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Recurrent Active Tuberculosis Prediction Using a Long Short-Term Memory Network

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Abstract

Tuberculosis infections that occur both within the medical facility environments and general population have long been attributed to unrecognised strains of the bacteria and to previously unsuccessful treatment. Identifying active pulmonary TB, for both the initial activation of the disease and recurring disease, is very crucial in breaking the transmission cycle of the disease, particularly in low resourced countries of the developing world. In this paper, a Long Short-Term Memory (LSTM) network was adopted for use by training it using radiological data and other admission specific data into a medical facility. This data is usually made available upon a patient's presentation onto a medical facility by the patient themselves, or through access to historical data. The objective of the LSTM network in this study is to complement the physician's expert opinion on point of presentation of the patient into a medical facility. This study was set up as a non-concurrent prospective study, using data from the National Tuberculosis Laboratory at Mpilo Hospital in Bulawayo, Zimbabwe. Participants were identified through access to laboratory historical data, and the participates were divided into two groups. The first group is referred to as a derivation group and had a total of 5630 isolated instances of suspected active pulmonary TB. The second group was identified as the validation group and had a total of 1388 isolated instances of suspected active pulmonary TB as was determined at the point of presentation. The Long Short-Term Memory (LSTM) network was adopted and employed to predict active recurrent TB cases given the data available on point of presentation. The results of the LSTM prediction were contrasted with both the physicians' assessments and results of subsequent investigations. The accuracy of both the physicians' assessments and LSTM predictions were measured by calculating a c-index based on the area under the receiver operating characteristics curve. The results of this process indicate that the LSTM network significantly outperformed the physicians' assessments, with calculated c-indices of 0.947 ± 0.028 and 0.61 ± 0.045, respectively ($p < 0.05$). By applying the LSTM network to the validation group, similar results are obtained where the corresponding c-indices were 0.923 ± 0.056 and 0.716 ± 0.095, respectively. In conclusion, the LSTM network was shown to have higher potential in identifying patients with recurring pulmonary TB, more accurately than physicians' clinical assessment. This property may prove useful in low resourced countries where health facilities have very high doctor-patient-ratios.

Keywords

Artificial Neural Networks, Tuberculosis, Active Tuberculosis, Recurrent Tuberculosis, Long Short-Term Memory Network

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1. Introduction

Tuberculosis is one of the diseases that require close monitoring and management at governmental and medical facility levels. Normally, the government department responsible for health, in many developing countries, attempts to achieve this by tracking TB infections and instituting an effective treatment and control program. The intended effective result is to identify new TB infections, recurrent infections, and isolate active cases so as to reduce the spread of the disease. Isolation of active TB cases is used as one of the methods to minimise the spread of the disease while intervention methods such as treatment are implemented to cure and/or manage the disease [1-3]. There are many challenges that are faced by physicians in the developing world when recognising and diagnosing persons with active TB. Some of these challenges emanate from the fact that in many cases the patients present with incomplete information, and in such cases the patients are not able to afford some requisite procedures. At the end, the physician will have to arrive at a conclusion in spite of the lack of information. The other source of challenges is to do with the behaviour of TB itself during a recurrence state. In TB recurrence, the symptoms vary widely so much that they may be similar to many other diseases, and without sufficient information, wrong diagnosis may be made [4]. As a result of these challenges, many cases of active tuberculosis, either as first-time activations or as recurrent activation, have gone unnoticed and have potentially spread as new infection to new hosts, thus causing pockets of outbreaks. Many developing countries have recorded numerous outbreaks of TB in different medical facilities and they have classified the cases into the three (3) categories. The first category has been identified as nosocomial outbreaks, and it has been attributed to late diagnosis of TB within health institutions. The second category has been identified as recurrent TB. This has been attributed to poor management of treatment, micro-bacterial drug resistance and poor adherence to treatment by the patient [5-8]. The third category has been identified as new TB infections. Typically, they are associated with contact with an infected person undergoing the active stage of the disease. A record of least 2100 recurring episodes of active tuberculosis were referred and documented at Mpilo Hospital in the year 2018 alone. TB recurrence has been considered one of major complication that occur post treatment. It has been suggested in literature that missed or delayed diagnoses are significantly associated with TB recurrence [9-12]. Other factors that contribute to TB recurrence include nonclassical and atypical radiographic presentation, delayed recognition of drug resistance of the bacteria, and poor management in health care facilities [11, 12].

In developing economies with low resource health care facilities, prediction models that can be used to identify patients with recurrent active TB, presenting itself with atypical radiologic findings have been lacking [10]. The reasons for poor prediction capabilities lie in the complexity of radiologic findings, the low patient samples to allow for generalisation, and the lack of inexpensive modelling techniques with inexpensive supporting equipment [10, 11, 13]. Efforts have been made in literature, to develop computer models through the use of stochastic methods, as well as neural network-based methods, such that they can be used for prediction of active TB at the point of presentation by an incoming patient. El-Solh et al [1] introduced a classification tree to assist physicians in their decision-making processes by regarding whether respiratory isolation for suspicion of active pulmonary TB is needed. The predictive neural network proposed by El-Solh et al [1] achieved a high degree of sensitivity at the expense of low specificity. Other researchers [14-17] have used different types of artificial neural networks to provide a prediction outcome for complex clinical problems, including identification of active TB. The Long Short-Term Memory network is a neural network that was proposed by Gers et al in an effort to develop a network capable of predicting future values given incomplete present value data [20]. The LSTM achieves this by minimising the gradient vanishing problem found in general recurrent neural networks. In essence, the LSTM uses an input gate, output gate and forget gate to control the behaviour of the recurrent learning procedure. Therefore, the LSTM uses a recurrent neural network structure to achieve computations using parallel information processing units, known as neurons [18]. The LSTM network has been shown to be very successful in tasks that involve pattern recognition, when the underlying function is unknown [19, 20]. These intrinsic properties of the LSTM network have been shown to have higher performance accuracy in outcome prediction compared to expert opinion or traditional stochastic methods [19, 20]. Therefore, in this study, we hypothesised that the ability to identify patients correctly with active recurrent pulmonary TB could be improved by using computer analysis involving an LSTM network in a low cost medical facility. To test this hypothesis, we applied an LSTM (available at the CRAN site, at: https://cran.r-project.org/web/packages/automl/) to the analysis of data from patients who are considered to be at high risk for recurrent active pulmonary TB and compared the network's output to physicians' prediction.

2. Materials and Methods

2.1. Study Setting

The study was conducted in retrospect by considering treatment data obtained at Mpilo Hospital, Bulawayo,

Zimbabwe. In this hospital, a total of 480 beds are dedicated for tertiary-care of TB patients. The data was collected from the central laboratory dedicated to TB management on site; the National Tuberculosis Laboratory, Mpilo Site. The data used was abridged to remove personal information, however, all other disease related properties ware available. At the Mpilo Site Laboratory, the study period under consideration ran from January 2012 to December 2017. Mpilo Hospital is the major referral centre for TB treatment and management for four (4) provinces of the country and provides all inpatient medical care for inmates from nearby State prisons and correctional facilities. Because of the shortcomings in the diagnosis of TB and the resulting delays in considering the diagnosis, an automatic isolation policy was instituted by the Ministry of Health and Child Welfare, beginning the early 1990s for all patients from whom an acid-fast smear and culture test was requested. In principle, isolation is discontinued only after documentation of three negative results of acid-fast bacilli smears that were obtained on 3 separate days, or a negative result of an acid-fast bacilli smear derived from BAL. In practice however, patients may abscond from isolation points without official discharge.

2.2. Study Population

Between January 2012 and December 2017, 7040 patients were isolated for suspicion of active recurrent pulmonary TB. Their data was used for retrospective analysis using the Long Short-Term Memory network, against physicians' decisions. Data from 22 patients was excluded from the study because 17 were discharged before three respiratory specimens were collected, and 5 refused diagnostic bronchoscopy. A total of 5630 consecutive patients were used to design a configuration of the LSTM network used in this study, and this dataset is thus referred to as the derivation set. The remaining data from 1388 patients formed the validation set. The decision to isolate patients for suspicion of active TB was made by emergency department physicians, medical residents' or infectious disease fellows after consultation with the attending physician based on symptoms, history of TB exposure, HIV status, positive results of tuberculin skin tests, and radiographic findings. Information regarding demographics (age, gender, date, and duration of isolation), social status, risk factors for HIV infection, and clinical symptoms (fever, night sweats, chest pain, and productive cough for ≥ 2 weeks) was collected from each patient at the time of presentation at the health-care facility. Significant weight loss was defined as a fall of $\geq 10\%$ of ideal body weight within the previous 6 months. The physicians' prediction regarding whether the patient had active recurrent pulmonary TB was also recorded. Data concerning the results of acid-fast bacilli smears and cultures were recorded once the data were available. For those patients who are known to be HIV seropositive, the cluster of differentiation 4 (CD4) counts were entered into the database only if they were obtained within the previous 3 months of patient isolation. HIV-seronegative patients were presumed to have CD4 counts > 200 cells/mL.

2.3. Radiographic Analysis

Chest roentgenograms were divided into two zones: the upper zones delineated by the area above the right and the left fifth ribs posteriorly, and the lower zones below the right and left fifth ribs posteriorly. Upper zone disease was defined as absent only if there were no radiographic abnormalities involving the area above the fifth rib posteriorly. The pattern and distribution of the parenchymal infiltrates (interstitial, nodular, or miliary) or cavities were recorded. The presence and location of adenopathy and pleural effusion were also noted. Interpretation of the chest radiographs was performed by a pulmonologist and a radiologist who were blinded to the microbiology, results of sputum stains, or cultures.

2.4. Bacteriology

The auramine-rhodamine fluorescent stain was used to detect acid-fast organisms on respiratory specimens. Radiometric broth medium (BACTEC; Becton Dickinson Diagnostic Instruments Systems; Sparks, MD) was used for inoculation of acid-fast bacilli cultures. Mycobacterium tuberculosis isolates were confirmed with nucleic acid probes. The bacteriology processes were conducted at the National Tuberculosis Laboratory at Mpilo Hospital in Bulawayo, Zimbabwe.

2.5. Development of the Long Short-Term Memory Network

A Long Short Term Memory (LSTM) network was used in the development of the predictive model. The advantage of the LSTM network lies in the fact that whereas conventional nonlinear regression techniques involve a priori specification of the structure of the regression equations to yield a best fit for the data presented, the LSTM network circumvents these restrictions by adjusting the surface dimension in which the regression surface resides without constraining it to a specific form [21-23]. Generalisation is optimised by modifying the learning rate factor, d, which determines how tightly the network matches its predictions to the data in the training patterns. The structure of the LSTM network used in this model consists of three stacked layers, that is, an input layer, three hidden layers, and an output layer. Input parameters were chosen based on data obtained from the laboratory. The input patterns are formed by 21 distinct parameters shown in Table 1. These parameters were divided into three groups: demographic variables, constitutional symptoms, and radiographic findings. Intervening layers of processors, called LSTM memory blocks, detect higher-order features in

the input layer, analyse the signal, and relay the output to other neurons to make a correct response. The number of neurons in each memory block is determined by the number of patterns in the training set as the LSTM requires one memory block per pattern processed. The output of the LSTM network provides an estimate of the likelihood of recurrent active pulmonary TB.

A 10-fold cross-validation approach was used for evaluation. The entire dataset of the derivation group was divided with a random number generator into 10 subsets. Nine of the 10 subsets were pooled and used for training. The data from the 10th subset was used as an evaluation set during training. The entire process was repeated nine additional times by rotating the subset that was used as the evaluation set during training. The Mean Square Error (MSE) was computed for each of the experimental instance on the entire derivation data set. The mean square errors were averaged, and the LSTM configuration that had a mean square error closest to the average was selected. To normalise the inputs, all independent variables were scaled to a value over a range between 0 and 1. Missing values were handled using data filling methods, where by the missing data item was substituted with the class mean.

2.6. Performance Evaluation

The predictive model derived from the LSTM was tested on an entirely different set of patients (validation dataset) who were not included in the derivation set. The validation dataset comprised all patients who were isolated between January 2011 and June 2012.

Table 1. Input Variables Used to Train the Long Short-Term Network*.

Class	Vulnerability Remark
Demographic variables	Age
	CD4 counts
	Diabetes mellitus
Constitutional symptoms	HIV Status
	PPD
	Chest pain
	Weight loss
	Cough
	Night sweats
	Fever
	Shortness of breath
Radiographic findings	Upper lobe infiltrate
	Lower lobe infiltrate
	Upper lobe cavity
	Lower lobe cavity
	Adenopathy
	Unilateral pleural effusion
	Bilateral pleural effusion
	Pleural thickening
	Miliary pattern
	Normal

*PPD 5 purified protein derivative.

A receiver operating characteristic curve was generated for the LSTM network against physicians' results. The receiver operating characteristic curve represents a graphic display of the true-positives (sensitivity) plotted against the false-positives (specificity) for various thresholds that are used to define active pulmonary TB [24-26]. The c-index was used to estimate diagnostic accuracy by a method described in detail elsewhere [27, 28]. The c-index is equivalent to the area under the receiver operating characteristic curve. In brief, it is calculated by determining the probability of diagnosing active recurrent TB correctly in every possible pair of patients: one who has active recurrent TB, against the other who does not. A bootstrap method was used to calculate directly this measure of accuracy by generating 1000 datasets from our database by random sampling with replacement. Comparisons between the c-indices were assessed based on the confidence intervals (CIs). Statistical significance was accepted at the 5% level.

3. Results

Table 2. Patients' Descriptive Characteristics.

Characteristics	Derivation Group (n = 5630)		Validation Group (n = 1388)	
	MTB (+) n = 2784	MTB (-) n = 2846	MTB (+) n = 604	MTB (-) n = 784
HIV (+)	1422	1666	185	443
PPD (+)	1481	254	258	65
Inmate	1659	987	110	341
DM	533	44	37	0
Cough	2251	2190	369	573
Fever	1955	1677	255	438
Weight loss	1777	772	221	174
Night sweats	1540	143	295	167
Upper lobe infiltrate	1836	171	182	203
Upper lobe cavity	711	66	74	1
Unilateral pleural effusion	237	215	70	43
Miliary pattern	118	0	35	0

Table 3. Comparison of the Clinician and the LSTM Network Performance on the Validation Group (*n = 1388*).

Group	Sensitivity		Specificity		c-Index	
	%	95% CI	%	95% CI	%	95% CI
Derivation						
Physicians	47	32-62	75	71-79	61.3	56.4 - 65.8
LSTM	100	91-100	72	65-77	94.8	91.0 - 98.2
Validation						
Physicians	64	31-89	80	72-89	71.7	64.5 - 78.9
LSTM	100	72-100	69	61-78	92.4	85.8 - 99.1

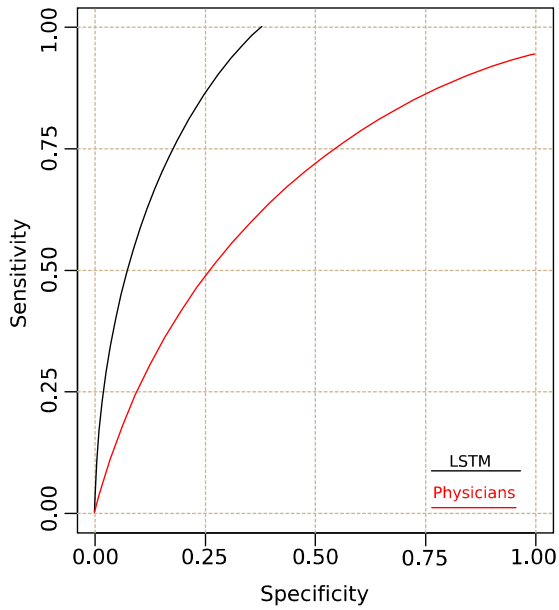

Figure 1. Comparison of the receiver operating characteristic curves for the Long Short Term Memory network (LSTM) and physicians' performance as applied to the validation set.

The characteristics of the population under study are shown in Table 2. A total of 10 experimental instances were conducted. The LSTM model was configured to produce normalised output, that is, output values ranging from 0 (no active pulmonary TB) to 1 (active pulmonary TB). The average mean squared error (MSE) for all 10 experimental instances was 0.009. The LSTM configuration that has an experimental instance with the closest mean square error to the average was used for further analysis. The chosen configuration achieved a sensitivity of 100% (at 95% CI) and a specificity of 72% (at 95% CI). From recorded data, the physicians correctly diagnosed active recurrent pulmonary TB in 654 of 1392 patients, thus an approximate human sensitivity of 47% (at 95% CI) and a specificity of 75% (at 95% CI). The corresponding c-indices for the Long Short-Term Memory network and the physicians were 0.947 ± 0.028 and 0.610 ± 0.045, respectively ($p < 0.001$). The performance of the LSTM network was tested prospectively on the validation dataset of 1388 patients isolated for suspicion of active TB. The LSTM network identified all 126 patients with recurrent active pulmonary TB for a sensitivity of 100% (at 95% CI), and a specificity of 69% (at 95% CI). In comparison, the physicians correctly diagnosed recurrent active pulmonary TB in 80 of the 126 patients, yielding a sensitivity of 64% (at 95% CI), and a specificity of 79% (at 95% CI). Table 3 depicts a comparison of the diagnostic performance of the LSTM network against that of the physicians. The diagnostic accuracy of the LSTM network, when applied to the validation set as reflected by the c-index, was 0.923 ± 0.056 compared with 0.716 ± 0.09 for the physicians' prediction ($p < 0.05$). Figure 1 shows a comparison of the receiver operating characteristic curves for the Long Short-Term Memory network (LSTM) and clinicians' performance as applied to the validation set.

4. Discussion

This study is, to our knowledge, the first to use a Long Short Term Memory network for the diagnosis of recurrent active pulmonary TB in resource constrained settings. The current recommendation issued by the Zimbabwean government to control the spread of TB calls for direct isolation of any patient suspected of having or known to have active TB [29]. However, in many cases, recurrent TB does not present with the standard symptoms, thus its identification in the general population is difficult [1, 29]. Therefore, a standard criterion for early identification of patients with recurrent TB, in resource constrained environments, has not been well established [9, 16, 17]. Further, the task is complicated by the ongoing HIV epidemic, which has created a new profile for patients with recurrent TB that has none of the typical features recognised in classic cases of active pulmonary TB [9]. Predictive models have been developed; however, they have been found to require expensive equipment, thus they are not adept for resource constrained environments such as the developing world [17]. For this reason, many predictive models are not readily usable in resource constrained environments, thus they have not fared very well. Further, many such models lack sensitivity required to operate with insufficient information, hence adding to evidence of the complexity of the problem. A review of the literature revealed only a handful of studies that have attempted to tackle this problem using cases from developing countries. In a study assessing the usefulness of routine admission chest radiography for the detection of pulmonary TB, Narula et al

[12] concluded that chest roentgenograms are still useful in suggesting the diagnosis, particularly in geographic areas with high prevalence for HIV and TB [12]. Nonetheless, failure to suspect TB occurred in 64 of 177 cases of culture-proven TB. Seventeen cases had atypical presentation, and in 29 patients, TB was not diagnosed because of the failure to consider TB despite the presence of upper lobe disease or miliary pattern.

In a similar study, Lakhani and Sundaram [17] evaluated the clinical symptoms and radiographic configuration in 101 patients who were isolated for suspicion of recurrent active TB. The absence of a typical chest radiograph along with the presence of cough, sputum production, and weight loss for 2 weeks were strong negative predictors of active TB. Lakhani and Sundaram [17] acknowledged, however, that the population under study was relatively small in number, and did not include HIV patients with normal radiographic presentation as has been described by Azeez et al [27]. Recently, Fojnica et al [15] developed a classification feed-forward neural network model to predict recurrent active pulmonary TB at the time of admission to a health-care facility. The predictor variables were upper zone disease on chest roentgenogram, fever, weight loss, and CD4 count. The FFANN model was validated in a separate cohort of patients yielding a sensitivity and a specificity of 100% and 48.1%, respectively. The high precision achieved in that population was supposedly less than perfect when tested in a different setting. In contrast to our study, Fojnica et al [15] had full access to information regarding the predictor variables. This is rather unusual for resource constrained health-care facilities, because more often than not, such decisions have to be made with incomplete information. In our LSTM network, an output value is still obtainable with up to 50% of predictor variables missing, however, specificity is significantly impacted by the missing information. The advantage of Long Short-Term Memory networks lies in their ability to process long chains of nonlinear relationships [20]. Because of the clinical complexity, and the pathologic heterogeneity of TB in both initial cases and recurrent cases, correct identification of patients with active disease is unlikely to depend on the presence or absence of a single defining feature. This is even more-so particularly true for resource constrained medical facilities, like those found in the developing world. Hence, it is not surprising that standard linear statistical methodologies are relatively inadequate solutions for this type of problem. In addition, previous studies [1, 3, 10, 16] have shown that clinicians are not exhaustive of the complex interaction among variables, likely due to the high doctor-patient ratio, yet a neural network can exploit these interactions exhaustively. In literature, there are some separate studies that have compared the accuracy of neural networks with that of clinicians to predict disease or outcome [18, 26]. In such studies, emergency department physicians and medical residents were asked to identify myocardial infarction in patients presenting at an emergency department based on clinical and ECG findings. Their conclusions suggest that about 22% of cases of myocardial infarction were missed by physicians, compared with only about 0.03% of cases missed by using a neural network of some kind, thus yielding sensitivities of 77.7% (95% CI, 77 to 82.9%) and 97.2% (95% CI, 97.2 to 97.5%), respectively. In an unrelated study, a conclusion was reached that the overall accuracy of physicians to predict outcome for colorectal cancer ranged from 75% (95% CI, 66 to 84%) to 79% (95% CI, 71 to 87%), compared with 90% (95% CI, 84 to 96%) for the neural network. Even though the study did not isolate for TB, the superior prediction capability of neural networks over physician assessment was observed, which implies that the complexity of biological systems may be beyond the quick field analytic capabilities of physicians in low cost settings.

The objective of the study was to establish the generalisability of LSTM predictive results on different and separate TB population samples. There are many factors that affected generalisability of TB prediction results in our LSTM design, and these include:

a) The structure of the neural network. Factors affecting the design of the LSTM are the number of neurons used, the activation function, the activation window of the forget gate, and the extent of training for the LSTM.

b) The quality of training data in the training dataset, herein referred to as the derivation set. The LSTM has a strong inclination towards overfitting if the derivation set is not wide enough. To avoid overfitting, the selection criteria for cases that were included in the derivation set had to be carefully designed.

c) The quality of data in the testing dataset, herein referred to as the validation set. The testing dataset has to be broad enough to include all reasonable possible TB scenarios such that the network is sufficiently tested.

The results obtained from the experiments reveal that the LSTM configured in this study was able to successfully generalise active TB cases, for both initial active cases and recurrent active cases. The strength of the LSTM network was clearly observed when dealing with incomplete data. The LSTM network was able to use data filling techniques for missing values, for example by using a mean of a class as the filling data-point. With this property, the LSTM was observed to out-perform traditional logistic regression

methods because they lack the ability to handle missing data values, since they omit incomplete tuples from analysis [6, 21]. In our study, the highest percentage of missing data occurred in recalling the result of the purified protein derivative skin test (23%), acid-fast bacilli smear test (9%), and CD4 counts (6%). The high amounts of missing data in the derivative skin test was associated to indeterminant results due to pre-exposure to TB and anti-TB vaccination in childhood. In this study, the LSTM network incorporated these cases after substituting the missing values with the respective class mean.

Many limitations were observed in the study, and they were noted to have the potential of affecting interpretation of results. The limitations include:

a) Training Convergence: The LSTM is a slow converging neural network; thus, it requires large training datasets in order to fully converge. In this study, the derivation set is considerably small at the size of 5630 instances in the data. In these experiments, the LSTM successfully converged however, it is not clear if these results are replicable on different data with the same configurations.

b) Overfitting due to overtraining: Typically, the problem of overfitting happens when the neural network is over-trained on a particular dataset. Since the training dataset was considerably small in this study, there was a danger of overfitting. To minimise the chances of overfitting, the number of neurons for each hidden layer of the LSTM were reduced accordingly such that they corresponded to the dataset size. This process was conducted empirically, and the resulting network size was obtained using the gradual adjustment-error minimisation method. In our case, the network was observed to end up learning not only the training set but also the noise in the data, which led to generalisation with reduced sensitivity. It is, however, encouraging that the accuracy of prediction observed in the validation set, points to the fact that the network architecture is based on robust features rather than memorising the idiosyncrasies embedded in the dataset.

c) Epidemiological differences: It can be postulated that the results obtained in this study may differ from results obtainable from a different population sample. This difference may be attributed to a variance in TB epidemiology based on location and other factors such as the rate of drug resistance, HIV/AIDS prevalence, and access to medical facilities by the general population. Until this model has been extended onto different populations, the study may be viewed only as a pioneering attempt in the use of the LSTM model in the diagnosis of recurrent pulmonary TB, in resource constrained environments.

In addition, only the diagnosis of recurring active pulmonary TB was studied. Application of the model to extrapulmonary or extra-thoracic TB was not conducted. A good case could be made for the extension of this technology for other aspects of TB, should this technique prove to be accurate and reproducible, as the data imply. Our study has several implications regarding the clinical application of artificial neural networks as diagnostic tools for recurrent active TB in resource constrained environments. The use of the LSTM network could provide physicians and health-care workers with a simple, and fast tool with which to assess the risk of recurrent active TB in any patient presenting at a health-care facility, given a history of initial TB treatment. The estimated probability would enable physicians to initiate isolation without delay, thus reducing the risk of TB exposure to health-care workers, and other members of society.

5. Conclusion

The significant effects of developments and novelties in machine learning tools and expert system methodologies have been widely used in different domains, with one of the most important fields being medicine. Based on experience from previous studies, decision making in the medical field has not been simple. The classification systems implemented in medical decision making deliver medical data for faster, and more detailed inspection. Analysis of national statistical data on tuberculosis, in Zimbabwe, indicates that this disease is amongst the most predominant kinds. In this research a new machine learning method of diagnosing active recurrent tuberculosis disease was proposed. The method is an adopted LSTM network developed to be a specialised predictive model. Furthermore, an initial randomised weighting procedure was employed prior to training with data, in order to increase generalisation. The dataset collected from the National Tuberculosis Laboratory at Mpilo Hospital in Bulawayo, Zimbabwe, was applied in this research, making it possible to compare the proposed classification accuracy with other methods. In the current work, an average of 99.1% classification precision was attained via 10-fold cross validation. This is undeniably the highest accuracy rate reported for recurrent TB diagnosis in resource constrained environments. In addition, it was proved in this research that the proposed system can be implemented for various TB diagnosis settings, with very little impact on classification accuracy, especially for large datasets. Further work is thus needed to prove the extensibility of this method across other low cost health-care environments. For further work, data from other countries in the SADC region may be used to further qualify the extensibility and applicability of the technique.

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