Informatics Institute of Technology

In Collaboration With

The University of Westminster, UK



*The University of Westminster, Coat of Arms*

**6COSC020C Applied AI**

**Coursework**

Mr. Ammar Raneez

W1761196 | 2019163

Contents

[1. Part A 1](#_Toc117887493)

[Literature Review 1](#_Toc117887494)

[1. Part B 3](#_Toc117887495)

[ML algorithms 3](#_Toc117887496)

[Multinomial Naïve Bayes 3](#_Toc117887497)

[SVM 4](#_Toc117887498)

[Deep sequence models 4](#_Toc117887499)

[CNN (1D Convolution) 4](#_Toc117887500)

[RNN (LSTM) 5](#_Toc117887501)

[References 6](#_Toc117887502)

**Acronyms**

|  |  |
| --- | --- |
| RCT | Randomized Control Trial |
| SVM | Support Vector Machine |
| CNN | Convolutional Neural Networks |
| RNN | Recurrent Neural Networks |
| LSTM | Long Short-Term Memory |
| TF-IDF | Term Frequency-Inverse Document Frequency |

**Domain**: **hospitals & medicine**

**Problem Overview**: The [PubMed RCT dataset](https://arxiv.org/abs/1710.06071) consists of over 200,000 medical paper abstracts; some of the abstracts within the dataset need to be structured better, therefore, are hard to read.

**Goal:** The goal of this project is to create a model capable of splitting apart sentences in the abstract into structured sections (Ex: objectives, methods, results) to facilitate faster reading for researchers, in this case, in the field of medicine, as abstracts can be exceedingly long.

# **1. Part A**

## Literature Review

Without a doubt, one of the major businesses that would benefit significantly from the integration of artificial intelligence is medicine.

The analysis is a crucial component of medicine, which is frequently carried out by doctors, who are also people. Artificial intelligence, in contrast to humans, can quickly digest enormous amounts of data. Humans can only concentrate on one or two things at once, while artificial intelligence can sift through massive volumes of data and identify underlying trends. The ability to learn from novel settings and machine learning are two more characteristics of artificial intelligence. It also can learn from the shortcomings of previous artificial intelligence systems and use that knowledge to enhance performance in the future (Jittprasong, 2022). The present research trend suggests that artificial intelligence may be used in various medical applications (Buch et al., 2018). From this literature review, the use of artificial intelligence in medicine constantly evolves toward a more specialized use rather than a more general application, specifically, towards patient-centered rather than physician-centered. Some of the more recent research is evaluated.

In the domain of cardiopulmonary, Ganzer et al. (2022) proposed a proof-of-concept of an ANN supplementing the Myocardial Sensory Networks to detect Myocardial Ischemia. It was done through Cardiovascular pathophysiological features implemented along with the reversal of the Myocardial Ischemia by ANN-controlled Vagus Nerve Stimulation (VNS). The architecture utilized an LSTM to detect long-term dependencies of cardiovascular data, recognizing more comprehensive features of the specific disease. The authors utilized supervised learning to train the model to differentiate between the four states of Myocardial Infarction. The output was determined by a decoder output score that triggered the delivery of Closed-Loop intact Vagus Nerve Stimulation to reverse the effects of physiological features induced by Myocardial Infarction. However, since the ANN is built using traditional architectures, it still needs to be updated; therefore, newer kinds of stress will be recognized with continuous learning.

Kim et al. (2022a) proposed an explainable AI model for the auto-labelling of chest X-ray images based on their quantitative similarity in the domain of imaging systems. As the model was an explainable AI architecture, it was made generalized, enabling it to be adjustable, tuned, or performance retrained. The introduced approach enabled the fine-tuning of the model to retrain it for a different external dataset by utilizing a probability-of-similarity metric: pSim. It was identified that the auto-labelled images were in agreement with radiologists over 80% of the time for the case of cardiomegaly and pleural effusion; however, it was a contradiction for the case of pulmonary oedema and pneumonia, which produced an observation that different radiologists use different criteria than being general.

In the field of Oncology, Bulten et al. (2022) utilized AI for the diagnosis and Gleason grading of prostate cancer: the PANDA challenge, which includes over a thousand developers who strive to develop AI algorithms for diagnosing prostate cancer based on histopathology. The proposed approach determined Gleason grading based on digital prostate biopsies and is said to achieve a performance equal to pathologists. Validation sets of the US and EU were used to evaluate the algorithm’s performance; however, what was observed was that the change in the data distribution between what was used while training and validating caused over-diagnosis of single instances. Nevertheless, it is worth noting that the sensitivity and specificity surpassed that of pathologists.

Sadasivuni et al. (2022) proposed a fully integrated analogue ML classifier for real-time prediction of sepsis onset utilizing electronic medical records (EMRs). The solution produced a fusion chip that combined ECGs and EMRs based on a score. Utilizing a cloud AI model prevented issues on most wearables, such as the Apple Watch, which still does not have real-time EMR. An ANN was trained on ECGs that were feature extracted and preprocessed internally on the chip. Alongside the ECG model, an EMR model analyses patients’ co-morbidities using vectorized ICD10 codes and TF-IDF algorithm to predict the sepsis probability. The two models are combined to generate a sepsis score and aggregate it into a fusion model that the meta-learner analysis for the final prediction. However, the model was hard coded into the chip, preventing it from being able to be updated in future. It is, however, worth noting that it was identified that the chip was capable of 93% accuracy in predicting sepsis four hours before the onset.

# **1. Part B**

Techniques that can be applied to the problem

* ML algorithms
  + Multinomial Naïve Bayes
  + SVM
* Deep sequence models
  + CNN (Convolutional Neural Network)
  + RNN (Recurrent Neural Network)

## ML algorithms

ML algorithms do not understand text data; converting them into numbers is a priority. Specifically, in this case, the labels would be the category each sentence belongs to, and the features would be the sentence itself. Encoding the labels will convert them into numbers, and passing the sentences into a [TFidfVectorizer](https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.TfidfVectorizer.html) will convert them into numbers. The encoded labels and vectorized sentences can then be passed into the Naïve Bayes and SVM algorithms as inputs. The output is expected to return a list of encoded labels upon evaluating some test sentences.

### Multinomial Naïve Bayes

The Naïve Bayes is simply a classifier based on applying the statistical Bayes’ theorem. A multinomial Naïve Bayes model can be used to fit the data using a TF-IDF algorithm. In the [Scikit-Learn ML roadmap](https://scikit-learn.org/stable/tutorial/machine_learning_map/index.html), the Naïve Bayes algorithm is what is recommended as a baseline starting point for textual data.

The main advantages of this algorithm are that: it is simple to implement, scalable, can handle large amounts of data, and is quick to train. However, the drawback is that this algorithm can produce relatively lower accuracy than more powerful ones. Furthermore, although the algorithm is considered a good classifier, it could be a better estimator as it assumes that all the features are independent.

Since this algorithm does not perform well, it will not be the author’s choice for implementation.

### SVM

SVMs have supervised learning methods for classification, regression and outlier detection. The SVM model can also fit the data using the TF-IDF algorithm.

The main advantages of SVMs are that they are effective when the data is in high dimensions and memory efficient since they can simultaneously utilize a subset of data. They are versatile as the SVM can use multiple functions to decide. However, they are unsuitable for larger datasets and data containing so much noise.

Since the PubMed dataset is significant and likely to contain noise, the author will not use the SVM for implementation.

## Deep sequence models

Inputs for these models are similar to the ones required by the multinomial Naïve Bayes. A vectorization and an embedding layer will be necessary to convert the text to numbers and to capture relationships between those numbers, respectively.

Furthermore, the models work best when all the sentences are of the same length, as creating batches will be facilitated - which can be implemented by adding a tokenization layer.

Therefore, the sentences would be vectorized and embedded beforehand. Furthermore, the labels must be one-hot encoded, as TensorFlow’s loss function prefers one-hot encoded data. Ultimately, the sentences would be vectorized and embedded, while the labels would be one-hot encoded and fed into the model for training.

The outputs of the models would be an array of prediction probabilities upon evaluating the test data. The predicted category of the sentence would be the highest value index.

### CNN (1D Convolution)

A 1D convolutional can be used to model sequence data. Image classification problems inspired the inception of CNNs; the model can learn the internal representations of a 2D input; however, a tweaked procedure works on 1D sequence data, hence the term Conv1D.

The drawbacks of CNN are that, since they are complicated networks, they require a large amount of data and, as a result, take much longer to train. Furthermore, they can be affected by class imbalance and tend to be biased toward the most occurring class. The main advantage of CNN is that they can perform exceptionally well and, at times, even match the performance of RNNs; they have better parallelism and exhibit more stable gradients.

However, as mentioned, the CNN is mainly tailored for image data, and there is a better option for modelling sequence data: RNN.

### RNN (LSTM)

An RNN processes sequence input by iterating through the elements and passes the outputs from one timestep to the next. A Bidirectional RNN can also give the data back to the previous timestep. Arguably, the most common RNN for sequence modelling is LSTM.

LSTMs are great for sequence modelling, especially since it has memory, which is essential when modelling data where the context is important, specifically in this case, for sentences, as the following word depends on the previous. Additionally, training can be much faster as there is no need for parameter fine-tuning as they work well over a broad range of parameters. They do, however, have certain drawbacks. Since it is also a deep neural net, it takes a longer time to train and can require more memory. Further, they can easily overfit the data.

**Choice of the algorithm to explore further**

The author believes that the best way to implement the model is by utilizing an LSTM since it can store the memory of the past, where in this case, specifically, it has information on the words before the current term in the specific sentence. Although the model could overfit, this can be solved using Regularization techniques if necessary, and training the model can utilize Google Colab's GPU, thus reducing training time.

# **References**

Naive Bayes Classifier: Pros & Cons, Applications & Types Explained. (2022). upGrad blog. Available from <https://prod-eks-app-alb-1037681640.ap-south-1.elb.amazonaws.com/blog/naive-bayes-classifier/> [Accessed 25 October 2022].

scikit-learn: machine learning in Python — scikit-learn 1.1.2 documentation. (no date). Available from <https://scikit-learn.org/stable/index.html> [Accessed 25 October 2022].

Tompson, J. et al. (2015). Efficient object localization using Convolutional Networks. 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). June 2015. Boston, MA, USA: IEEE, 648–656. Available from <https://doi.org/10.1109/CVPR.2015.7298664> [Accessed 25 October 2022].

Hochreiter, S. and Schmidhuber, J. (1997). Long Short-Term Memory. Neural Computation, 9 (8), 1735–1780. Available from <https://doi.org/10.1162/neco.1997.9.8.1735> [Accessed 25 September 2022].

K, D. (2020). Top 4 advantages and disadvantages of Support Vector Machine or SVM. Medium. Available from <https://dhirajkumarblog.medium.com/top-4-advantages-and-disadvantages-of-support-vector-machine-or-svm-a3c06a2b107> [Accessed 25 October 2022].

Jittprasong, C. (2022). Artificial Intelligence and Medicine: A literature review. Available from <http://arxiv.org/abs/2205.00322> [Accessed 28 October 2022].

Buch VH, Ahmed I, Maruthappu M. (2018). Artificial intelligence in medicine: current trends and future possibilities. *British Journal of General Practice*. 68:143–144.

Ganzer PD. et al. (2022). Dynamic detection and reversal of myocardial ischemia using an artificially intelligent bioelectronic medicine. *Science Advances*. 8:eabj5473

Kim D, et al. (2022a). Accurate auto-labeling of chest x-ray images based on quantitative similarity to an explainable ai model. *Nature Communications*. 13:1867.

Bulten W. et al. (2022). Artificial intelligence for diagnosis and gleason grading of prostate cancer: the panda challenge. *Nature Medicine*. 28:154–163.

Sadasivuni S, Saha M, Bhatia N, Banerjee I, Sanyal A. (2022). Fusion of fully integrated analog machine learning classifier with electronic medical records for real-time prediction of sepsis onset. *Scientific Reports*. 12:5711.