International Journal of Mathematics and Computer Research

ISSN: 2320-7167

Volume 13 Issue 07 July 2025, Page no. – 5487-5491

Index Copernicus ICV: 57.55, Impact Factor: 8.615

DOI: 10.47191/ijmcr/v13i7.19

Predicting Tuberculosis Treatment Outcome Using Machine Learning Techniques

Akeredolu Motolani Deborah[1], Adeniji Oluwashola David[2], Adeyemi Samuel Oladele[3], Adelusi Bamidele Samuel[4]

[1]Department of Computer Science, Faculty of Science, University of Ibadan, Ibadan, Nigeria
[2]Department of Computer Science, Faculty of Science, University of Ibadan, Ibadan, Nigeria
[3]University of Ibadan college hospital, University of Ibadan.
[3]Department of Computer Science, Faculty of Science, University of Ibadan, Ibadan, Nigeria

ARTICLE INFO

Published Online:
30 July 2025

Corresponding Author:
Adeniji Oluwashola David

ABSTRACT

The cause of tuberculosis can be dangerous and even be a fatal disorder, the mainstream of patients are able to recover with prompt diagnosis and treatment. After a few weeks of treatment, you won't be contagious, and you could start feeling better and as a result most people don’t take their TB medications as prescribed by their doctor. Also taking TB medications or not completing the entire therapy could lead to the bacteria still alive in them to develop antibiotics resistance, which is far more dangerous and difficult to treat. In this research, two (2) machine learning algorithms; Logistic Regression (LR) and Random Forest (RF) were employed for predicting tuberculosis treatment outcome in order to ensure treatment completion for favorable outcome. GridSearchCV was used to improve the models performance and of the two developed model, both models performed very well with LR having an accuracy of 75%, and RF an accuracy of 55%.

KEYWORDS: Tuberculosis, machine learning, outcome, predicting, resistance

I. INTRODUCTION

The world health organization (who) views tuberculosis (tb), a disease brought on by the mycobacterium uberculosis bacillus, as an international epidemic owing to its large projection of over 1.4 million casualties in the past three years [1]. across the globe, tuberculosis is the 9th killer of humans and the most highly transmissible disease [2]. in 2018, an estimated 1.2 million hiv-negative people died from tuberculosis, and an additional 251,000 died from hiv infection. in 2018, about 10 million people worldwide developed tuberculosis, and this figure has remained relatively stable in recent years. The burden of disease varies widely across countries, ranging from less than 5 to more than 500 cases per 100,000 population per year [3]. Tuberculosis (TB) is a treatable and curable infectious disease [4], however, the global burden remains high with over 10.4million TB cases and 1.7 million deaths, 95% of which occurred in developing countries. TB is now ranked the ninth leading cause of death globally and first among single infectious diseases. The WHO identified 30 countries as high burden countries (HBC) for TB, multi-drug resistant TB (MDR-TB), and TB/HIV; these countries accounted for 87% of all estimated TB cases in 2017 . Yet, only seven nations, including Nigeria, carried 64% of the world's TB burden. In 2016, only 6.6 million TB cases were notified to the National TB Programs (NTPs) from estimated global TB cases of 10.4 million, and subsequently to WHO, translating to a global treatment coverage of 61%. Similarly, of the 10 million estimated cases for 2017, 3.4 million TB cases were missed or not notified globally. Confusion surrounding the estimated incidence, underdiagnoses, and underreporting are three causes for the missing instances [5]. Nigeria placed 7th amongst some of the Thirty HBCs worldwide and the top nation in Africa [6]. The treatment coverage for Nigeria in 2017 was 27%, with more than 302,906 drug-susceptible TB cases, 18,000 drug-resistant TB cases, and 48,550 child TB cases missing . Nigeria contributed 9% of the unreported cases worldwide and was one of the top 10 nations responsible for 80% of the unreported Tuberculosis cases in 2017 . In Nigeria, just 26% of all medical institutions and 5% of privately owned medical centers were served by Tuberculosis service delivery. Just under 20% of primary medical centers delivered Tuberculosis services, compared to 75.5% of secondary medical centers. Last but not least, there were insufficient amounts of testing support delivered, with just 390 GeneXpert locations nationwide (48% local government area insurance with 38% use level) as well as 2,650 microscopy facilities nationwide. Although tuberculosis can be a dangerous and even fatal condition, the majority of patients are able to fully recover with prompt diagnosis and treatment. You might only need one or two TB drugs if you have latent tuberculosis but for active TB, several medications must be taken at once, especially if the strain is drug-resistant. Common symptoms of active lung TB are cough with sputum and blood at times, chest pains, weakness, weight loss, fever and night sweats. WHO recommends the use of rapid molecular diagnostic tests as the initial diagnostic test in all persons with signs and symptoms of TB as they have high diagnostic accuracy and will lead to major improvements in the early detection of TB and drug-resistant TB. Rapid tests recommended by WHO are the Xpert MTB/RIF Ultra and Truenat assays.

Tuberculosis is a deadly infection that can be cured with the right diagnosis and treatments, after a few weeks, you won't be contagious, and you could start feeling better and as a result most people don’t take their TB meds as prescribed by their doctor, quit taking them or don’t complete the entire term of therapy which could lead to the bacteria still alive in them to develop antibiotics resistance, and this is far more dangerous and difficult to treat. This research aims at developing a machine-learning model that will predict the outcome of a TB patient treatment course in order to ensure treatment completion for better outcome.

II. RELATED WORKS

According to Ekins et al. [7], Approaches utilizing machine learning and AI are crucial for detecting and forecasting tuberculosis. A collection of bio-inspired algorithms known as artificial intelligence (AI) are employed to address issues in a variety of applications. Machine learning (ML), a popular topic within this broad field, uses the concept of modifying variables in either regression or classification operations to enable models to learn from instances of data [8]. Depending on how the metrics are adjusted, there are various machine learning (ML) techniques. Asad et al [11] used five algorithms; ANN, SVM, K-NN, RF and J48 in order to identify and find the association between the attributes that were the main cause behind treatment failure.

Results were obtained of all and top-11 features in order to evaluate the performance of selected attributes. This study gave the highest average accuracy of 78% using ANN, RF came up with 71% of accuracy and SVM gave 75% accuracy. The result showed that the top attributes were the great cause of leading a patient towards the treatment failure. Balogun et al [12] evaluated different machine learning methods for predicting tuberculosis (TB) patients' treatment outcomes. The findings indicated that MLP (Multi-layer Perceptron) performed the best in predicting treatment outcomes among the tested models. Additionally, age and how long people stay in the hospital were major risk factors for getting TB. However, the study was gathered using the hospital's record, which introduces a potential vulnerability to biases in the estimation of criteria such as sensitivity. While the findings gives insights of the performance of machine learning methods for TB risk factor prediction, care should be taken when analyzing results due to limitations associated with the data source and the possibility of biases.

Hayes [13] employed the use of a random forest based dynamic predictive model for predicting of outcomes in recurrent (relapsed) TB patients with the aid of their demography and clinical data. The goal was to be able to determine whether a patient with recurrent TB would be cured after treatment period of 24 months. A dataset of about 281 patients which contained patients who had TB relapse was used. He then trained the model using several time epochs, from the first month to the 24th month. He discovered that according to his initial hypo-dissertation that adding months of data to the model would increase its accuracy, it fluctuates a little and stays high at each time epoch, but the F1 score for model validation did not increase as data increased. The limitations to his study was in the dataset being used not including patients who had died which could cause the evaluation to be biased, also lead to imbalance in the classification for response variable resulting in one class outweighing others. It focused on the development of a hybrid predictive model for determining the risk level of mental disorders among employees in IT industry in [14]. The prime focus of the study is to predict the possibility of a zero day attack using parameter setting in [15]. Classification of Family Planning Services Utilization for Prediction of Social and Economic Factors in [16] was addressed. *Prediction of Breast Cancer Images Classification Using Bidirectional Long Short Term Memory in [17] was investigated.*

III. METHODOLOGY

In this study, treatment results for TB patients treated in a government hospital in Nigeria was examined. A shortcourse treatment program of directly observed treatment was administered to confirmed TB patients, and the clinical outcome was observed. Figure 1 is the system architecture that shows the process taken for the methodology. The data gotten from the hospital is analyzed, missing values are checked for and replaced. The data is cleaned and the numerical data are scaled using Sklearn StandardScalar. The data has four outcomes; cured, completed, failure, and loss to follow up. All the features in the dataset are used and the heatmap (Fig. 2) shows the relationship between the features to have better understanding of the dataset.

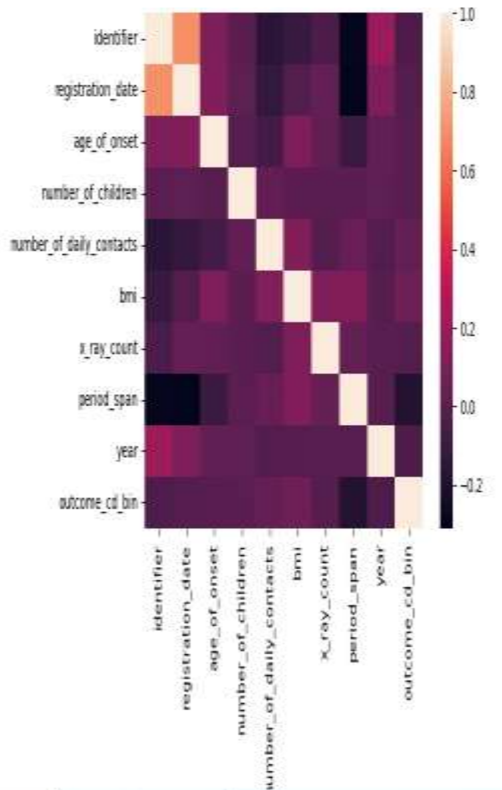

Fig. 2. Heatmap depicting the correlation of the features

3.1 Data Gathering

The data was primarily sourced from Government Chest Hospital, Jericho, Ibadan, DOTS Center. The dataset has 246 rows and 20 columns. Information in the columns contains the following and more: age, gender, lung localization, x-ray count, Comorbidity, regimen count, regimen drug, daily contacts count etc.

3.2 Machine Learning Algorithm

Two machine learning algorithms were employed for the purpose of this research;

Logistic Regression. Is designed to handle classification problems, wherein target variable is a categorical one. The primary objective of logistic regression is about making a function that predicts how likely a new example is to belong to a particular target class. It does this by connecting the features of the data set to the target variable. Logistic model uses logistic function to model binary dependent variable. Parameters of a logistic model is been estimated in regression analysis, using logistic model. It can have binary values like win/lose, pass/fail, true/false; which are indicated using values “0” and “1”. Multinomial Logistic Regression can have 3 or more categories without ordering. Multinomial Logistic Regression are mostly used when there are more than three dependent variables are used for prediction.

Random Forest. Is an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time. It is also an estimator that fits a number of decision tree classifiers on various sub-samples of the data set and uses averaging to improve the predictive accuracy and control over-fitting. For classification tasks, the output of the random forest is the class selected by most trees.

GridSearchCV is used for hyperparameter tuning to identify the most suitable parameter value for each model. Data is split into 70% for training and 30% for testing with 10% from training used for validation. Stratified K-fold validation with 10 splits is also done to evaluate the models performance.

3.3 Result Evaluation. The models performance is then evaluated using performance metrics like;

Accuracy. It is the percentage of all correct predictions made divided by the total number of predictions.

$$TP+TN/ (TP+TN+FP+FN) \quad (1)$$

Precision. It shows how well the model is able to accurately identify true positive instances. It is measured as:

$$TP / (TP + FP) \quad (2)$$

Recall (sensitivity). It shows how well the model is able to identify all positive cases correctly. It is measure as:

$$TP / (TP + FN) \quad (3)$$

F1 score. It is used to measure the how the model performed in a balanced manner, taking into account both precision and recall. It is measured as:

$$2* ((Precision * Recall) / (Precision + Recall) \quad (4)$$

The figure below shows the system Architecture.

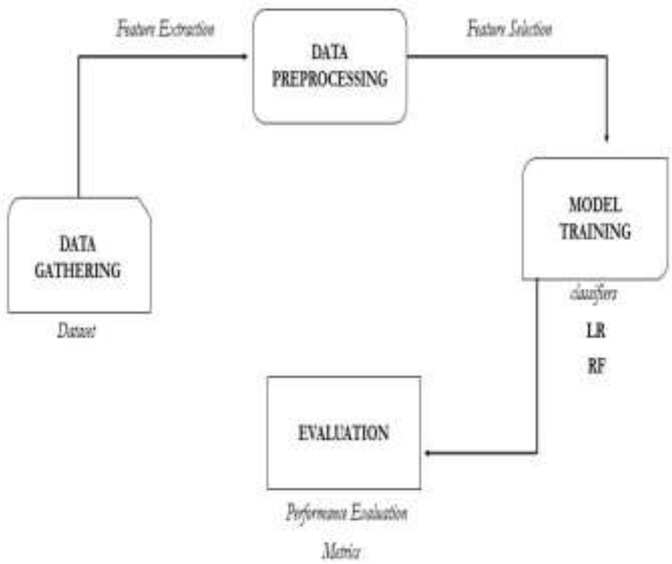

Fig. 1. System Architecture (Source: Akeredolu, 2023)

IV. RESULT AND DISCUSSION

A. The processed data, which is split into 70% for training, is trained on the models developed and the remaining 30% for testing the models. Result of the models discussed is based on the testing dataset. The classification report for Logistic Regression (Table 1) shows a very high percentage of performance metrics which means the model predicts most of the values in each classes correctly which will in turn results in to a very high accuracy of the model.

Table1: Classification Report for LR

accuracy score: 0.9324324324324325

classification report:

	precision	recall	f1-score	support
1	0.83	1.00	0.91	25
2	1.00	0.67	0.80	15
3	1.00	1.00	1.00	34
accuracy			0.93	74
macro avg	0.94	0.89	0.90	74
weighted avg	0.94	0.93	0.93	74

This The classes 2 and 3 shows that the model accurately predicts all the positive instances in the class. The recall score of class 1 and 3 shows that the model did not predict or have any false negative values but the recall for class 2 shows that there were false instances predicted. A closer look at the matrix (Fig. 3) shows us that a class is missing from the test data, this is a result of the test portion of the split data not having any instances of the class thereby reducing the classes to three

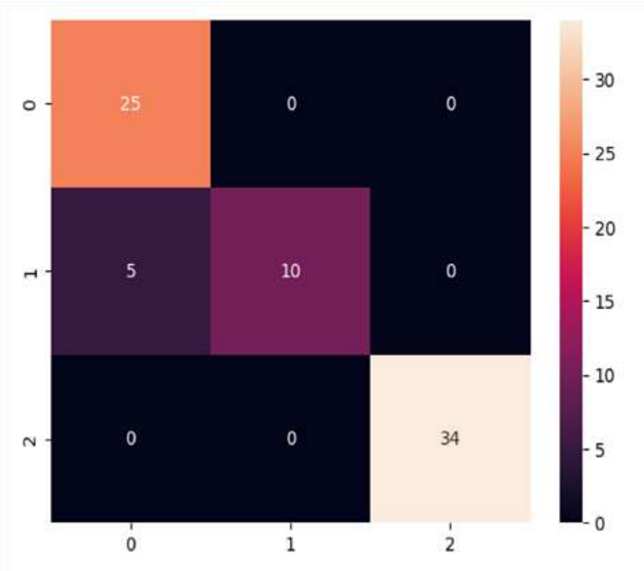

Fig. 3. Logistic Regression

Random Forest classification report (Table 2) also shows very high percentage of performance metrics, which means the model also did a good job of predicting most of the values in each classes correctly which in turn resulted in a very high accuracy of the model.

Table1: Classification Report for RF

accuracy score: 0.9324324324324325

classification report:

	precision	recall	f1-score	support
0	0.00	0.00	0.00	0
1	0.83	1.00	0.91	25
2	1.00	0.67	0.80	15
3	1.00	1.00	1.00	34
micro avg	0.93	0.93	0.93	74
macro avg	0.71	0.67	0.68	74
weighted avg	0.94	0.93	0.93	74

The classes 2 and 3 shows that the model correctly predicts all the values in the class. And the recall score of class 1 and 3 shows that the model did not predict or have any false negative values. Also a closer look at the matrix (Fig. 4) shows us that a class is missing from the test data, which is also a result of the test portion of the split data not having any instances of the class thereby reducing the classes to three.

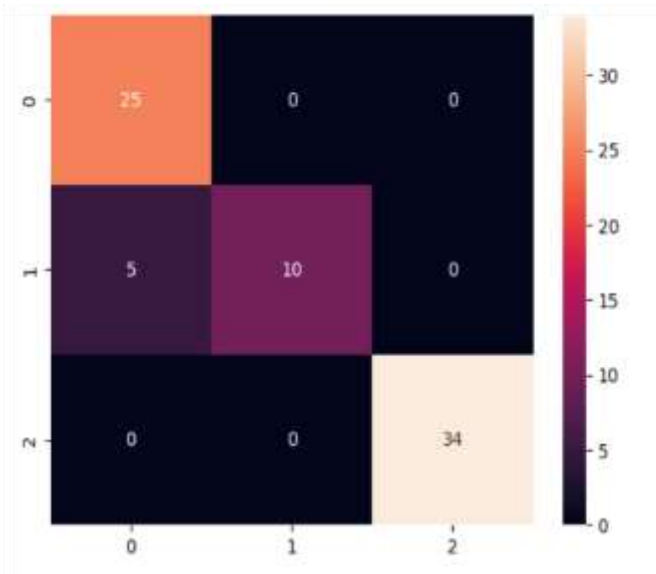

Fig. 4. Random Forest

V. CONCLUSION

This research used trained dataset on two (2) machine learning algorithms to predict tuberculosis treatment outcome in patient and the model with the best performance in terms of prediction accuracy was determined. Both models performed well with accuracy of over 90%. Although the limited number of dataset available might lead to bias in the result. This models can be used to determine how new TB diagnosed patients will respond to their treatment therapy. This work recognizes that TB patients whose supervision in line with DOTS therapy needs to be more active as they are at risk for treatment course interruption which could lead to unfavorable treatment outcome.

VI. ACKNOWLEDGMENT

This research work thank the Ibadan ministry of health for granting us permission and Government Chest Hospital, Jericho, Ibadan for data access.

REFERENCES

1. Annabel, B., Anna, D., Hannah, M.: Global Tuberculosis Report 2019. Geneva: World Heal Organ (2019).
2. World Health Organization. Global tuberculosis report 2017. https://www.who.int/tb/publications/global_report/gtbr2017_main_text.pdf?u%20a=1
3. World Health Organization Global tuberculosis report 2019. http://apps.who.int/iris/bitstream/handle/10665/329368/9789241565714-eng.pdf?ua=1
4. World Health Organization Global tuberculosis report 2018. https://www.who.int/teams/global-tuberculosisprogramme/tb-reports.
5. Daniel, P.C., Christy, L.H.: Finding the Missing Tuberculosis Patients. The Journal of Infectious Diseases, Volume 216, Issue suppl_7, 1 October 2017, Pages S675–S678 (2017)
6. Federal Ministry of Health. (2017). National TB and leprosy control program annual report. Retrieved from www.ntblcp.or.ng/resources
7. Ekins, S., Godbole, A.A., Kéri, G., Orfi, L., Pato, J., Bhat, R.S., Verma, R., Bradley, E.K., Nagaraja, V.: Machine learning and docking models for Mycobacterium tuberculosis topoisomerase I. Tuberculosis, vol. 103, pp. 52–60, Mar. (2017)
8. Panch, T., Szolovits, P., Atun, R.: Artificial intelligence, machine learning and health systems. J Glob Health. 2018 Dec;8(2):020303 (2008)
9. Wang, J., Wang, C., Zhang, W.: Data analysis and forecasting of tuberculosis prevalence rates for smart healthcare based on a novel combination model. Applied sciences, 8(9), 1693 (2018)
10. Awaysheh, A., Wilcke, J., Elvinger, F., Rees, L., Fan, W., Zimmerman, K.L.: Review of medical decision support and machine-learning methods. Veterinary pathology, 56(4), 512-525 (2019)
11. Asad, M., Mahmood, A., Usman, M.: (2020) A machine learning-based framework for Predicting Treatment Failure in tuberculosis: A case study of six countries. Tuberculosis .
12. Balogun, O.S., Olaleye, S.A., Mohsin, M., Toivanen, P.: (2021). Investigating Machine Learning Methods for Tuberculosis Risk Factors Prediction - A Comparative Analysis and Evaluation. Proceedings of the 37th International Business Information Management Association (IBIMA), 2021, 1056-1070
13. Hayes, N.: (2019).Dynamic Prediction of Treatment Outcomes for Recurrent Tuberculosis Patients. Industrial Engineering Undergraduate Honors
14. Adeniji, O.D., Adeyemi, S.O, Ajagbe. (2022). Improved Bagging Ensemble in Predicting Mental Disorder Using Hybridized Random Forest - Artificial Neural Network Model. Informatics Vol.46. 543–550.
15. Adeniji, O. D., Olatunji, O.O (2020).. Zero Day Attack Prediction with Parameter Setting Using Bi Direction Recurrent Neural Network in Cyber Security. International Journal of Computer Science and Information Security IJCSIS Vol. 18. No. 3: 111-118.
16. Adeyemi, S.O., Ochanya., R.A., Adeniji, O.D. (2022).Classification of Family Planning Services Utilization for Prediction of Social and Economic Factors, International Journal of Advanced Engineering and Management Research Vol. 7, No. 05;
17. Idowu, I.R, *Adeniji O.D.*,Shehu, A.E and Togun , O.A.*(2021*) *Prediction of Breast Cancer Images Classification Using Bidirectional Long Short Term Memory and Two-Dimensional Convolutional Neural network. Journal Transactions on Networks and Communications - Vol. 9, No. 25.pp* 29-38.