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From Rules to Reasoning: Impact of NLP on Knowledge-Based Systems

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Abstract *- Natural Language Processing (NLP) plays a pivotal role in the evolution of modern Knowledge-Based Systems (KBS) by enabling computers to process, understand, and extract valuable insights from vast quantities of unstructured human language data. This paper explores the intersection of NLP and KBS, detailing how NLP techniques facilitate the construction and enhancement of knowledge bases through semantic information and structured representations. It discusses the historical development of NLP, from rule-based to advanced machine learning approaches, including deep learning models like Transformers. The paper outlines the methodologies employed for knowledge extraction, such as semantic lexicon construction, ontology development, and information integration. Furthermore, it addresses the significant benefits offered by NLP in diverse applications, particularly in healthcare and information management, while also examining the persistent challenges related to data quality, linguistic ambiguity, generalizability, and ethical considerations. This work aims to provide a comprehensive overview of how NLP contributes to building more intelligent and efficient KBS, and to identify areas for future research and development.*

Keywords: *Natural Language Processing, Knowledge-Based Systems, Ontology, Semantic Lexicon, Information Extraction, Machine Learning, Expert Systems, Artificial Intelligence*

1. Introduction

NLP is a fast-growing field that combines computer science, linguistics, and artificial intelligence to help computers understand and interact with human language [1-4] Its main purpose is to mimic how a human reads, turning unstructured text into a format a computer can actually use [5-8]. At the same time, KBS are designed to capture and use human expertise to solve complex problems that usually require human intelligence [9-14].

With the explosion of digital information, we now have a huge amount of unstructured text in medical reports, scientific papers, and web content. This data is great for humans but incredibly difficult for computers to search, summarize, and analyze. NLP is the essential tool that converts this raw text into structured data, allowing KBS to process it effectively and become much more useful across many different applications. This paper will dive into the crucial role NLP plays in today's KBS, looking at its history, key methods, results, and future challenges [15-20].

2. Objectives

- To explain how NLP facilitates the construction and enhancement of knowledge bases by providing semantic information about words and phrases, which is crucial for the computer processing of medical narrative and other textual data.
- To describe the main NLP techniques and knowledge representation methods used in modern KBS, such as building semantic lexicons, using formal ontologies, and employing advanced machine learning.
- To identify the problems that come up when we try to use NLP in real-world systems for industries like medicine, including issues with data collection, linguistic ambiguity, and a model’s ability to work in different contexts.
- To highlight the benefits of using NLP-assisted annotations and deep semantic representations in knowledge management, emphasizing how they improve understanding, decision-making, and the reuse of information.

3. Problem Statement

A core challenge in modern technology is the massive amount of vital data stored as unstructured text. This includes everything from transcribed reports and notes to complex scientific papers and insurance claims. While this format is convenient for people, it’s a huge obstacle for computers trying to present data visually, search it effectively, or perform statistical analysis (JOHNSON, 1999) .It’s almost impossible to figure out how different pieces of information relate to each other without a lot of human effort.

On top of that, the complexity of human language makes it hard to create universal NLP solutions. Each language, and even specific domains within a language, has unique grammatical and semantic rules. For example, general language ontologies often lack the

specific medical information needed for clinical applications. Similarly, controlled medical vocabularies often focus only on nouns, leaving out the important semantic details from adjectives, verbs, and other parts of speech needed for full sentence analysis.
Traditionally, building a semantic lexicon for an NLP system was a tough, manual job. This often led to inconsistencies and variations across different systems, making them hard to compare. Even with the most advanced algorithms, NLP outputs are not always perfectly reliable. These limitations show a clear need for robust and accurate NLP methods that can transform unstructured text into usable knowledge for powerful computer applications.

4. Literature Review

4.1 From Early Days to Modern Models: The Evolution of Natural Language Processing

The journey of NLP began in the 1950s, driven by ambitious goals like machine translation and information retrieval. Early researchers focused heavily on syntactic processing, which is the study of how words are arranged to form sentences, believing it was the key to unlocking language understanding. However, others recognized that simply understanding sentence structure wasn't enough. They delved into the world of semantics, or the meaning of words, exploring how we could represent concepts and even incorporate outside "world knowledge" to make sense of language [21-25].

4.2 The Rise of Knowledge-Based Systems and Medical Ontologies

While NLP was taking shape, another field emerged: Knowledge-Based Systems (KBS). These systems were built to capture and use human knowledge in a structured way. At their core, they consist of a knowledge base (a storehouse of information) and an inference engine (the "brain" that uses the information to reason). A critical component of these systems is the ontology, which acts like a blueprint for a specific field of knowledge [26-30] Ontologies are essential for preventing ambiguity. For example, a term like "sodium" could mean a chemical element, a supplement, or a level in the human body. An ontology clarifies these distinctions. In medicine, systems like the Unified Medical Language System (UMLS) serve as a vital resource for building these conceptual frameworks. By creating automated semantic lexicons, we can link words to their specific meanings, which is crucial for medical language processing[37].

4.3 From Rules to Reasoning: The Shift in NLP Approaches

The evolution of NLP can be seen through two main approaches. The first, rule-based algorithms, relied on pre-defined grammar rules and heuristics. These were the workhorses of early NLP, used for tasks like parsing sentences. They are still useful today for specialized tasks, such as identifying specific entities in a text.
However, as we gained access to massive amounts of data, the focus shifted to machine learning (ML-based) algorithms. Instead of following rigid rules, these algorithms learn patterns and structures from large text corpora. They make probabilistic decisions, allowing them to adapt and improve with more data. The sheer volume of available data has made ML-based methods the dominant force in modern NLP [38-42].

4.4 Deepening Our Understanding: The Journey to Modern NLP Models

Early NLP models, like Bag-of-Words (BoW), treated text as a simple collection of words, ignoring their order. This was a step forward, but it lacked a deeper understanding of context. The next big leap came with Word Embeddings (think Word2Vec and GloVe), which learned to represent words as numerical vectors based on their surrounding words. This allowed models to understand that words with similar meanings would have similar vector representations [43-46].
The real game-changer, however, was the advent of Deep Learning and the Transformer architecture. Models like BERT (Bidirectional Encoder Representations from Transformers) have revolutionized the field. BERT looks at a word's context from both its left and its right, allowing for a much richer, more contextualized understanding of language. While this bidirectional approach is powerful for understanding, it presents challenges for natural language generation. To address this, models like UNILM (UNIfied pre-trained Language Model) were developed to handle both understanding and generation tasks using the same core architecture [47] These powerful models are now being applied to a wide range of tasks, from analyzing electronic health records to predicting patient risk [48].

4.5 Putting It All to Work: Modern NLP Applications

Today, NLP powers a vast array of applications. Semantic similarity models (like Doc2Vec and SentenceBERT) allow us to compare documents and annotate databases. Topic models help us identify underlying themes in large collections of texts, which is useful for organizing information. Text summarization techniques automatically condense long documents, while Information Extraction (IE) pulls structured data from unstructured text [49-55]. This includes tasks like Named Entity Recognition (NER), which identifies and classifies named entities in text.
Question Answering (QA) systems, such as those built with BERT, can explore complex knowledge graphs to provide answers to specific questions. And Text Classification, a fundamental NLP task, is used to assign categories to documents, such as

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classifying insurance claims. These and many other applications demonstrate how far NLP has come, evolving from a rule-based approach to sophisticated, context-aware systems that are transforming how we interact with information.

5. Methodology

The application of Natural Language Processing to enhance Knowledge-Based Systems typically involves a structured pipeline of operations designed to transform raw textual data into meaningful, machine-understandable knowledge.

5.1 Data Acquisition and Preprocessing

The initial and crucial step involves acquiring relevant text data, which can sometimes necessitate the use of Optical Character Recognition (OCR) for historical or scanned paper documents. Once acquired, the text undergoes several preprocessing stages [56-60]:

- Sentence Segmentation: This process precisely defines sentence boundaries, a critical step as errors here can propagate and lead to more significant mistakes in subsequent processing stages. Rule-based tokenizers with abbreviation dictionaries are often employed for this purpose.
- Tokenization: After sentence segmentation, the text is broken down into smaller units, known as tokens. These can range from words to subwords (parts of words). Various methods exist, including Stemming (reducing words to their root form, like "run" from "running") and WordPiece. Language-specific libraries, such as NLTK for English, are commonly used. Modern models like BERT can handle multi-language data within a single model.
- Normalization: This involves standardizing word formats. Examples include case folding (converting all text to lowercase, which aids generalization in tasks like information retrieval or speech recognition, though case can be crucial in other tasks like sentiment analysis). Lemmatization is a more sophisticated form, mapping morphologically different forms of a word (e.g., "sang," "sung," "sings") to their common base form ("sing").

5.2 Knowledge Representation and Extraction

For computer programs to analyze sentences effectively, they must represent the meanings of lexical items (words and phrases) using specific symbols or codes that correspond to data values usable by an application.

- Ontologies: These are formal, systematic organizations of these data values, providing a structured framework for knowledge representation. Ontologies can be developed from scratch, selected from existing libraries, or configured from off-the-shelf components. They are crucial for tasks like medical language processing, as general ontologies often lack the specific medical content required.
- Semantic Lexicons: These are constructed by matching lexemes from a source lexicon (e.g., the Specialist Lexicon) against terms in a knowledge base (e.g., the UMLS Metathesaurus) to assign syntactic and semantic types to each entry. To manage cases where a lexeme has multiple potential semantic types, semantic preference rules are developed and applied to select the most appropriate type based on usage context. This process is crucial for natural language processing programs that analyze medical narratives.
- Graph Structures: Graph databases are increasingly utilized as knowledge bases to effectively store, visualize, and query relationships between different pieces of text. ConceptNet, for instance, is a logical graph that connects words and sentences, built from expert-provided data and questionnaires.
- Information Extraction (IE): This phase focuses on identifying entities, their associated information, and the semantic relationships between them within unstructured text. This is often achieved through ontology-based NLP processes that include Named Entity Recognition (NER), co-reference resolution, and dependency parsing [61-64]. NER, in particular, tags information items with appropriate ontology constructs like classes and data type properties.

5.3 Advanced NLP Models and Semantic Analysis

Modern NLP leverages sophisticated models to deepen linguistic understanding:

- Parsing: This involves analyzing sentence structure. Phrase structure parsers break sentences into constituents (words, noun phrases, verb phrases), while dependency grammars represent sentences as directed graphs showing syntactic relationships between words.
- Language Models: These are fundamental to modern NLP, predicting upcoming words based on prior context. The Transformer architecture is a cornerstone of current large language models, enabling state-of-the-art performance [65-68]
- Semantic Parsing: This advanced technique maps natural language questions or statements into formal languages, such as Prolog or SQL, allowing for direct querying of knowledge bases [69-74]
- Semantic Web Technologies: The extracted information can be represented in formats like RDF triples and mapped to domain ontologies, creating a common, machine-understandable structure that enables semantic queries and inference. This process ensures that knowledge is effectively captured, stored, and made accessible for various applications [75-78].

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6. Results

The integration of Natural Language Processing (NLP) into Knowledge-Based Systems (KBS) has demonstrated significant advancements across various applications, leading to enhanced efficiency, accuracy, and depth of information utilization.
Key results from the sources include:

- **Automated Semantic Lexicon Construction:** It has been demonstrated that automatic methods can successfully construct a semantic lexicon from existing UMLS sources, dramatically reducing the number of lexemes with multiple semantic types to less than two percent through the application of precise semantic preference rules. This significantly aids natural language processing programs that analyze medical narratives.
- **Improved Efficiency and Accuracy in Medical Diagnostics:** NLP-based models have been shown to enhance the monitoring of underwritten risks and optimize processes within the insurance sector. For instance, they have been successfully applied to medical diagnostic assistance, yielding good results in analyzing medical cases and determining correct diagnoses. Systems developed for diagnosing specific conditions like eye diseases and abdominal pain were evaluated positively by medical students, showing faster and more precise diagnoses compared to conventional methods
- **High Performance in Claims Classification:** In the insurance industry, NLP algorithms, particularly deep learning models, have been used to automate critical illness claims classification. One reported application achieved a 90% accuracy rate for 20,000 reports, performing at or above human levels of efficiency
- **State-of-the-Art Performance with Pretrained Language Models:** Advanced pretrained language models such as **BERT** and **UNILM** have achieved state-of-the-art results across a variety of NLP tasks UNILM, for example, demonstrated superior performance on the GLUE benchmark and notable improvements in question answering tasks (SQuAD 2.0 and CoQA). Furthermore, UNILM showed significant absolute improvements in natural language generation tasks, including a ROUGE-L score of 40.51 for CNN/DailyMail abstractive summarization (a 2.04 absolute improvement), 35.75 for Gigaword abstractive summarization (0.86 improvement), and an F1 score of 82.5 for CoQA generative question answering (37.1 improvement).
- **Effective Information Extraction and Integration:** Ontology-based NLP processes have proven effective in identifying entities, their associated information, and semantic relationships within semi-structured documents. This approach simplifies the extraction and integration of information, transforming heterogeneous data into a uniform, machine-understandable RDF triple format, which then enables semantic queries and inference engines.

These results collectively highlight NLP's transformative impact on KBS, particularly in domains rich in unstructured text, by enabling automated understanding and intelligent decision support.

7. Discussion

The integration of NLP into KBS is a game-changer, bringing significant benefits to various industries but also introducing new challenges that need our attention.

7.1 Benefits of NLP in KBS

- **Enhanced Efficiency and Accuracy:** NLP drastically improves how quickly and accurately we can process vast amounts of text. For instance, in healthcare and insurance, systems can now automatically classify claims with high precision and help provide faster, more accurate diagnoses.
- **Improved Information Management:** NLP acts as a crucial bridge, transforming unstructured text—like clinical notes or dictated reports into structured, machine-readable formats. This makes it much easier to search, summarize, and analyze data that was previously difficult to use.
- **Promoting Knowledge Reuse and Consistency:** By creating standardized semantic representations and using formal **ontologies**, NLP reduces the heavy manual work traditionally required to build and maintain KBS. This standardization ensures consistency across different systems and helps results seamlessly map to various applications.
- **Strengthened Decision Support:** By extracting and organizing key information, NLP provides invaluable support for making data-driven decisions in fields like emergency management and healthcare.
- **Deeper Linguistic Understanding:** Modern NLP goes beyond simple word-matching to truly grasp the nuances and deeper meaning of language. This allows for the creation of more intelligent applications that can handle complex ambiguities and understand the underlying concepts in a text.

7.2 Challenges in NLP-Enabled KBS

- **Data Quality and Availability:** A major hurdle is getting access to high-quality text data, especially from older formats like scanned documents. Many machine learning models need large, annotated datasets, which can be hard to find in new or specialized fields.
- **Linguistic Ambiguity and Contextual Understanding:** Natural language is inherently complex and full of ambiguities that are tough for computers to resolve without a deep understanding of context and the real world.

- **Generalizability and Domain Specificity:** It's difficult to create a single NLP model that works well everywhere. Models trained on general language often lack the specific knowledge needed for specialized fields like medicine.
- **Computational Resource Demands:** While advanced neural models perform exceptionally well, they require significant computational power for training and deployment, which can be a barrier for many organizations.
- **Interpretability and Trust:** The "black box" nature of some complex AI models makes it hard to understand how they arrive at a decision. This lack of transparency can hinder trust, especially in critical applications where knowing the reasoning behind an outcome is vital.
- **Ethical and Societal Considerations:** Using AI with sensitive human data, such as health information, brings up serious ethical concerns. We must ensure data is anonymized, secure, and that models don't perpetuate biases found in their training data.

7.3 Future Directions

The future of NLP for KBS will likely focus on:

- **Enhancing Contextual Understanding:** We need to keep expanding semantic lexicons and use more contextual information to better resolve ambiguities.
- **Integration of Knowledge Sources:** Combining linguistic knowledge with real-world knowledge in NLP models is essential for achieving a more human-like understanding.
- **Robustness for Unstructured Data:** Continued efforts to build models that can handle truly unstructured text will expand the practical applications of KBS.
- Human-System Collaboration: Designing better user interfaces will encourage human experts to collaborate with intelligent systems, helping to capture and update knowledge more effectively.
- **Addressing Ethical Implications:** Ongoing research is needed to develop methods for anonymizing data, ensuring security, and mitigating biases in AI models, especially in sensitive areas like healthcare. This includes creating transparency through "model cards" that detail a model's training data and potential biases.
- **Narrative Understanding and Sensemaking:** The ultimate goal is to move beyond processing individual words and concepts to understanding entire narratives, a process called "sensemaking," which will allow for a more nuanced grasp of human communication.

8. Conclusion

Natural Language Processing (NLP) has revolutionized how computers handle human language, completely changing the landscape for Knowledge-Based Systems (KBS). We've come a long way from the rigid, rule-based methods of the past to the flexible and powerful machine learning and deep learning models we use today. This progress allows us to automatically create detailed semantic lexicons and strong ontologies, which are crucial for organizing and representing knowledge clearly. These advancements have real-world benefits, from improving medical diagnoses and streamlining insurance claims to enabling us to truly understand the core meaning of information, not just the words on the page. While challenges remain, such as ensuring data quality, handling linguistic ambiguities, and addressing ethical concerns around privacy and bias, the future is bright. As NLP continues to get better at understanding context and complex narratives, we can look forward to even more intelligent and capable KBS that will transform how we manage and use information for years to come.

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References

1. Abu-Jamie, T. N., et al. (2021). "Diagnosing Cough Problem Expert System Using CLIPS." International Journal of Academic Information Systems Research (IJAISR) 5(5): 79-90.
2. Abu-Saqer, M. M. and S. S. Abu-Naser (2019). "Developing an Expert System for Papaya Plant Disease Diagnosis." International Journal of Academic Engineering Research (IJAER) 3(4): 14-21.
3. Abu-Saqer, M. M. and S. S. Abu-Naser (2019). "Knowledge Based System for Uveitis Disease Diagnosis." International Journal of Academic Information Systems Research (IJAISR) 3(5): 18-25.
4. Ahmed, A., et al. (2019). "Knowledge-Based Systems Survey." International Journal of Academic Engineering Research (IJAER) 3(7): 1-22.
5. Aish, M. A., et al. (2021). "Lower Back Pain Expert System Using CLIPS." International Journal of Academic Information Systems Research (IJAISR) 5(5): 57-67.
6. Alajrami, M. A. and S. S. Abu-Naser (2019). "Grapes Expert System Diagnosis and Treatment." International Journal of Academic Engineering Research (IJAER) 3(5): 38-46.
7. Albadrasawi, S. J., et al. (2023). "Development and Evaluation of an Expert System for Diagnosing Kidney Diseases." International Journal of Academic Engineering Research (IJAER) 7(6): 16-22.
8. Albanna, R. N., et al. (2023). "Colon Cancer Knowledge-Based System." International Journal of Engineering and Information Systems (IJEAIS) 7(6): 27-36.
9. Albanna, R. N., et al. (2023). "Knowledge-Based System for Diagnosing Colon Cancer." International Journal of Engineering and Information Systems (IJEAIS) 7(6): 27-36.
10. Al-Borno, D. F. and S. S. Abu-Naser (2023). "A Proposed Expert System for Vertigo Diseases Diagnosis." International Journal of Academic Information Systems Research (IJAISR) 7(6): 1-9.
11. Aldaour, A. F. and S. S. Abu-Naser (2019). "An Expert System for Diagnosing Tobacco Diseases Using CLIPS." International Journal of Academic Engineering Research (IJAER) 3(3): 12-18.
12. Aldaour, A. F. and S. S. Abu-Naser (2019). "Anemia Expert System Diagnosis Using Sl5 Object." International Journal of Academic Information Systems Research (IJAISR) 3(5): 9-17.
13. Aldeeb, M. H. and S. S. Abu-Naser (2023). "Breast Cancer Knowledge Based System." International Journal of Engineering and Information Systems (IJEAIS) 7(6): 46-51.
14. Aldeeb, M. H. and S. S. Abu-Naser (2023). "Knowledge Based System for Breast Cancer Diagnosis." International Journal of Engineering and Information Systems (IJEAIS) 7(6): 46-51.
15. Alfarra, A. H., et al. (2021). "An Expert System for Neck Pain Diagnosis." rnal of Academic Information Systems Research (IJAISR) 5(7): 1-8.
16. Al-Ghoul, M. M., et al. (2022). "Knowledge Based System for Diagnosing Custard Apple Diseases and Treatment." International Journal of Academic Engineering Research (IJAER) 6(5): 41-45.
17. Alkahlout, M. A., et al. (2021). "Expert System Diagnosing Facial-Swelling Using CLIPS." International Journal of Academic Information Systems Research (IJAISR) 5(5): 29-36.
18. Alkahlout, M. A., et al. (2021). "Expert System for Throat Problems Using SL5 Object." International Journal of Academic Information Systems Research (IJAISR) 5(5): 68-78.
19. Alkahlout, M. A., et al. (2021). "Knowledge Based System for Diagnosing Throat Problem CLIPS and Delphi languages." International Journal of Academic Engineering Research (IJAER) 5(6): 7-12.
20. Alkurd, Y. M. and S. S. Abu-Naser (2025). "A proposed accurate system for diagnosing hypertension."
21. Almadhoun, H. R. and S. S. Abu-Naser (2020). "An Expert System for Diagnosing Coronavirus (COVID-19) Using SL5." International Journal of Academic Engineering Research (IJAER) 4(4): 1-9.
22. Al-Masawabe, M. M. and S. S. Abu-Naser (2021). "Expert System for Short-term Abdominal Pain (Stomach Pain) Diagnosis and Treatment." International Journal of Academic Information Systems Research (IJAISR) 5(5): 37-56.
23. Almzainy, M. M., et al. (2023). "Development and Evaluation of an Expert System for Diagnosing Tinnitus Disease." International Journal of Academic Information Systems Research (IJAISR) 7(6): 46-52.
24. Al-Qadi, M. H., et al. (2022). "Developing an Expert System to Diagnose Tomato Diseases." International Journal of Academic Engineering Research (IJAER) 6(5): 34-40.
25. AlQatrawi, M. J., et al. (2022). "Rule Based System for Diagnosing Lablab Problems." International Journal of Academic and Applied Research (IJAAR) 6(5): 249-256.
26. Al-Qumboz, M. N. A. and S. S. Abu-Naser (2019). "Spinach Expert System: Diseases and Symptoms." International Journal of Academic Information Systems Research (IJAISR) 3(3): 16-22.
27. Al-Qumboz, M. N. A., et al. (2019). "Kidney Expert System Diseases and Symptoms." International Journal of Academic Engineering Research (IJAER) 3(5): 1-10.
28. Al-Saloul, N. J., et al. (2022). "A Knowledge Based System for Cucumber Diseases Diagnosis." International Journal of Academic Information Systems Research (IJAISR) 6(5): 29-45.
29. Alsaqqa, A. H., et al. (2021). "Knowledge Based for Tooth Problems." International Journal of Academic Information Systems Research (IJAISR) 5(5).
30. Alshawwa, I. A., et al. (2019). "An Expert System for Coconut Diseases Diagnosis." International Journal of Academic Engineering Research (IJAER) 3(4): 8-13.
31. Alshawwa, I. A., et al. (2019). "An Expert System for Depression Diagnosis." International Journal of Academic Health and Medical Research (IJAHMR) 3(4): 20-27.
32. Al-Shawwa, M. and S. S. Abu-Naser (2019). "Knowledge Based System for Apple Problems Using CLIPS." International Journal of Academic Engineering Research (IJAER) 3(3): 1-11.
33. Al-Shawwa, M. O. and S. S. Abu-Naser (2019). "A Proposed Expert System for Diagnosing Skin Cancer Using SL5 Object." International Journal of Academic Information Systems Research (IJAISR) 3(4): 1-9.
34. Altarazi, R. E., et al. (2023). "A CLIPS-Based Expert System for Brain Tumor Diagnosis." International Journal of Academic Engineering Research (IJAER) 7(6): 9-15.
35. Altayeb, J. M., et al. (2023). "Mango Pests Identification Expert System." International Journal of Engineering and Information Systems (IJEAIS) 7(6): 17-26.
36. Aslem, Y. and S. S. Abu-Naser (2022). "CLIPS-Expert System to Predict Coriander Diseases." International Journal of Engineering and Information Systems (IJEAIS) 6(6): 89-95.
37. Dheir, I. and S. S. Abu-Naser (2019). "Knowledge Based System for Diagnosing Guava Problems." International Journal of Academic Information Systems Research (IJAISR) 3(3): 9-15.
38. Dheir, I. M., et al. (2019). "Knowledge Based System for Diabetes Diagnosis Using SL5 Object." International Journal of Academic Pedagogical Research (IJAPR) 3(4): 1-10.
39. El Kahlout, F. and S. S. Abu-Naser (2023). "Developing an Expert System to Computer Troubleshooting." International Journal of Academic Information Systems Research (IJAISR) 7(6): 16-26.
40. El Kahlout, M. I. and S. S. Abu-Naser (2019). "An Expert System for Citrus Diseases Diagnosis." International Journal of Academic Engineering Research (IJAER) 3(4): 1-7.
41. El Kahlout, M. I., et al. (2019). "Silicosis Expert System Diagnosis and Treatment." International Journal of Academic Information Systems Research (IJAISR) 3(5): 1-8.
42. Eleyan, H. A. R., et al. (2023). "An Expert System for Diagnosing West Nile virus Problem Using CLIPS." International Journal of Academic Information Systems Research (IJAISR) 7(6): 27-37.
43. El-Habibi, M. F., et al. (2022). "A Proposed Expert System for Obstetrics & Gynecology Diseases Diagnosis." International Journal of Academic Multidisciplinary Research (IJAMR) 6(5): 305-321.
44. Elhabil, B. Y. and S. S. Abu-Naser (2021). "An Expert System for Ankle Problems." International Journal of Engineering and Information Systems (IJEAIS) 5(4): 57-66.
45. Elhabil, B. Y. and S. S. Abu-Naser (2021). "An Expert System for Tooth Problems." International Journal of Academic Information Systems Research (IJAISR) 5(4).
46. Elhabil, B. Y. and S. S. Abu-Naser (2021). "Expert System for Hib Problems." International Journal of Academic Information Systems Research (IJAISR) 5(5): 5-16.
47. El-Hamarnah, H. A., et al. (2022). "Proposed Expert System for Pear Fruit Diseases." International Journal of Academic and Applied Research (IJAAR) 6(5): 237-248.
48. Elsharif, A. A. and S. S. Abu-Naser (2019). "An Expert System for Diagnosing Sugarcane Diseases." International Journal of Academic Engineering Research (IJAER) 3(3): 19-27.
49. Hamadaqa, M. H. M. and S. S. Abu-Naser (2021). "Hair Loss Diagnosis Expert System and Treatment Using CLIPS." International Journal of Academic Engineering Research (IJAER) 5(5): 37-42.
50. Hammad, M. S., et al. (2023). "A Proposed Expert System for Diagnosis of Migraine." International Journal of Academic Engineering Research (IJAER) 7(6): 1-8.
51. Harara, F. E., et al. (2022). "Figs Knowledge Based System Disease Diagnosis and Treatment." International Journal of Academic Engineering Research (IJAER) 6(5): 41-45.
52. Harazin, D. and S. S. Abu-Naser (2023). "Developing an Expert System to Warts and Verruca." International Journal of Engineering and Information Systems (IJEAIS) 7(6): 37-45.
53. Jamala, M. N. and S. S. Abu-Naser (2023). "Knowledge Based System for Diagnosing Lung Cancer Diagnosis and Treatment." International Journal of Academic Information Systems Research (IJAISR) 7(6): 38-45.
54. Khalil, A. J., et al. (2019). "Apple Trees Knowledge Based System." International Journal of Academic Engineering Research (IJAER) 3(9): 1-7.
55. LAfi, O. I., et al. (2022). "A Proposed Expert System for Broccoli Diseases Diagnosis." International Journal of Engineering and Information Systems (IJEAIS) 6(5): 43-51.
56. Mahmum, A. S., et al. (2023). "An Expert System for Diagnosing Whooping Cough Using CLIPS." International Journal of Engineering and Information Systems (IJEAIS) 7(6): 1-8.
57. Mansour, A. I. and S. S. Abu-Naser (2019). "Expert System for the Diagnosis of Wheat Diseases." International Journal of Academic Information Systems Research (IJAISR) 3(4): 19-26.
58. Mansour, A. I. and S. S. Abu-Naser (2019). "Knowledge Based System for the Diagnosis of Dengue Disease." International Journal of Academic Health and Medical Research (IJAHMR) 3(4): 12-19.
59. Mansour, A. I. and S. S. Abu-Naser (2021). "Expert system for the diagnosis of high blood pressure diseases." International Journal of Academic Information Systems Research (IJAISR) 5(5): 23-28.
60. Mansour, A. I., et al. (2021). "An Expert System for Diagnosing Cough Using SL5 Object." International Journal of Academic Engineering Research (IJAER) 5(6): 13-27.
61. Masri, N., et al. (2019). "Survey of Rule-Based Systems." International Journal of Academic Information Systems Research (IJAISR) 3(7): 1-23.
62. Megdad, M. M., et al. (2022). "Mint Expert System Diagnosis and Treatment." International Journal of Academic Information Systems Research (IJAISR) 6(5): 22-28.
63. Mettleq, A. S. A. and S. S. Abu-Naser (2019). "A Rule Based System for the Diagnosis of Coffee Diseases." International Journal of Academic Information Systems Research (IJAISR) 3(3): 1-8.
64. Mettleq, A. S. A., et al. (2019). "Expert System for the Diagnosis of Seventh Nerve Inflammation (Bell's palsy) Disease." International Journal of Academic Information Systems Research (IJAISR) 3(4): 27-35.
65. Mettleq, M. S. A. and S. S. Abu-Naser (2025). "Expert System for the Diagnosis of coffee Diseases."
66. Murad, W. F. and S. S. Abu-Naser (2023). "An Expert System for Diagnosing Mouth Ulcer Disease Using CLIPS." International Journal of Academic Engineering Research (IJAER) 7(6): 30-37.
67. Okasha, S. M., et al. (2022). "A knowledge Based System for Diagnosing Persimmon Diseases." International Journal of Academic and Applied Research (IJAAR) 6(6): 53-60.
68. Qanoo, F. N., et al. (2023). "A CLIPS-Based Expert System for Heart Palpitations Diagnosis." International Journal of Academic Information Systems Research (IJAISR) 7(6): 10-15.
69. Qaoud, A. N. and S. S. Abu-Naser (2023). "Developing an Expert System to Diagnose Malaria." International Journal of Academic Information Systems Research (IJAISR) 7(6): 9-18.
70. Qunoo, M. M. and S. S. Abu-Naser (2025). "A proposed accurate system for diagnosing low vision." International Journal of Engineering and Information Systems (IJEAIS) 9(6): 23-32.
71. Radwan, H. I., et al. (2022). "A Proposed Expert System for Passion Fruit Diseases." International Journal of Academic Engineering Research (IJAER) 6(5): 24-33.
72. Sababa, R. Z., et al. (2022). "A Proposed Expert System for Strawberry Diseases Diagnosis." International Journal of Engineering and Information Systems (IJEAIS) 6(5): 52-66.
73. Salman, F. M. and S. S. Abu-Naser (2019). "Expert System for Castor Diseases and Diagnosis." International Journal of Engineering and Information Systems (IJEAIS) 3(3): 1-10.
74. Salman, F. M. and S. S. Abu-Naser (2019). "Thyroid Knowledge Based System." International Journal of Academic Engineering Research (IJAER) 3(5): 11-20.
75. Salman, F. M. and S. S. Abu-Naser (2020). "Expert System for COVID-19 Diagnosis." International Journal of Academic Information Systems Research (IJAISR) 4(3): 1-13.
76. Samhan, L. F., et al. (2021). "Expert System for Knee Problems Diagnosis." International Journal of Academic Information Systems Research (IJAISR) 5(4): 59-66.
77. Tantawi, J. and S. S. Abu-Naser (2023). "Knowledge-Based System for the Diagnosis of Flatulence." International Journal of Academic Engineering Research (IJAER) 7(6): 23-29.
78. Wishah, N. D., et al. (2023). "Developing a Knowledge-Based System for Diagnosis and Treatment Recommendation of Neonatal Diseases Using CLIPS." International Journal of Academic Engineering Research (IJAER) 7(6): 38-50.