International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 06 | June - 2023 SJIF Rating: 8.176 ISSN: 2582-3930

AUTOMATIC TEXT CLASSIFICATION TO SUPPORT SYSTEMATIC REVIEWS IN MEDICINE

[1]Vishnu Vardhan, [2]Vivek,[3] B Kalyani Rao,[4]S.Satyanarayana Reddy, [1]Venkateswara

Department of AIML School of Engineering Malla Reddy University, Hyderabad.

ABSTRACT:

Medical publications continue to be a prolific source of information at an astronomical rate, with the amount of information added every day. Increasing amounts of information are being processed through systematic reviews. EBM relies on them as a fundamental tool. In this paper, we demonstrate that automatic text classification can speed up the reviewing process for medical topics. we propose a per-question classification strategy that exploits the specific protocol of a systematic review. This study shows that when integrating the classifier into the review workflow, the per-question method outperforms the global method. By locating and investigating the most recent applicable research, medical systematic reviews present thorough responses to specific concerns within an admittedly restricted field of expertise. A group of experts in the field must evaluate numerous articles as part of this procedure in order to discover the suitable instances, which typically takes a lot of time and effort. Encouraging this method is our aim. employing automated tools. A few weeks ago, it was trendy to use text methodologies for classification to partially automate the screening process by giving the panel of experts decisions support, thereby lowering the time and labour demands. In the present article, we make an impact on this field of research by performing a thorough set of categorization of text tests on a corpus created with an analysis, we make a contribution to this field of research in this paper.

INTRODUCTION: Medical systematic reviews help integrate medical research into everyday use by assembling the body of existing research that is pertinent to a given medical issue. This gathering of the latest information is helpful for all to consider, particularly as experts and those making decisions.
Systematic reviews their output surged in the second half of the 20th century along with a considerable rise in publications in various areas of medical research, nursing, and allied health care. Unfortunately, an adequate quantity of systematic reviews haven't been done to keep up with the enormous growth of clinical trials over the last thirty years. When the situation was looked at the time. The popularity of different text mining methods has risen over the past couple of decades as consequence of the continuously increasing number of related to the popularity of unstructured text documents in electronic formats and the need for flexible evaluation of content Of those techniques, text classification using machine learning is one of the most famous. It involves detecting one or more suitable categories for unstructured texts written in natural languages (such as English, Spanish, etc.). A key area of research right now is the categorization of texts, which has numerous commercial and academic applications in an unlimited number of domains. One of the most visible areas where methods of text mining are utilised in medicine is the discovery of new literature and concept-based search, among other uses. After the collection of data had already been manually screened, the trainee was trained with a set of documents from the applicable medical discipline. These primary research documents corresponded well to the paradigm of a two-class text classifier, as they had been manually rated as either relevant or irrelevant. Once learned, the system was ready to classify unopened papers automatically, helping

the screening process in the same way a human expert does. Therefore, this kind of technology would be intended to help and improve the decision-making process instead of replacing it. Contrary to the previous studies talked about in Section 4, the participants selected either the full research or the abstract.

KEYWORD: Medical systematic reviews, Text mining, Text classification.

AIM: Identifying the predictive algorithm of deep learning for text classification.

OBJECT:

To make it easier to conduct systematic reviews in medicine, automated text classification is used to boost the efficiency and accuracy of the review process. Researchers may carry out reviews more effectively by automating certain steps to save time and resources. Employing manufactured text classification in systematic reviews provides a number of specific objectives. In brief, the implementation of automatic text classification in systematic reviews is designed to optimise the review process by automating routine tasks, improving performance, decreasing bias, and improving the validity and reliability of the review findings.

LITERATURE REVIEW: The task of carefully categorising and evaluating significant research articles in the area of medicine can be greatly helped by performing a literature review using the NLP algorithm for automatic categorization of words. While the algorithm itself is a tool that may help in the literature review process rather that comprehensive approach to carrying out a literature review, includes a number of NLP characteristics, including text classification. The table that follows is an example of how to use text categorization algorithm in a literature review. An automatic medical encoding system relying on the SNOMED classification system had been developed by Ruch, and in 2010. They demonstrated how this technique could properly category medical records and enhance classification process throughput. A support vector machine (SVM) system for organising scientific research was devised by Zhu and Jiang in 2017. They showed that the SVM model might substantially increase the article selection procedure by accurately categorising articles based on their text

EXISTING SYSTEM:

There is ongoing research and development in order to enhance both the precision and efficacy of text classification algorithms, despite the fact that present tools like Covidence, and SWIFT-Review give helpful capabilities for automatic text classification to support systematic reviews in medicine.

PROPOSED SYSTEM:

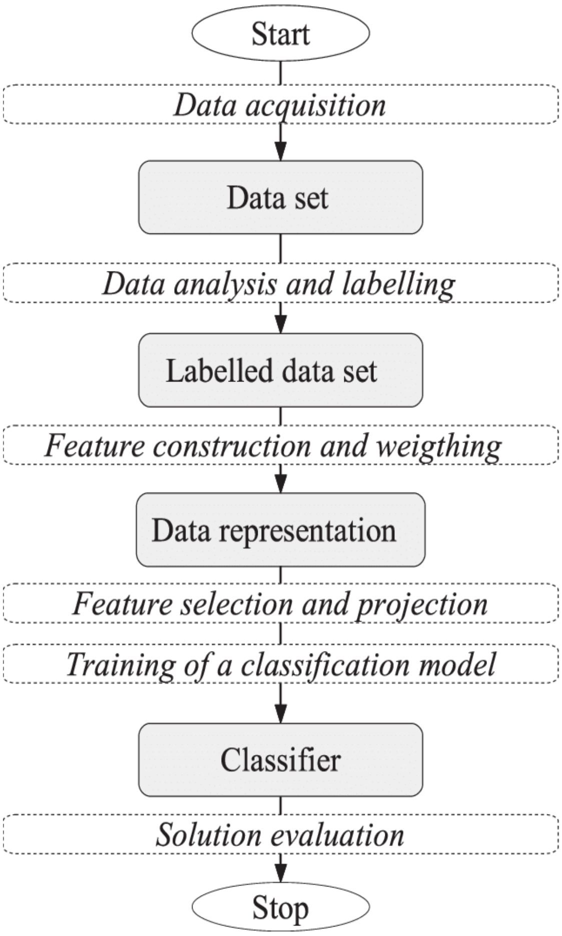
Data Preprocess: The system is going to execute tasks including tokenization, sentence segmentation, stop word removal, and lemmatization on the text data from the articles. The text data is currently prepared for further analysis and feature extraction. Feature Extraction: The system will process the text data and extract the features that are relevant. Word frequencies, n-grammes, TF-IDF values, and word embeddings are a few instances of these features. The articles are meant to be presented quantitatively in order to capture their data and make classification easier. The suggested method aims to automate text classification, decrease laborious work, and raise the clinical efficacy of systematic reviews in medicine. It's necessary that one keep in mind that human reviewers' experience and taste remain crucial for making the final decision and ensuring the high standard of the systematic review.

METHODS:

The proposed methodology involves a systematic approach to developing an automatic text classification application to support systematic reviews in medicine. The key steps involve defining the research question, collecting and pre-processing data, extracting relevant features, selecting an appropriate algorithm, training and evaluating the model, developing the application, testing with users, and deploying the application.

FLOWCHART:

Fig:



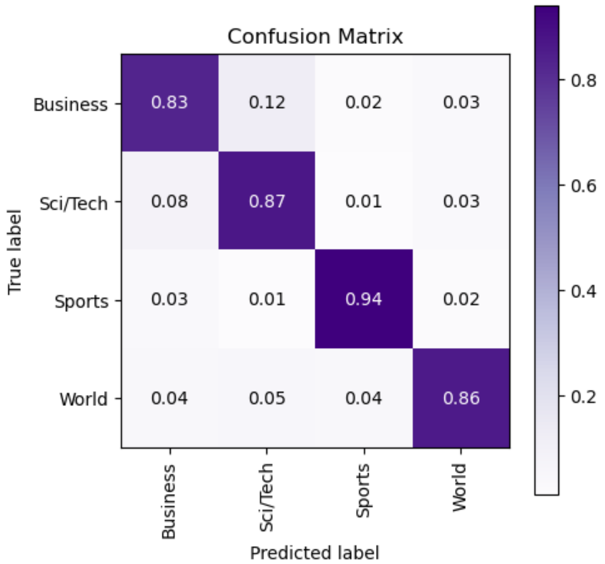
BUILDLING A MODEL:

1. The automatic text classification system's subsequent steps, such as data preprocessin, feature extraction, model training, and evaluation, can be tailored to effectively address this specific study's question and classification task once the research question and task are defined.
2. Gather and preprocess the data: Collecting and preparing the text data is the next stage. To do this, data needs to be washed up, normalised tokenized in order and stemmed or lemmatized. Text data should be as consistent as possible and be free of any unnecessary data, such as stop words or punctuation.
3. Build training and test sets from the data: Construct two sets from the preprocessed data: a training set and a test set. The classification model will be taught with the training set, and its performance can be evaluated using the test set.
4. Once the model has been trained, you can assess how well it works using the test set. Accuracy, precision, recall, and F1-score are some of the common gauges of performance. The efficiency of the model can be further checked out using methods like cross-validation.

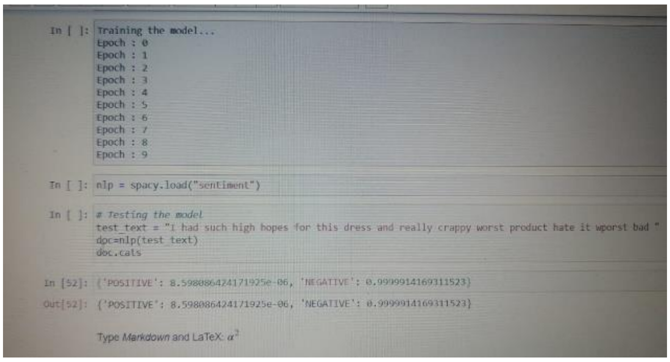
International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 06 | June - 2023 SJIF Rating: 8.176 ISSN: 2582-3930

CONFUSION MATRIX:

- These are the evaluation measures to evaluate the performance of the model.
- Dark blue boxes are the correct prediction with trained model and skyblue boxes shows the wrong predictions.



RESULTS:



CONCLUSION:

We empirically examined the use of automatic text classification in the framework of medical systematic reviews to support the human labour done by experts during the citation screening phase. In the experiments, different feature selection methods, classification algorithms, and feature numbers were all applied to various sections of the provided articles. When the algorithms ignorant Bayes and SVM were used in the analysis of these experiments, overall positive observations were seen.
For all types of articles, the naive Bayes model provided the lowest rate of mistakes in the form of FN, but SVM did just as well when using only titles and incorporating abstracts thereafter. Contrary to the general consensus, the results of this discussion showed how feature selection can make a substantial difference Contrary to accepted knowledge, this part of the text classification process should not be neglected. In this sense, research also offered an intriguing insight into how the best outcomes might be achieved with a small number of attributes. In conclusion, the results showed that systematic reviews can significantly cut down on the number of articles that reviewers must assess by incorporating automatic text classification into the manual screening process.

Reference:[1] Kowsari, Jafari Meimandi, Heidarysafa, Mendu, Barnes, & Brown. (2019). Text Classification Algorithms: A Survey. Information, 10(4), 150.

https://doi.org/10.3390/info10040150

[2] Minaee, S., Kalchbrenner, N., Cambria, E., Nikzad, N., Chenaghlu, M., & Gao, J. (2020).

Deep Learning-Based Text Classification: A Comprehensive Review.

http://arxiv.org/abs/2004.03705

[3] Chaya Liebeskind, S. L. (2020). Deep Learning for Period Classification of Historical Hebrew Texts. Journal of Data Mining and Digital Humanities ISSN 2416-5999, an Open-Access

Journal.

[4] Yi, S., & Liu, X. (2020). Machine learningbased customer sentiment analysis for recommending shoppers, shops based on

customers' review. Complex & Intelligent Systems, 6(3), 621–634.

https://doi.org/10.1007/s40747-020-00155-2

[5] Thangaraj, M., & Sivakami, M. (2018). Text Classification Techniques: A Literature Review.

Interdisciplinary Journal of Information,

Knowledge, and Management, 13, 117–135.

https://doi.org/10.28945/4066

[6] Wahdan, A., AL Hantoobi, S., Salloum, S. A., & Shaalan, K. (2020). A systematic review of text classification research based on deep learning models in the Arabic language. International Journal of Electrical and Computer Engineering (IJECE), 10(6), 6629.https://doi.org/10.11591/ijece.v10i6.pp6629-6643

[7] C A Padmanabha Reddy, Y., Viswanath, P., & Eswara Reddy, B. (2018). Semi-supervised learning: a brief review. International Journal of Engineering & Technology, 7(1.8), 81.

https://doi.org/10.14419/ijet.v7i1.8.9977

[8] Kazeem Moses, A., Joseph Bamidele, A., Roseline Oluwaseun, O., Misra, S., & Abidemi Emmanuel, A. (2021). Applicability of MMRR load balancing algorithm in cloud computing.

International Journal of Computer Mathematics:

Computer Systems Theory, 6(1), 7-20.

[9] Brownlee, J. (2020). Supervised and

unsupervised machine learning algorithms.

Machine Learning Mastery.

https://machinelearningmastery.com/supervised-and-unsupervised-machine-learningalgorithms/

[10] Abiodun, M. K., Awotunde, J. B., Ogundokun,R. O., Misra, S., Adeniyi, E. A., Arowolo, M. O., & Jaglan, V. (2021). Cloud and Big Data: A Mutual Benefit for Organization Development.

In Journal of Physics: Conference Series,

1767(1) IOP Publishing.

[11] Jin Huang, and Ling, C. X. (2005). Using AUC and accuracy in evaluating learning algorithms.

IEEE Transactions on Knowledge and Data Engineering, 17(3), 299–310.

https://doi.org/10.1109/TKDE.2005.50

[12] Ramola, R., Jain, S., and Radivojac, P. (2019). Estimating classification accuracy in positiveunlabeled

learning: characterization and

correction strategies. Pacific Symposium on Biocomputing. Pacific Symposium on

Biocomputing, 24, 124–135.

http://www.ncbi.nlm.nih.gov/pubmed/30864316

[13] Dada, E. G., Bassi, J. S., Chiroma, H.,

Abdulhamid, S. M., Adetunmbi, A. O., and Ajibuwa, O. E. (2019). Machine learning for email spam filtering: review, approaches and open research problems. Heliyon, 5(6), e01802.

https://doi.org/10.1016/j.heliyon.2019.e01802

[14] Hartmann, J., Huppertz, J., Schamp, C., and Heitmann, M. (2019). Comparing automated text classification methods. International Journal of Research in Marketing, 36(1), 20–38.

https://doi.org/10.1016/j.ijresmar.2018.09.009

[15] Soria, D., Garibaldi, J. M., Ambrogi, F., Biganzoli, E. M., and Ellis, I. O. (2011). A 'non-parametric' version of the naive Bayes classifier. Knowledge-Based Systems, 24(6), 775–784.

https://doi.org/10.1016/j.knosys.2011.02.0

[16] Tsangaratos, P., and Ilia, I. (2016). Comparison of a logistic regression and Naïve Bayes classifier in landslide susceptibility assessments: The influence of models complexity and training dataset size. CATENA, 145, 164–179.

https://doi.org/10.1016/j.catena.2016.06.004

[17] Burba, F., Ferraty, F., and Vieu, P. (2009). k - Nearest Neighbour method in functional nonparametric regression. Journal of Nonparametric Statistics, 21(4), 453–469.

https://doi.org/10.1080/10485250802668909

[18] Thanh Noi, P., and Kappas, M. (2017).Comparison of Random Forest, k-NearestNeighbor, and Support Vector MachineClassifiers for Land Cover Classification Using Sentinel-2 Imagery. Sensors, 18(2), 18.https://doi.org/10.3390/s18010018.

[19] Apaydin, H., Feizi, H., Sattari, M. T., Colak, M. S., Shamshirband, S., & Chau, K.-W. (2020). Comparative Analysis of Recurrent Neural Network Architectures for Reservoir Inflow Forecasting. Water, 12(5), 1500.

https://doi.org/10.3390/w12051500

[20] Schmidhuber, J. (2015). Deep learning in neural

networks: An overview. Neural Networks, 61, 85–117.

https://doi.org/10.1016/j.neunet.2014.09.003

[21] Shan Lee, V. L., Gan, K. H., Tan, T. P., & Abdullah, R. (2019). Semi-supervised Learning for Sentiment Classification using a Small Number of Labeled Data. Procedia Computer Science, 161, 577–584.

https://doi.org/10.1016/j.procs.2019.11.159

[22] Boiy, E., & Moens, M.-F. (2009). A machine learning approach to sentiment analysis in multilingual Web texts. Information Retrieval,

12(5), 526–558. https://doi.org/10.1007/s10791-

008-9070-z

[23] Chauhan, P. (2017). Sentiment Analysis: A Comparative Study of Supervised Machine Learning Algorithms Using Rapid miner. International Journal for Research in Applied Science and Engineering Technology, V(XI), 80–89.
https://doi.org/10.22214/ijraset.2017.11011

[24] Kumar, S., & Zymbler, M. (2019). A machine learning approach to analyze customer satisfaction from airline tweets. Journal of Big Data, 6(1), 62. https://doi.org/10.1186/s40537-019-0224-1

[25] Yin-Wen Chang, Cho-Jui Hsieh, Kai-Wei Chang, M. R. and C.-J. L. (2010). Training and Testing Low-degree Polynomial Data Mappings via Linear SVM. Journal of Machine Learning Research.