A Data Mining and Ontology-Based Approach for Predicting the Research Ideas in the Wildlife Sector of Sri Lanka

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***Abstract*— Sri Lanka, is the global biodiversity hotspot, which contains a wide variety of fauna & flora. Also, wildlife is the key player in the tourism industry of Sri Lanka. But still, Sri Lankan wildlife faced many conflicts to protect their biodiversity because of a lack of technical and research support. There were significant research gaps and data resources but still, researchers retreat to select this domain as their study. This study demonstrates a novel approach to data mining to find hidden keywords and automated labeling for past research work in this area. To model topics and recognize the major keywords for future researchers, we used Latent Dirichlet Allocation (LDA) algorithms to build an ontology model to visualize the relationships between each keyword and similar keywords cluster into creative topics. These techniques are also useful for potential research ideas, for identifying hidden research gaps and to classify domain-related publications. The experiment results demonstrate the validity and efficiency as well as it will make a platform for all researchers to interact easily with the wildlife domain.**

Keywords*— *wildlife, LDA, ontology, topic modeling

I. INTRODUCTION

Wildlife is critical for the sustenance of life on earth. Biodiversity conservation is crucial to preserving a stable global ecological balance.

Sri Lanka is a global biodiversity hotspot consisting of a large variety of fauna and flora. It is one of the main sources of income generation through tourism and other means. The diversity of ecosystems is primarily due to its topographical and climatic heterogeneity, as well as its coastal effect [1]. This rich biodiversity is threatened due to unplanned land use, pollution, overexploitation, etc.

Data from wildlife research can contribute to a large extent is proper conservation and management. However, there is a gap between research and application. Most of the existing research work is not converted into applications while there are many data gaps. Limited numbers of researchers are focusing on the actual research needs from conservation. The selection of research topics is often not compatible with the actual research needs due to multiple reasons. This is a disheartening scenario as there are plenty of opportunities for such work. Inadequate knowledge of the existing research and their applicability, inadequate use of technology, and inability to locate some research are some of the contributing factors. Other than the research published in a known journal, some past research information available online cannot be found properly because they belong to conventional archives, unfortunately.

Increasing public awareness on the values of wildlife and the consequences of losing this heritage can assist conservation to a large extent. To achieve this, we have to simplify the gap between the public and the accessibility to information on wildlife. Technology can play a major role in filling the gap between them.

Mostly wildlife studies aimed to understand species diversity, behavior, and habitat use, and ecology, the role of wildlife in disease transmission, species conservation, population management, and methods to control threats to diversity.

In our study, we focus on analyzing past research papers using data mining techniques to give potential research ideas to the future. To fill the data demands for conservation our solution focuses mainly on semi-automating the finding of research gaps via abstract analysis. Finally, the model includes the most commonly used keywords and question top. This will be an important milestone for researchers as well as wildlife activists to give tips on recent problems that need a solution urgently.

From a technological perspective, there was prior work [2] [3] that has shown A data-driven model of hierarchical subjects to obtain terminology ontology from a large number of amalgamated documents represented using hierarchical relationship-based latent Dirichlet allocation (hrLDA). In comparison to conventional topic models, instead of unigrams, hrLDA relies on noun phrases, deals with syntax and text structures, and enriches topic hierarchies with topic relations. Through a series of experiments, we show the superiority of hrLDA over existing topic models, especially for the construction of hierarchy.

So we have to vary past research techniques to find our final solution. Some trending techniques are used here to improve the outputs. Our research mainly focuses to resolve the inadequate application of wildlife research and technologies in the decision-making process. This paper is structured as follows. In Section II, we describe our proposed methodology and its core theories. and we discuss the results

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of the study in Section III. In Section IV, we discuss the conclusion of our experiment and suggest areas for future study at the end.

II. Methodology

We used a semi-automated methodology which shows in Fig 1. This methodology developed using Latent Dirichlet Allocation (LDA) and Ontology in this study. The text data of the defined domain were collected and pre-processed for the input to LDA algorithms then compared with the ontology graph to the final output. The steps of our methodology are defined below.

A. Data Collection

We collected information about past wildlife researches in Sri Lanka from 2006 to 2019, with the aid of the Department of Natural Resources, Sabaragamuwa University of Sri Lanka, and an extreme literature survey. After that, we accessed full research papers of selected papers from each domain. We've selectively applied the title and abstract data to the CSV file from those research papers.

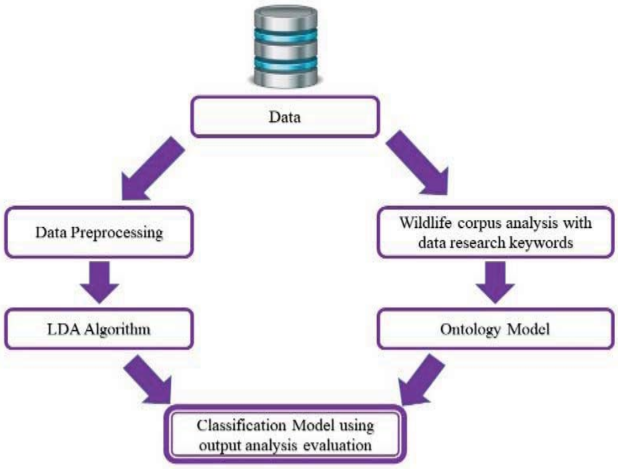

Data
Data Preprocessing
Wildlife corpus analysis with data research keywords
LDA Algorithm
Ontology Model
Classification Model using output analysis evaluation

Fig. 1. Methodological framework

B. Data Pre-processing

Data pre-processing is so important because if our data set contained mistakes, redundancies, missing values, and inconsistencies that all compromised the integrity of the set, we need to fix all those issues for a more accurate outcome [4]. We performed the following steps:

- Tokenization: Divide the text into sentences, and the sentences into words. Lower case the words and smooth punctuation
- Stop word removal: Delete words that have fewer than 3 letters. All stop words are removed.
- Lemmatizing: Words in the third person are shifted to first-person and verbs shifted to present from past and future tenses.
- Words are stemmed — words are reduced to their root form

C. Topic Modelling-LDA

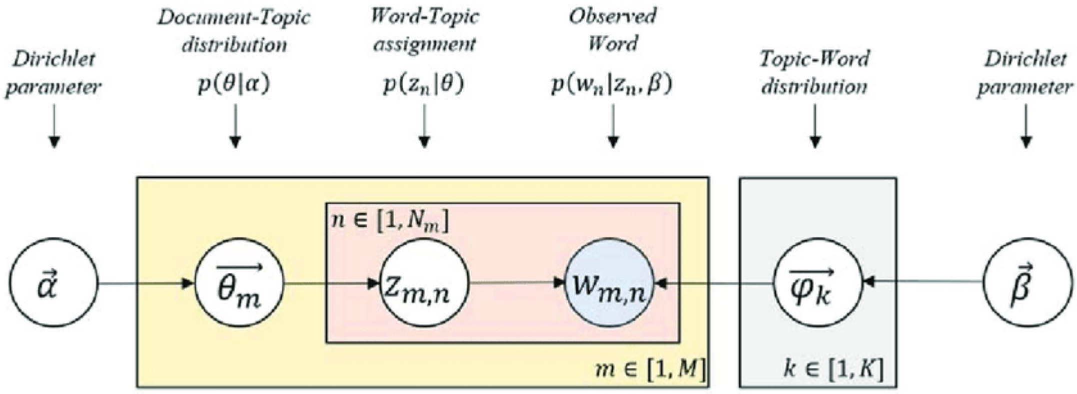
LDA helped adapt the textual data into a format that could act as an input to the LDA model for training. We began by converting the documents to a simple representation of the vectors as a group of words called Bag of Words (BOW) [6]. First, we translated a list of titles into vector lists, all with vocabulary-capable lengths.

Fig. 2 has shown the topic modeling which is one of the trending unsupervised methods. In other words, it is a text mining method in which it is possible to extract from a wider collection of documents the subjects or themes of the documents [5]. A probabilistic model of a domain based on Bayesian methods is the LDA algorithm, one of the most common modeling techniques. This is often considered to be a Latent Semantic Analysis (LSA) probabilistic extensions. LDA's basic idea is that each document has a word distribution that can be defined as.

D. Ontology Modelling

Ontologies contain features such as general vocabulary, reusability, machine-readable content, as well as ordering and structuring information for the Semantic Web application, enabling agent interaction, and semantic searching [7]. Automated learning is the problem in ontology engineering, such as the lack of a fully automated approach to shape ontology using machine learning techniques from a subject corpus or dataset of different topics.

The ontology model was finalized using protégé tools, which is the most popular tool of ontology visualization [8]. The Protégé 5.5.0 tool is being applied for further development in various disciplines for a better understanding of knowledge with the aid of domain professionals in the wildlife.



Graphical model for LDA*Source: Adapted from [5]*

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E. Comparison

Our interactive, web-based visualization framework, LDAvis, has two key functionalities that allow users to understand the topic-term relationships within a fitted LDA model, as well as several additional features that provide additional perspectives on the model [9]. First and foremost, LDAvis allows one to pick a topic to report the words most applicable to the subject. We compared the total term frequency to the approximate term frequency for finding the keywords that appear and are most significant.

F. Evaluation

In our research, we used the output analysis method which was used to assess the outcomes of the research concerning its objectives. Through our research, a novel approach used the LDA visualization model and Ontology model to evaluate each other to windup final output analysis evaluation on this research.[10]. Specified domain classes helped to improve the prediction of hidden topics and keywords from past research papers.

III. Results

The results of this study were represented using abstract past research which serves as an input in Sri Lanka. We used python language for LDA implementation. The abstract of each research paper used as input is interpreted and tokenized with the result that input nouns, adjectives, and verbs are compiled to machine-understandable format. Besides, it removes all the stop words in the research papers.

The tokenized and trimmed text is then processed to the LDA modeling algorithm. That gave production as word sets that could contain keywords that are linked to each other. Such collections of words are classified as various subjects. The LDA model visualization is used to arrange, synthesize broad corpus, and to retrieve topics and hidden keywords.

Fig. 3 and Fig. 4 are the final visualizations of the LDA model which shows the overall keyword for each research paper and the essential keyword using the pyLDAvis library in python. This output allowed the detection of hidden keywords from every abstract. To get the output of the pyLDAvis method we used the equation of saliency and relevance to accommodate the keyword distributions.

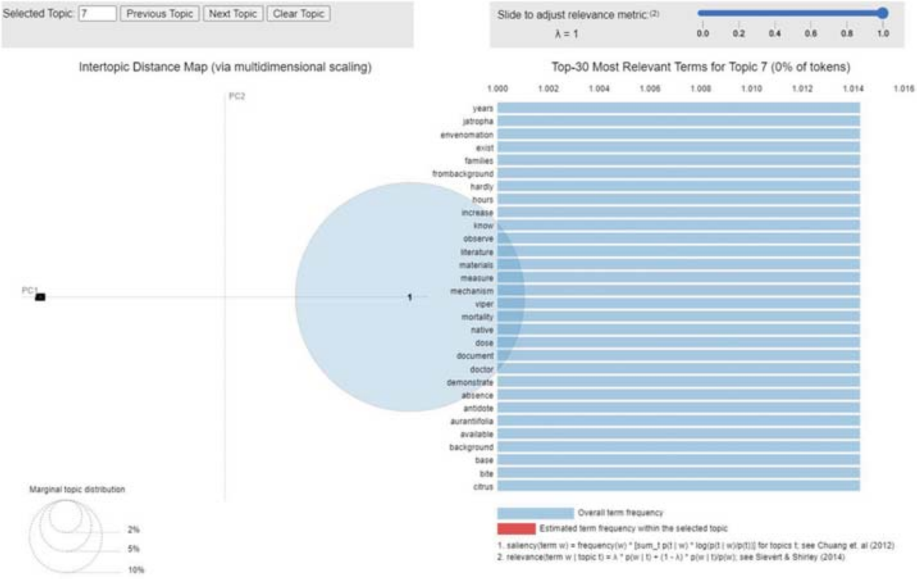
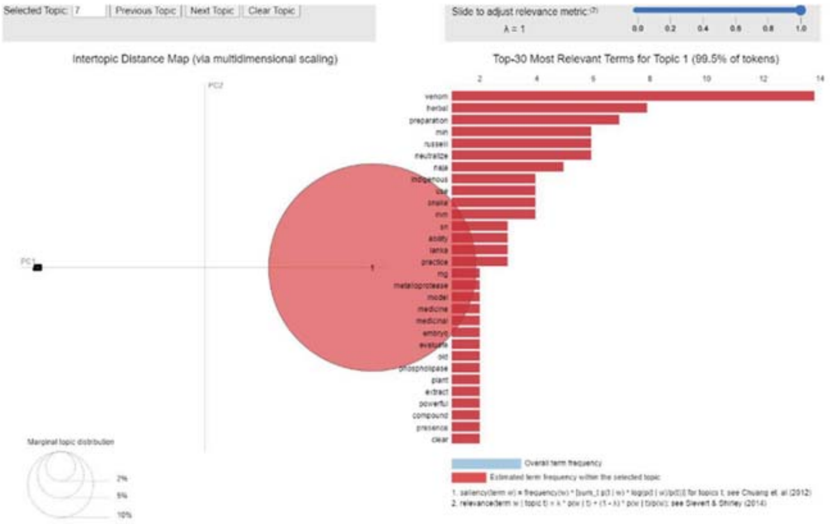

Selected Topic: 7
Previous Topic
Next Topic
Clear Topic
Slide to adjust relevance metric:(2)
λ = 1
0.0
0.2
0.4
0.6
0.8
1.0
Intertopic Distance Map (via multidimensional scaling)
PC2
PC1
1
Marginal topic distribution
2%
5%
10%
Top-30 Most Relevant Terms for Topic 7 (0% of tokens)
1.000
1.002
1.004
1.006
1.008
1.010
1.012
1.014
1.016
years
jatropha
envenomation
exist
families
frombackground
hardly
hours
increase
know
observe
literature
materials
measure
mechanism
viper
mortality
native
dose
document
doctor
demonstrate
absence
antidote
aurantifolia
available
background
base
bite
citrus
Overall term frequency
Estimated term frequency within the selected topic
1. saliency(term w) = frequency(w) * [sum_t p(t | w) * log(p(t | w)/p(t))] for topics t; see Chuang et. al (2012)
2. relevance(term w | topic t) = λ * p(w | t) + (1 - λ) * p(w | t)/p(w); see Sievert & Shirley (2014)

Fig. 2. LDA model for overall keyword


Selected Topic: 7
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Marginal topic distribution
2%
5%
10%
Top-30 Most Relevant Terms for Topic 1 (99.5% of tokens)
2
4
6
8
10
12
14
venom
herbal
preparation
min
russell
neutralize
naja
indigenous
use
snake
mm
sri
ability
lanka
practice
mg
metalloprotease
model
medicine
medicinal
embryo
evaluate
old
phospholipase
plant
extract
powerful
compound
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clear
Overall term frequency
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2. relevance(term w | topic t) = λ * p(w | t) + (1 - λ) * p(w | t)/p(w); see Sievert & Shirley (2014)

Fig 4 LDA model for estimated keyword

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The intertropical distance map is indicated via multidimensional scaling by our LDA output. In CE literature and inter-topic distance, the top 20 salient keywords.

$$Saliency = frequency \times \left[sum\, p(t|w) \times \log\left(p\left((t|w)/p(t)\right)\right)\right] \qquad (1)$$

Where (1), t- Topic, Frequency (w) –frequency of word w, p (t|w) - conditional probability: the probability that observed word w was formed by latent topic t, p (t) - the probability of topic t, sum p (t|w) - aggregation of the probability of observed word w was generated by latent topic t

This equation (1) defines (in a theoretical context of information Sense) for determining the generating topic, how informative the particular term w, versus a randomly selected term, is. For example, if a word w appears in all subjects, observing the word tells us nothing about the document's topical mixture; therefore, the word will obtain a low distinctive score. The saliency of a term [11] shall be determined by the product:

$$Relevance = \lambda * p(w|t) + (1-\lambda) * p(w|t)/p(w) \qquad (2)$$

Where (2), λ –slide to adjust relevant metric, p (w|t) - conditional probability: the probability of observed word w was generated by t which is the latent topic, p (w) –the likelihood of word w [12]

Using this output from LDA we compared the ontology output. Analyzed the estimated keywords and their ontology domain formation. The protégé tool used the Sri Lankan wildlife research domain ontology to be developed. The partial view of the final ontology production is shown in Fig 5 and Fig 6.

Each research papers' keyword generated by LDA visualization model estimation was analyzed through the ontograph and each paper classification performed. Table I shows the partial outcome of the study. We manually compared the results from both LDA and terminology ontology. Our study's output evaluation was 92% accuracy to the overall conclusion.

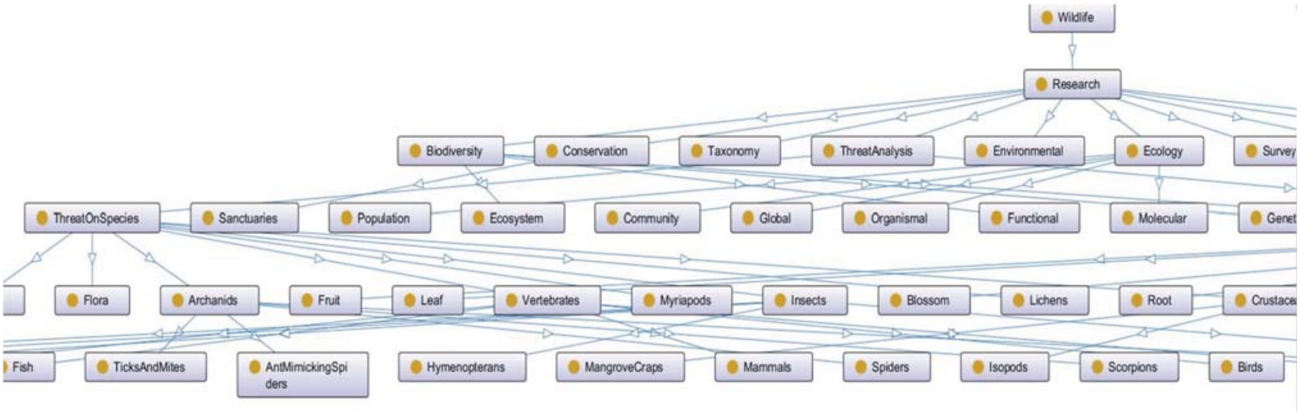

Fig. 3. Ontograph partial view

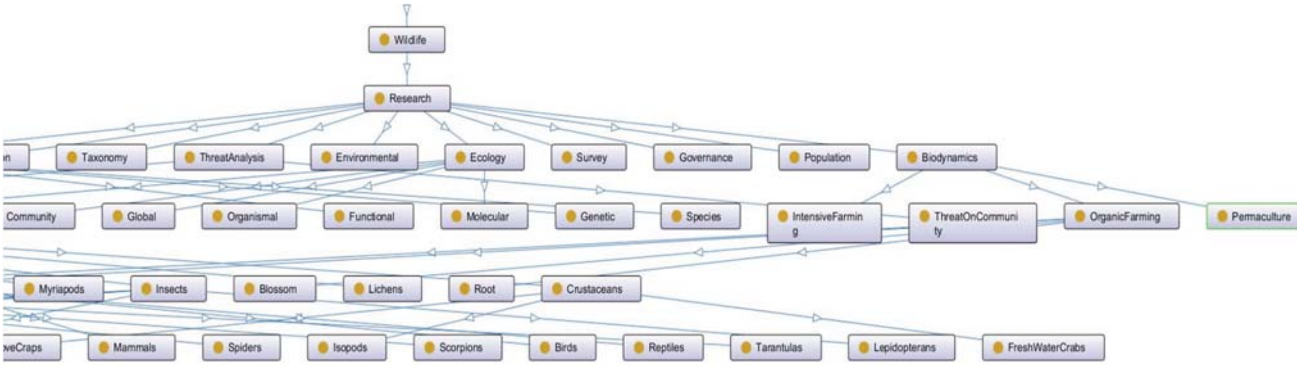

Fig. 4. Ontograph partial view

TABLE I. PARTIAL FINAL OUTPUT

Paper Name	Top 3 Main keywords	Main classes
Characterization of Daboia russelii and Naja naja venom neutralizing ability of an undocumented indigenous medication in Sri Lanka [13]	Venom, Herbal, Preparation	Reptile, Conservation
Marine bacteria and fungi as sources for bioactive compounds: present status and future trends [14]	Marine, bacteria, fungi	Biodiversity, ThreatOnSpecies
Reptile diversity in *beraliya mukalana* proposed forest reserve, Galle district, Sri Lanka [15]	Forest, reptile, anthropogenic	Environment, Reptile
Changes in soil carbon stocks under different agricultural management practices in North Sri Lanka [16]	Soil, fertilizer, fraction	Ecology, Permaculture

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IV. Conclusion And Future Works

In this paper, we have suggested a domain-based and self-learning model that is used to identify the hidden keyword of the research area and suggesting creative new topics from past research works. For past research papers using terminology ontologies, we had developed a new approach for automatic classification, and this approach applied the LDA model to generate topics, and the progress of ontology does not need the seed of domain knowledge, it only requires a given document corpus. We generated LDA keywords for selected research abstracts of the past wildlife domain in Sri Lanka. We devise a semi-automated topic labeling for the research papers. The final experiment has proved effective results.

This work reduced the complexity to label the research papers without any domain pre-knowledge. Using this method the hidden keyword and the relations between the keywords also identify to help future research ideas.

In this topic labeling method, there is some inefficient while ontology classification. Because there are several cross path hierarchy moves of keywords identified from LDA. So when we used ontology it collapsed the different path into ontograph. So we will use other classification methods to fully automated our methods.

ACKNOWLEDGEMENT

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