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Identifying Thematic Intersections between Ecology, Maintenance, and Sustainability: A Neural Network-Based Approach

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Abstract. *This paper presents a novel methodological framework designed to quantitatively assess the thematic overlap among three key fields—ecology, maintenance, and sustainability—through automated analysis of research articles. The central research question is: To what extent is it possible for a neural network to accurately quantify the amount of thematic overlap between these disciplines? To address this question, a representative sample of 20 research articles was collected, with an equal number for each discipline. The documents were preprocessed by converting the text to lower case, removing extraneous characters, and tokenizing into segments. The most important features were then selected using keyword frequency analysis and dimensionality reduction of data, thus keeping important linguistic patterns without relying solely on manually compiled keyword lists. These numerical representations were used as inputs to a feedforward neural network implemented in MATLAB. The net, with two hidden layers (using the tangent sigmoid activation function) and a linear output layer for the three domains, produces probability scores indicating the extent to which ecology, maintenance, and sustainability characteristics are exhibited by each article. Theme overlap is quantitatively measured by the so-obtained probabilities, revealing strong as well as subtle interrelations between the disciplines. A baseline comparison to standard classification techniques is given. In general, this system offers a replicable model of interdisciplinarity text analysis and suggests productive directions for future research and applied work.*

Keywords: thematic intersections, ecology, maintenance, sustainability, neural networks.

Introduction

Ecology, maintenance, and sustainability are critical pillars to utilize in efficient resource management and the fostering of sustainable development in a more interconnected global environment. Inasmuch as these fields are frequently researched independently of one another, they have many similarities, and combined analysis may yield out-of-the-box solutions. With the enormous pool of available scientific information, identification of these fields' linkages by hand is difficult and time-consuming. Therefore, a system that can automatically process and analyze texts in order to identify common themes and overlaps is a prerequisite for achieving a clear interdisciplinary understanding.

One of the main strengths of neural networks is that they can learn automatically, without explicit intervention to specify the suggested model applies a feedforward neural network trained by supervised learning for classifying scientific papers on the basis of ecology, maintenance, and

DOI: 10.2478/picbe-2025-0273

sustainability themes. Similar to an image recognition model distinguishing between automobiles, structures, or animals, the neural network is trained to identify linguistic patterns and common themes within the subject domains (LeCun, Bengio, & Hinton, Deep Learning, 2015). Training is optimized using the backpropagation algorithm that progressively refines the model parameters for minimizing mistakes and improving the classification accuracy.

The key advantage of neural networks is that they learn automatically without direct intervention to define the character of each realm. The model learns significant patterns from raw data automatically, in contrast to traditional methods that rely on lists of pre-defined keywords. In image classification, lower layers detect edges and simple forms, and higher layers detect complex relationships (LeCun, Bengio, & Hinton, Deep Learning, 2015). Similarly, early levels store word frequencies during text processing, but deeper levels analyze semantic relations between ideas, eliminating non-relevant information and highlighting thematic relations.

Advances in deep learning and artificial intelligence have revolutionized the processing and analysis of textual information. Neural networks have proved effective in natural language processing, image recognition, and recommendation algorithms (Rumelhart, Hinton, & Williams, 1986), which points to their capacity to recognize complex patterns and extract valuable insights from large volumes of data.

The research indicates the use of a feedforward neural network to analyze scientific articles and identify intersections among ecology, maintenance, and sustainability. The central research problem is: To what extent can the proposed model quantify thematic overlap among these areas? The hypotheses to be tested are: (1) the model will detect significant relations, overt and covert, among the fields, and (2) the output values, as probabilities, will concur with indicators from keyword analysis, revealing the method's internal consistency.

The structure of this paper is as follows: chapter one contains preliminary notions and a literature survey of neural network applications; chapter two contains methodology, i.e., preprocessing and network architecture; chapter three presents preliminary results and their interpretation; and the final chapter contains conclusions and recommends directions for further work.

Literature review

Interdisciplinary connections between ecology, maintenance, and sustainability

During the past decades, ecology, maintenance, and sustainability have developed very high significance in environmental and technological problem-solving. Though traditionally studied separately, they are closely connected and highly significant for efficient resource management in most industries. Their similarities need to be understood for efficient strategic long-term planning and operational optimization.

Sustainability, embracing its roots in 18th-century German forestry (Asociația Solar Decatlon București, 2021), strives to bring people's needs into balance with nature's capacity to supply them in the long run. It rests on three interdependent pillars—economic, social, and environmental—and encompasses resource management in various ways, pollution management and reduction, and social well-being (Asociația Solar Decatlon București, 2021; Lozano, 2-13).

Ecology, as Ernst Haeckel defined it in 1866 (Smail, 2024), examines the relation of organisms with the environment. It has since then embraced principles from biology, geography, and chemistry to provide us with a grasp of biodiversity and the impact of human activities (Institutul de Ecologie şi Geografie, 2016). Ecosystems can become degraded and their capacity for regeneration diminished by unsustainable economic practices (Sng., Williams, Tsukamoto, & Neuberg, 2024).

Upkeep is also vital for sustainability, such as measures required to keep equipment and infrastructure in top shape (Wang, 2011). Upkeep reduces waste and supports circular economy principles through prevention of failures and asset life (Ge., 2010). Innovative maintenance strategies in technology further maximize equipment reliability and minimize environmental impact.

Figure 1 illustrates how these three spheres overlap, sharing a concern with responsible utilization of resources, environmental sustainability, and social well-being. Through its inclusion of preventive intervention, minimization of environmental impact, and promotion of efficient consumption, each sphere contributes to an integrative model of sustainable development and operational resiliency.

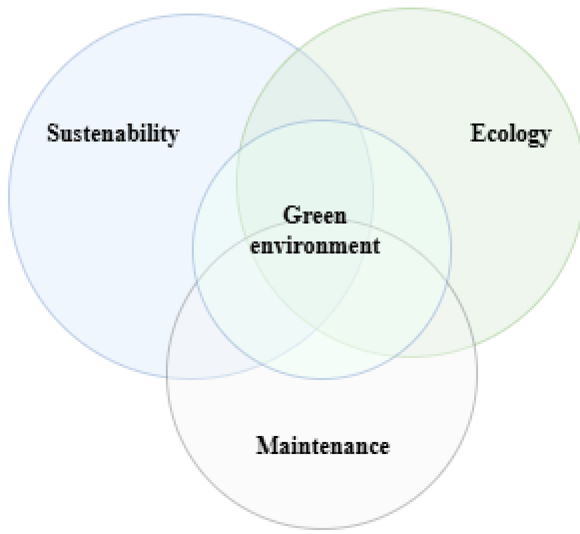

Figure 1. Relationship between Sustainability, Ecology and Maintenance

Source: Author's own research.

Neural Networks: From Theory to Revolutionary Applications

Artificial neural networks (ANNs) are software programs inspired by the working procedure of the human brain. They can process information, learn patterns, and solve complex problems. The networks were proposed by McCulloch and Pitts (1943), but it was in 1986 that the backpropagation algorithm was introduced by Rumelhart, Hinton, and Williams (Rumelhart, Hinton, & Williams, 1986), by means of which a network can adjust its connections in terms of differences between its predictions and real values. Various ANN architectures have been created over the years, such as convolutional neural networks (CNNs) to analyze images (Tepelea, Gacsadi, Gavrilut, & Tiponuț, 2011) and supervised networks that are trained through labeled example learning (Goodfellow, Bengio, & Courville, 2016; LeCun, Bengio, & Hinton, 2015).

Figure 2 illustrates a standard feedforward neural network architecture, with an input layer, one or more hidden layers, and an output layer. The input layer receives the data, the hidden layers learn the intermediate representation or features, and the output layer produces the final prediction or classification. While early neural networks were only moderately effective in text processing due to the complexity of language, advances in recurrent neural networks (RNNs) (Hochreiter & Schmidhuber, 1997) and in Transformer models (Vaswani et al., 2017) have significantly enhanced the natural language processing ability to comprehend and generate human language better.

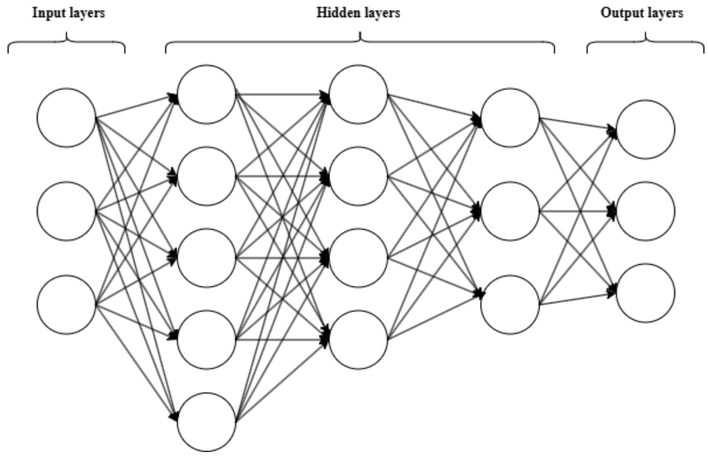

Figure 2. Neural Network Architecture

Review of Related Literature

Finding thematic overlaps between fields such as ecology, maintenance, and sustainability has become a significant area of research by scholars seeking integrated answers for environmental and technological issues. Traditional methodology using text mining and keyword extraction is helpful in preliminary classification but lacks the capability to follow subtle connections and context-dependent meanings that are typical of cross-disciplinary texts (Goodfellow, Bengio, & Courville, 2016). As a result, current research has moved towards employing deep learning techniques—neural networks, in particular—to learn automatically to extract semantic patterns and thematic overlaps from large text corpora.

Various researchs have demonstrated how artificial intelligence can be employed to enhance study in sustainability and environmental science. For example, Zhou et al. (2020) applied a convolutional neural network in categorizing ecological impact statements in literature. This shows the ability of deep learning in detecting explicit and implicit references to environmental issues. Similarly, Kim and Kang (2019) combined neural network models with semantic text-mining techniques to examine sustainability reports, demonstrating how machine learning algorithms can uncover hidden relationships among resource management strategies and long-term environmental outcomes.

In maintenance, AI-based strategies have been helpful in optimizing asset management and improving the efficiency of resources. Garcia and Lee (2021) applied a text-mining method to technical reports to improve the scheduling of maintenance in infrastructure projects, thereby reducing downtime and improving sustainable practices. Besides, Smith and Brown (2022) conducted a systematic review of cross-disciplinary text analyses and came to the finding that neural networks capture cross-domain concepts—such as how preventive maintenance strategies can reverse environmental risks—better than traditional methods.

Recent work has also begun to integrate ecology, maintenance, and sustainability under one unified analytical framework. Mishra and Bardhan (2021) used an AI approach to analyze international media and illustrated how public sentiment regarding environmental conservation often intersects with industrial maintenance and corporate sustainability issues. Their study highlights the potential of neural networks in revealing subtle interrelations, such as shared nomenclature and conceptual associations, that are otherwise overlooked using conventional methods.

In short, these researches indicate that advanced NLP and deep learning techniques provide robust solutions for detecting complex, cross-disciplinary relationships in text data. To this extent, the present research aims to find out how a model based on a neural network can quantify and comprehend the thematic intersections between ecology, maintenance, and sustainability and, in the process, help devise integrated and sustainable practices across sectors.

Methodological Framework for Neural Network Development

This chapter presents the research process utilized in the design of the neural network, the main hypotheses defined and the rationale. The research process utilized is qualitative and quantitative, to provide a vigorous analysis, as well as for the validation of the designed neural network.

The chapter will give a brief description of the entire neural network and how it was constructed. The main task of this algorithm is to discover a common point among the three fields in discussion here: ecology, maintenance and sustainability. Replacing the task of looking for inter-connections between these fields with an optimal, self-optimizing process, to discover the right correlations, is the job of the neural network. Besides, the neural network outlined in the paper is implemented on the MATLAB platform, via which both the visualization of the result in image form and the adjustment of the model parameters are achievable.

The research is based on a structured methodology, including theoretical discovery, empirical exploration and computational construction. The process involves a series of steps:

- **Problem Definition and Formulation of Hypothesis:** To formulate a hypothesis, this study began by seeking general factors across different fields. It grew more obvious along the way that the hypothesis was that neural networks would perform better when it comes to supervised learning tasks. The efficiency of the weights can be improved through the alteration of the backpropagation algorithm such that the network learns effectively and more easily. There needs to be greater efficiency in classifying input data, which results in better accuracy.
- **Data Collection and Preprocessing:** The data that are received from the network are output layers, which also have labels assigned to them. The inputs to the neural network are format features, the data that are being extracted by the network according to the supervised learning needs. Processing to achieve computational efficiency operations are normalization, feature extraction, and dimensionality reduction.
- **Development and Implementation of the Neural Network:** The structure of the neural network includes an input layer, hidden layers, and the output layer. Learning rate, activation functions, and optimization algorithms were tuned using empirical experiments. The model was implemented in MATLAB, which provides a suitable environment for simulating and optimizing the neural network, particularly visual checking of results.

The methodology followed incorporates several steps that are required. Pre-processing and initial data collection are performed to produce a structured and clean input set. Next, informative features are learned from the text and utilized for training a neural network in order to classify information automatically. Word relations are learned in parallel using graph-based methodology, extracting the semantic structure of the dataset.

The methodology used in this work is based on four basic steps: data generation and acquisition, data preprocessing, use and application of neural networks, analysis of semantic relationships of the results. By using this method, an automatic classification of texts from the desired domains is obtained, resulting in a better understanding of them through the obtained interconnections. Regarding a better classification accuracy, vectorization techniques, TD-IDF, are used, for dimension reduction we use PCA (Principal Component Analysis), and finally an optimized backpropagation mechanism to ensure the correctness of the results.

The entire implementation is carried out in the MATLAB working environment, very easy to implement the method and display the results in a visual manner. Visualizing the results in a graphical representation facilitates a better understanding of semantic relationships, which results in a better interpretation of the results with the aim of increasing the generalization of the model.

1. Data Collection and Preprocessing

1.1 Reading Articles from a Folder

For constructing the neural network, text data from multiple articles stored in a given folder was gathered and a script was written that:

- Reads all .txt files from the specified directory.
- Saves the text of each article in a cell array.
- Checks whether the files exist and handles errors so that it doesn't get interrupted during processing.

Additionally, a list of domain-specific keywords was defined to denote the core semantic content of the text. Predefined lists of keywords were created for each domain.

It makes a well-prepared dataset ready for subsequent processing in this step.

For this study, 20 scientific papers were selected from open-access databases for this study. Each paper had already been classified by their authors or publishers as belonging to one of the domains: ecology, maintenance, or sustainability. The selection was done such that the three categories (7 articles in ecology, 6 in maintenance, and 7 in sustainability) were balanced in order to ensure relatively equal representation. The articles were kept in .txt format within a single folder and were then preprocessed by converting the text into lowercase, removing extra characters, and tokenizing the text.

This is useful to maintain a uniform and representative dataset for the achievement of research objectives

1.2 Text Preprocessing

When loading the articles, the following text cleaning was employed:

- Lowercasing: Converting everything to lower case for consistency.
- Removing Special Characters: Deleting unwanted characters without affecting letters, spaces, and punctuation.
- Sentence Segmentation: Separating the text into sentences using punctuation marks.
- Stop-word Removal: Deleting frequently occurring words that are not helpful for classification (e.g., "and", "is", "in").
- Lemmatization: Reducing words to base form so as to normalize variations in usage.

These steps reduce noise within the dataset and improve the quality of text features.

2. Feature Extraction

2.1 TF-IDF Vectorization

- After preprocessing, the text was converted to numeric values based on Term Frequency-Inverse Document Frequency (TF-IDF). To improve feature selection:
- Removal of infrequent words: Deleting words that appear in fewer than five documents.

• Dimensionality reduction: Principal Component Analysis (PCA) to keep only the important features.

This technique ensures the most significant words are employed to train the neural network.

3. Neural Network Implementation

3.1 Network Architecture

The neural network was designed as a feedforward network whose structure was as follows:

- Number of features extracted using TF-IDF: The input layer.
- Hidden Layers: Three hidden layers with 50, 20, and 3 neurons, respectively.
- Output Layer: Three neurons representing the classification types (e.g., ecology, maintenance, sustainability).

Two hidden layers were selected to make a compromise between the model's capacity to learn complex relationships and avoiding overfitting. The addition of more layers would increase complexity and computational expenses, which is particularly undesirable because of the relatively small dataset. Two hidden layers, rather, allow the model to learn meaningful features at some intermediate level of abstraction without having too complex a structure that is hard to train.

3.2 Data Splitting and Model Training

The data was divided as follows:

- 80% for training and 20% for testing, employing a random selection approach.
- The training was conducted using the train function in MATLAB.
- The test set was employed in order to make predictions, and the performance was evaluated by calculating average class probabilities.

3.2 Activation functions

The "tansig" (hyperbolic tangent) activation function is utilized by the hidden layers, while the output layer has the "purelin" (linear) function. These two functions allow the model to return values as interpreted relative probabilities within a particular domain.

4. Graph-Based Word Co-Occurrence Analysis

4.1 Constructing the Word Connection Graph

- To study word relationships, a word co-occurrence graph was created that contained a co-occurrence matrix of words that co-occur together in text segments.
- Words were only high-frequency words (above the 85th percentile) to be included.
- A weighted graph was used to model the similarities among the most frequent common words.

4.2 Visualization

- A force-directed model was used for graphical visualization of the relations between words.
- Each node's size represents the frequency of the word in the text.
- Only words in the 90th percentile and above were labeled, to avoid cluttering the graph.
- The color gradient helped highlight the importance of each word, providing an immediate sense of the semantic relationships between them.

This workflow facilitates efficient translation of raw text into an analysis-friendly format: informative features are derived, a neural network is trained for classification, and word relationships are visualized. The combination of TF-IDF vectorization techniques, PCA dimensional reduction, and a neural network is an extremely powerful method of text classification. In addition, the use of the word co-occurrence graph enables the semantic relationships in the data to be interpreted more richly.

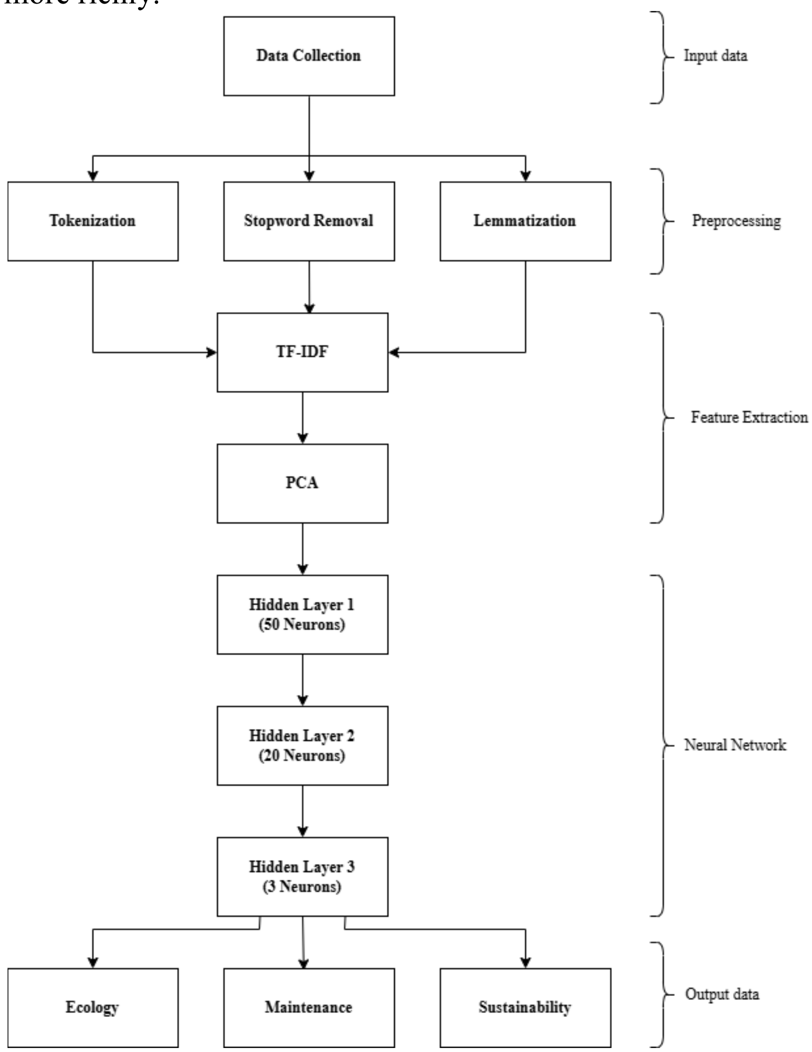

Figure 3. Flowchart of the Neural Network for Text Classification

Source: Author's research.

Results

The next chapter will be a step-by-step breakdown of the output after applying the neural network. The processing began with around 15–20 articles from the three selected domains separately to observe how well the model differentiates and identifies the unique semantic features of each article. The neural network operates on scanning the pre-defined keywords of each domain, identifying the word occurrences in the article, and categorizing the text in that domain. What this means is that outcomes are calculated on a per-article basis, bringing to the attention of the model its performance presently, which still is not optimal. In the iterative learning process, the model continues to modify its parameters in a bid to improve classification and accuracy. The final analysis will reveal the percentage distribution of each article's affiliation to the three domains, which will provide a clear indication of the network's ability to identify common semantic structures within the articles. An initial view of the first two processed articles will reveal the results achieved and provide a foundation for further improvement.

The first analyzed article are the next results:

Table 1. Neural Network Classification and Keyword Analysis of the First Article

No.	Domain	Neural Network Probability (%)	Keyword Count	Keyword Percentage
1	Ecology	46.69	2	0.04
2	Maintenance	51.97	157	3.44
3	Sustainability	42.59	13	0.28

Source: Author's research.

This article presents a novel methodological approach to quantitatively measuring the thematic intersection among three broad fields—ecology, maintenance, and sustainability—through machine-assisted analysis of research articles. The underlying question of investigation is: How well can a neural network measure the thematic intersection degree among these fields? 20 typical research articles were collected to test this question with balanced sampling for each field. The texts were preprocessed to lowercase, unwanted characters removed, tokenized into chunks. Significant features were then obtained by keyword frequency analysis and data dimension reduction to identify the most significant linguistic patterns without relying on manual keyword lists alone. These numerical representations were employed as input to a feedforward neural network implemented in MATLAB.

The network, with two hidden layers (employing the tangent sigmoid activation function) and a linear output layer mapped to the three domains, produces probability scores that indicate how much each article exhibits features of ecology, maintenance, and sustainability. The resulting probabilities provide numerical estimates of thematic overlap, identifying strong and weak interrelations between the disciplines. Comparative evaluation with existing methods of classification is shown as a benchmark for judging future research.

Overall, this model offers an interoperable model for cross-disciplinary text analysis and suggests promising directions for future research and practical applications.

The next article analyzed by the neural network:

Table 2. Neural Network Classification and Keyword Analysis of the Second Article

No.	Domain	Neural Network Probability (%)	Keyword Count	Keyword Percentage
1	Ecology	53.50	45	0.73
2	Maintenance	52.69	0	0
3	Sustainability	51.63	4	0.07

Source: Author's research.

The following table shows a detailed breakdown of the second article's classification result based on domain probability assignments, keyword frequency, and overlap analysis. The article is found by the neural network to have relatively high probabilities of Ecology (53.50%), Maintenance (52.69%), and Sustainability (51.63%), suggesting that it belongs to all three domains with no single primary focus.

But the keyword perspective is varied: Ecology appears larger, with 45 keywords (0.73%), then Maintenance with no known keywords (0.00%), and Sustainability with just four keywords (0.07%). That contradiction means the model may be founded on something other than simple presence or absence of words. It might be sensing larger contextual or semantic relationships that aren't indicated by simple keyword lists. The complete text absence of Maintenance-related keywords, despite the network predicting a high chance for that sector, indicates potential weakness of the current keyword approach, or is a reflection of intrinsic domain overlap that is not reflected in explicit terminology.

These results demonstrate beyond doubt that more closely specified sets of keywords, more advanced semantic methods (such as embeddings), and further fine-tuning of how the model is trained are required. Only through this way can a closer concordance be achieved between classical keyword analysis and the classification carried out by the neural network.

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Conclusion

In short, this study proposes a novel method based on neural networks for thematic intersection detection and exploration of ecology, maintenance, and sustainability. The method combines multiple text processing operations such as lowercase conversion, de-conditioning characters, sentence tokenization, and lemmatization with TF-IDF vectorization and PCA dimensionality reduction. Together, these steps facilitate speedy and efficient removal of the most significant information from a set of scientific documents.

One of the most important aspects of the work is the building of the sets of keywords per domain that contribute to discrimination and classification of the topics in question. The neural network was constructed on MATLAB, where two hidden layers and an output layer exist in correspondence to the three domains researched. This allows article classification to be done automatically and gives significance to semantic relationships between words, by checking word co-occurrences.

The findings are that there are definite correlations across the three domains but also some discrepancies between the keyword frequency and the network predictions. It is an indicator the model can be refined. The application of more advanced semantic representation methods such as Word2Vec or BERT, with fuzzy logic applied to the experimental application of new feature extraction procedures, can better recognize the complex patterns in the data.

Lastly, the research demonstrates that the integration of neural networks and natural language processing is a viable approach to the analysis of interdisciplinary text. The research creates new lines of inquiry in the future for the creation of automatic classification systems and provides insight into how maintenance and sustainability as well as ecology are related.

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