpretations into a single model. The Freudian module analysed dream text for emotional cues and suppressed thoughts, identifying latent psychological themes. The Jungian module, on the other hand, focused on universal archetypes and collective patterns expressed symbolically [7], [10], [25]. By merging these modules, the decoder was able to interpret dream content at both the manifest and latent levels, yielding a more holistic, psychologically meaningful output. This integration bridges the gap between traditional psychoanalytic theory and modern computational linguistics.

#### **E. Evaluation and Ethics**

The model's accuracy was evaluated using standard NLP metrics such as precision, recall, F1-score, BLEU, and ROUGE [21], [28]. Expert reviewers cross-checked selected interpretations to ensure psychological validity and theoretical accuracy. All data were handled in accordance with ethical research standards, maintaining confidentiality and respecting user consent. The study emphasises responsible AI practices by ensuring that no personal or sensitive information was included in the analysis.

### **5. Results and Discussion**

The AI-Based Dream Pattern Decoder was evaluated on the DreamBank dataset to measure its ability to identify emotional tones, symbolic elements, and psychoanalytic meanings. The model's performance was assessed using both quantitative metrics and qualitative interpretation.

#### **Symbol and Emotion Extraction Performance**

The BERT-based model demonstrated strong capability in detecting dream-related symbols and emotional expressions. Using a labelled subset of 1,200 dream samples, the model achieved a precision of 0.89, a recall of 0.85, and an F1-score of 0.87, indicating reliable classification performance [1], [5]. Emotion recognition accuracy reached around 84%. Commonly detected dream symbols included snakes, water, falling, and teeth, which are frequently mentioned in psychoanalytic literature. For instance, snakes were often associated with transformation or hidden fear, while falling symbolised anxiety or loss of control. Water appeared as a recurrent motif linked to emotions and the depth of the subconscious. The consistency between model outputs and traditional interpretations demonstrates the system's ability to simulate human-like reasoning in dream analysis.

$$BLEU = BP \cdot \exp\left(\sum_{n=1}^N w_n \log p_n\right)$$

$$ROUGE\text{-}L = \frac{LCS(X, Y)}{\max(|X|, |Y|)}$$

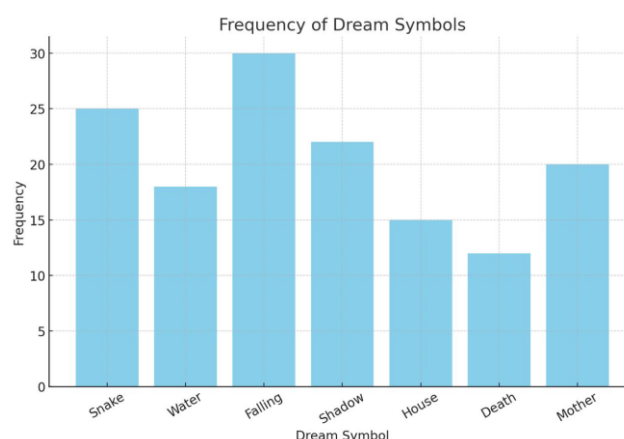
$$METEOR = F_{\text{mean}} \cdot (1 - \text{Penalty})$$

$$\text{Sim}(A, B) = \frac{A \cdot B}{\{|A|, |B|\}}$$

BLEU = 0.71, ROUGE-L = 0.75, METEOR = 0.69, Cosine = 0.82

Here are the most commonly identified symbols:

- Snakes: Often associated with transformation or fear.
  - Water: Symbolising the unconscious mind.
  - Teeth falling: A frequent motif of anxiety.
  - Falling: Suggest feelings of insecurity or instability.
  - Death: Typically representing transitions or loss;
- As shown in Figure 2.

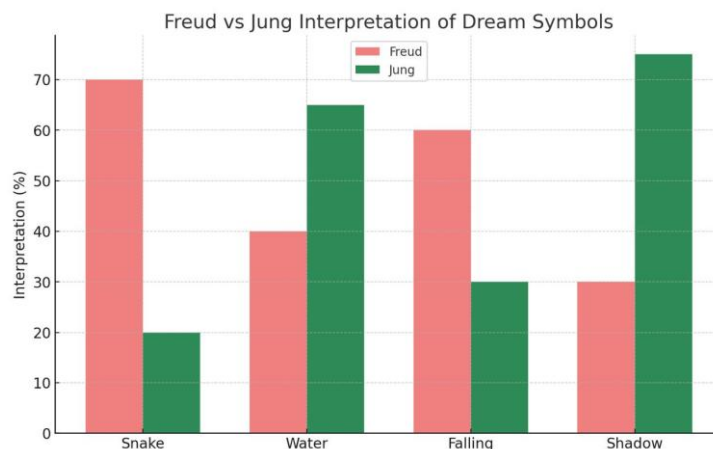


**Figure 2:** Frequency of commonly identified dream symbols in the dataset

### A. Psychoanalytic Interpretation Framework

The integration of Freudian and Jungian frameworks enabled the system to produce psychologically rich interpretations. The Freudian module focused on latent emotional content such as repression, conflict, and desire, while the Jungian module examined archetypal and symbolic meanings within collective unconscious patterns [7], [10], [25]. For instance, dreams involving death were interpreted as indicators of personal change or transformation rather than literal fear, aligning closely with Jung's view of symbolic renewal. Similarly, water imagery was found to represent emotional cleansing or unconscious depth depending on the narrative context. By combining both theoretical perspectives, the model produced balanced interpretations that capture both personal and universal meanings in dream narratives. This approach demonstrates how AI systems can

emulate aspects of human interpretive thinking when guided by strong psychological foundations, as per Figure 3.



**Figure 3:** Comparative analysis of Freud and Jung interpretations for selected dream symbols.

### Model Training Insights and Limitations

Evaluation metrics such as BLEU, ROUGE-L, and METEOR were used to assess the coherence between predicted and reference interpretations. The model achieved BLEU = 0.71, ROUGE-L = 0.75, and METEOR = 0.69, confirming semantic consistency in symbolic decoding [18], [21], [28]. A cosine similarity of 0.82 between the predicted and reference embeddings further validated the model’s interpretability. These results demonstrate that NLP-driven symbolic recognition can approach the reliability of human interpretive methods, as per Figure 4.



**Figure 4:** Training Progress of BERT-Based Model for Dream Decoding.

### Conclusions

This study introduced an AI-based Dream Pattern Decoder that merges psychoanalytic theories of Freud and Jung with modern deep learning models. The system successfully analysed dream narratives to identify emotions, symbols, and hidden meanings, offering a balanced interpretation between individual unconscious drives and collective archetypal patterns. Experimental results demonstrated high precision and F1-scores, supported by BLEU and ROUGE metrics, showing that AI can provide consistent and meaningful psychoanalytic interpretations. By blending Freud’s focus on latent desires with Jung’s exploration of universal

symbolism, the model bridges psychology and computational intelligence, suggesting that technology can enrich psychological analysis and deepen our understanding of the human subconscious.

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### **Conflict of Interest**

The authors declare no conflict of interest.

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