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| Autor | Title | Work Done | Methodology | Gap |
| Samuel Danso et al. | A verbal autopsy corpus for machine learning of cause of  death | The Verbal Autopsy corpus has human language properties as well as similarities to other corpora. | employing NLP with Machine Learning. | Using medical language questions for additional research outside of their work |
| Samuel Danso et al. | A comparative Study of Machine Learning Methodology for Verbal Autopsy Text Classification | They concentrated on establishing the best baseline results that could be obtained from the methodologies investigated using a Bag-of-Words approach, which will serve as a foundation for creating a classifier with greater accuracy using machine learning techniques. | To improve performance accuracy, use support Vector Machine and a locally-semi-supervised feature reduction strategy. | To increase the Support Vector Machine's accuracy, change or modify the features' identities. |
| Abraham D Flaxman et al. | Random forests for verbal autopsy analysis multisite validation study using clinical diagnostic gold standards | Random forest technique performance for neonatal verbal autopsy without medical training compared to physician-certified verbal autopsy in chance corrected concordance and Cause-Specific Mortality portion accuracy | By teaching random forests to distinguish between each pair of causes, and then aggregating the results using a novel ranking technique, the Random Forest (RF) Method from Machine Learning (ML) was modified to predict the cause of death. | Analyzing current and historical Verbal autopsy with Random Forest methodology |
| Susan Idicula-Thomas et al. | Comparison of Machine learning algorithms applied to symptoms to determine infectious causes of death in children: a national survey of 18,000 verbal autopsies in the Million Death Study in India | The top indications and symptoms for the classification of these Causes of Death are retrieved for each of the diseases, showing that the Support Vector Machine method performed the best with a prediction accuracy of above 0.8. Additionally, they demonstrate how the deceased person's mix of symptoms and indicators could successfully result in the Cause of Death diagnosis. | Building the Cause of Death prediction models is demonstrated utilizing six well-known ML-based techniques, including the support vector machine, gradient boosting modeling, C5.0, artificial neural network, k-nearest neighbor, classification, and regression tree. | To enhance the classification of causes of death from verbal autopsies, automated classification criteria obtained by Machine Learning might be included. |
| Serena Jeblee et al. | Automatically determining cause of death from verbal autopsy naratives | Their best classifier for identifying individual CoDs obtains a sensitivity of.770 for adult fatalities for 15 CoD categories (as opposed to the best sensitivity currently reported, which is.57) and.662 for 48 WHO categories. Our top classifier matches established CoD distribution estimation techniques when it comes to cause-specific mortality fraction accuracy, achieving.962 for 15 categories and.908 for 48 categories when predicting the CoD distribution at the population level. | using four distinct machine learning classifiers: a neural network, a support vector machine, a random forest, and naive Bayes. | Verbal Autopsy narratives provide important information that can  be used by a machine learning system for automated Cause of Death classification |
| Alberto Blanco Alicia Perez et al. | Extracting Cause of Death from verbal Autopsy with Deep Learning interpretable methods | assigning the correct  Cause of Death to a given Verbal Autopsy | Using Deep Learning alongside methods for Natural Language Processing | In order to compare our top models with the current techniques, we are focusing on algebraic operations to take use of dual input combination and alternate representations for conventional classifiers. |
| Sean T. Green et al. | Machine Learning Methods for Verbal Autopsy in Developing Countries | early research on using machine learning algorithms to categorize causes of death in underdeveloped nations is demonstrated. | Using of Support vector machines, boosting with CART, Random Forest, and R programming environment. | age and sexuality to determine the cause of death |
| Jordana Leitao et al. | Revising the WHO verbal autopsy instrument to facilitate routine cause-of-death monitoring | a method of making it widely available for use and evaluation | A review of existing VA instruments was conducted. The World Health Organization (WHO) then facilitated an international consultation process to review existing VA instrument experiences, including those from WHO, the Demographic Evaluation of Populations and their Health in Developing Countries (INDEPTH) Network, Inter VA, and the Population Health Metrics Research Consortium (PHMRC). An expert meeting was held to consider developing a workable VA CoD list [with mapping to the International Classification of Diseases and Related Health Problems, Tenth Revision (ICD-10) CoD] as well as the viability and utility of existing VA interview questions in order to undertake systematic simplification. | Instead of involving physicians, this is intended to be used in conjunction with automated models for assigning CoD from VA data. |
| Micheal T. Mapundu et al. | Robust Application of Supervised Machine Learning Techniques for Cause of Death Determination from Verbal Autopsies | evaluating the reliability of different machine learning (ML) methods in identifying the cause of death exclusively from VA narratives that showed to have rich, valuable information | The RF, ANN, KNN, SVM, and bagging in that order beat the other classifiers when eight machine learning methods were used. | The limitation is the usage of VA narratives from the Agincourt Health and Demographic Surveillance Site (HDSS) with only twelve disease categories. Andi using a small dataset |
| Robert E.Schapire | Random Forests | The suggested framework provides information on the predictive power of the random forest based on the weights of the individual predictors and their correlations. | Random forests (RF) | On the smaller data sets, the effect was less pronounced. It does, however, imply that alternative injections of randomness can result in better outcomes, thus more research is necessary in this area. |
| [Siruo Wang](https://www.pnas.org/doi/full/10.1073/pnas.2001238117#con1) et al. | Methods for correcting inference based on outcomes predicted by machine learning | They show how postpi can enhance inference in two separate fields by modeling expected phenotypes in repurposed gene expression data and modeling predicted causes of death in spoken autopsy data. | development methods for correcting statistical inference using outcomes predicted with arbitrarily complicated machine-learning models including random forests and deep neural networks | prediction problems, that they can no longer assume and those errors are independent of the predicted values, since the machine-learning predictions may be more accurate for subsets of the values. |
| Gary king et al. | Verbal Autopsy Methods with Multiple Causes of Death | computationally intensive approach and estimating aggregate proportions | Illustration of the accuracy of this approach. While no method of analyzing verbal autopsy data | intrinsic to the classical supervised classification paradigm is the assumption that the data in the design set are randomly drawn from the same distribution as the points to be classified in the future |
| Muhammad I. A. Durrani et al. | A Semantic-Based Framework for Verbal Autopsy to Identify the Cause of Maternal Death | The semantic-based verbal autopsy framework for maternal death (SVAF-MD) accurately matched manual reports created by gynecologists in 92 percent of the cases where the cause of death was determined to be maternal. | By introducing a semantic-based verbal autopsy framework for maternal death (SVAF-MD) to determine the cause of death, this research offers a solution.  It comprises of the following four primary parts: clinical practice standards, knowledge modeling, and codification of knowledge | None of the authors of this article conducted any potentially harmful experiments on humans or animals. |
| Barnaby C Reeves et Al. | A review of data-derived methods for assigning causes of death from verbal autopsy data. | The necessity for a classifier to be understandable, the number of validated causes of death given to each case, the characteristics of verbal autopsy data, and the goal for which a classifier is being constructed are the four key criteria that impact the choice of classification method. | It examines the benefits and drawbacks of the three primary strategies for determining classification rules empirically: probability density estimates, decision trees using rule-based methods, and linear and other discriminant algorithms. Second, it discusses the considerations that must be made when deciding on a classification approach for determining the cause of death from verbal autopsy data. | A big verbal autopsy dataset is required for comparison of the performance of classifiers developed using various approaches, and this dataset is provided to them. |
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